Thermal Image-Based Fault Detection and Localization Using Deep Learning

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1. Abstract

This report outlines a deep-learning approach for detecting and locating faults in electrical systems through thermal imaging. While traditional thermography is a non-intrusive method, it often suffers from the limitations of manual analysis and environmental factors that can impact accuracy. This project incorporates YOLOv8, a cutting-edge object detection model, to automate the fault detection process, improving diagnostic accuracy, operational safety, and preventive maintenance. The proposed solution was tested on a dataset of annotated thermal images, showing strong performance in identifying common electrical faults. Future improvements will focus on expanding applications to high-voltage systems and addressing the limitations of the dataset.

2. Introduction

Electrical systems can experience faults like loose connections, overloaded circuits, and failing components, which often show up as increased heat. Thermography, which uses infrared imaging to detect temperature differences, is a non-invasive technique for spotting these issues. However, traditional thermography methods can be time-consuming, depend heavily on manual interpretation, and may lead to inaccuracies.

A significant drawback of conventional thermography is that it is not performed frequently enough. Inspections are usually done once or twice a year, which can result in missing faults that develop outside of these scheduled checks. By automating and increasing the frequency of inspections with the help of artificial intelligence, this gap can be filled, allowing for real-time detection and preventive maintenance. Identifying faults early enables prompt corrective actions, which helps minimize damage and cut operational costs.

Integrating AI greatly improves thermography by facilitating automation, real-time analysis, and standardization. Deep learning models, especially, can enhance the accuracy of fault detection and lessen the reliance on human expertise. This project utilizes YOLOv8, a real-time object detection model, to identify and locate electrical faults, thereby boosting safety measures, enhancing efficiency, and overcoming the limitations of manual inspections.

3. Methodology

3.1 Generalization Across Sites

To ensure adaptability, the deep learning model was trained using data gathered from various sites, which included a range of environmental and operational conditions. By incorporating images from different panels and locations, the model was able to learn how to handle variations like emissivity, reflectivity, and temperature discrepancies. This training method allows the model to generalize fault detection patterns across new and previously unseen panels, making it suitable for a wide range of applications.

3.2 Thermography Process Overview

Thermography is based on the detection of infrared radiation emitted by objects that are above absolute zero. FLIR T335 infrared cameras were utilized to capture thermal images, which convert temperature differences into visual representations. During data collection, factors such as emissivity, reflectivity, humidity, and proximity to heat sources were considered to ensure accuracy.

3.3 Data Collection and Preparation

- **Source:** Over 1,000 infrared images of electrical panels were collected from Amithi Power Consultants (Pvt.) Ltd. The dataset focused on medium- and low-voltage systems, but the approach can be extended to other components with appropriate datasets.
- **Annotation:** Faults were categorized and labeled using Roboflow, with bounding boxes drawn around fault areas.
- **Augmentation:** Techniques such as flipping and color adjustments expanded the dataset to 1,676 images.
- **Dataset Split:** The dataset was divided into 70% training, 20% validation, and 10% testing.

Link to the Dataset

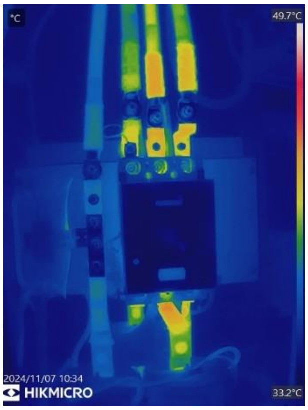


Figure 1:FLIR Camera Therma Image Capturing

3.4 Standards and Assumptions

The project followed specific standards to ensure its practical relevance. During the Manual Annotation of the Dataset, we relied on these standards and assumptions to identify relevant fault classes

Standards:

- **IEC 61439-1:** This standard specifies the allowable temperature rises for low-voltage panel boards, including busbars, conductors, and insulated enclosures. Thermography surveys based on this standard help confirm that component temperatures stay within safe limits.

- **IEC 60502:** This outlines the temperature limits for power cables under both normal and fault conditions.
- **IEC 62271:** This provides guidelines for conducting thermography surveys of high-voltage switchgear, ensuring compliance and safety.

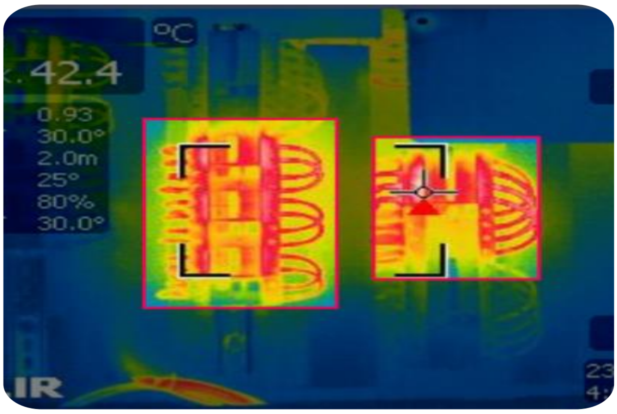
Assumptions:

- The reflection temperature was consistent across all images.
- The temperature range was restricted to 30°C–60°C. In this case, the Temperature Variation Bar on the right side of the image was disregarded to train the model on heat patterns.
- Factors such as emissivity, reflectivity, relative humidity, and proximity to heat-emitting sources were considered to reduce errors in thermal image readings.

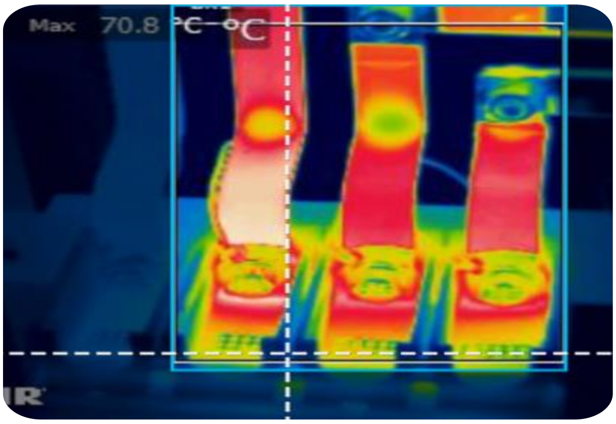
3.5 Fault Categories

The dataset included images of various fault categories:

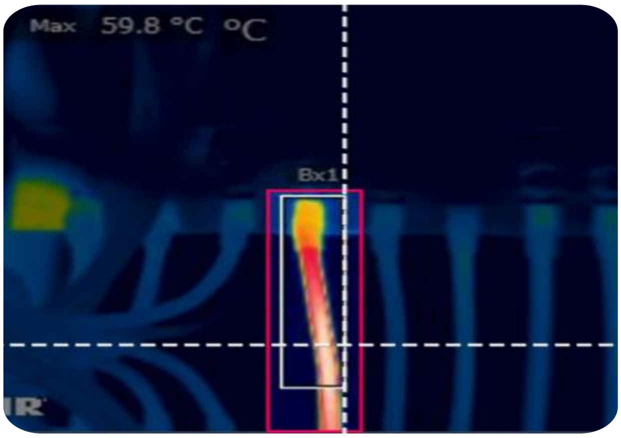
- **Overload Circuits:** Indicated by excessive heat patterns on wires and components.



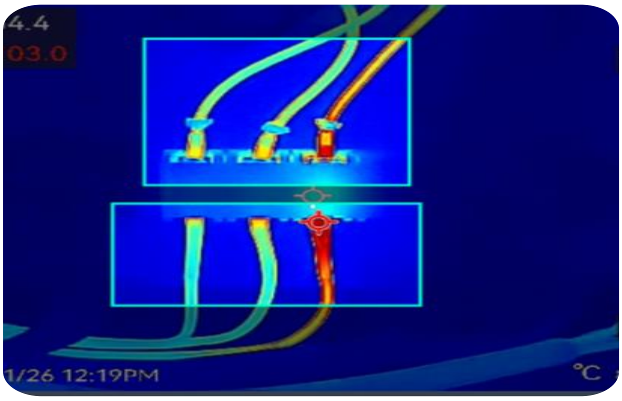
- **Connectivity Issue**: Loose connections or corrosion visible through irregular heat patterns.



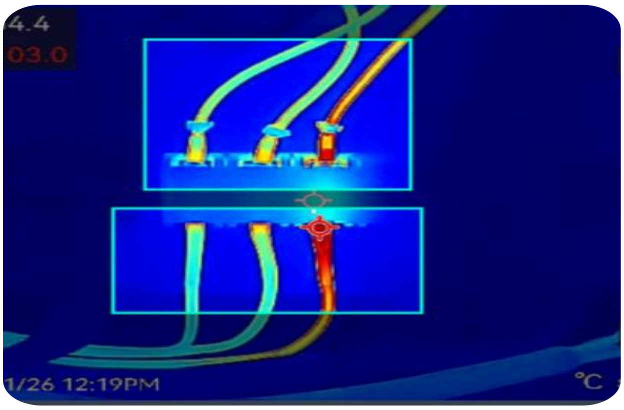
- **Deteriorated Insulation:** Characterized by irregular heat patterns near connection points.



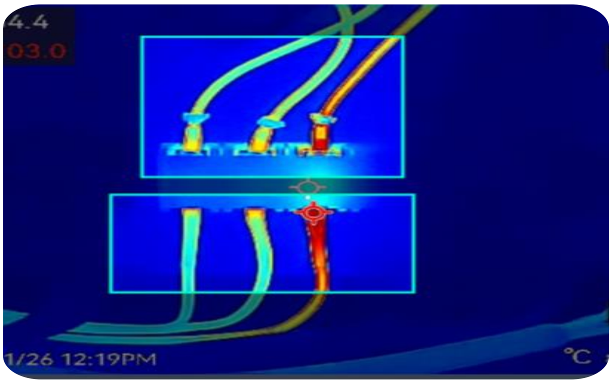
- **Phase Imbalance:** Shown by unequal heat distribution across phases.



- **Faulty Circuit Breakers:** Identified by unusual heat concentrations.



- **Normal Operation:** Represented by expected and uniform heat patterns.



3.6 Deep Learning Model Selection

This project is a computer vision problem so we consider computer vision task models for this project.

YOLOv8 was selected for its real-time object detection capabilities, balancing speed and accuracy. A comparison of potential models is shown below:

Model	Advantages	Limitations	Suitability
ResNet	High classification accuracy	Not specialized for localization	Not ideal for fault localization
Faster R-CNN	High object detection accuracy	Slower inference speed	Impractical for real-time use
YOLOv8	Fast and accurate detection	Requires a large dataset	Chosen for real-time fault detection

4. Implementation

4.1 Training Environment

- Platform: Google Colab
- Framework: PyTorch

The reason to select Pytorch is the easiness of using the Yolo model using Pytorch.

4.2 Training Data and Model Configuration

The YOLOv8 model was trained on a carefully prepared dataset comprising 668 thermal images with 6 fault classes: Connectivity Issues (Loose Connection/ Corroded), Deteriorated Insulation, Faulty Circuit Breakers, Normal Operation Conditions, Overloaded Circuits, and Phase Imbalance. The dataset was divided into training (504 images), validation (102 images), and testing (62 images), ensuring a balanced evaluation across all stages.

Preprocessing involved resizing images to 640×640 pixels. This dimension is a well-balanced size, being computational-efficient and at the same time allowing the resolution needed to detect complicated fault features in thermal images. The square format adheres well to the structure of YOLOv8, where the network functionality is optimized with constant input sizes.

- **Augmentation Techniques:** Horizontal and vertical flipping, cropping, and little blurring were applied to enhance the generalization of the model and help in the detection of faults under differing conditions.
- **Epochs and Training Time:** The model was trained through 50 epochs, a time length decided on the basis of seeing convergence loss and accuracy measures through preliminary runs. This process was conducted on Google Colab with GPU acceleration which took up to about 29 minutes. This is a fair balance between the computational cost and performance of the model.

```
50 epochs completed in 0.481 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 6.3MB
Optimizer stripped from runs/detect/train/weights/best.pt, 6.3MB

Validating runs/detect/train/weights/best.pt...
Ultralytics 8.3.54 🚀 Python-3.10.12 torch-2.5.1+cu121 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 168 layers, 3,006,818 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4
                   all        102        167      0.728      0.794      0.811       0.51
Connectivity Issue-Loose ConnectionCorroded-         37         50      0.571       0.62      0.619      0.328
Deteriorated Insulation         13         14      0.688      0.474      0.631       0.36
Faulty Circuit Breakers         12         19      0.689      0.895      0.827      0.526
Normal Operation Condition         35         45      0.937      0.844      0.928      0.675
   Overloaded Circuits         22         28      0.682      0.929      0.878      0.585
       Phase Imbalance          9         11      0.798          1      0.981      0.585
Speed: 0.2ms preprocess, 3.9ms inference, 0.0ms loss, 3.1ms postprocess per image
```

Link to the code

4.3 Performance Metrics

The model's performance was evaluated using the following metrics:

- **Precision:** 72.8% (correct fault detections).
- **Recall:** 79.3% (proportion of actual faults detected).
- **mAP50:** 81.1% (mean average precision at 50% Intersection Over Union).

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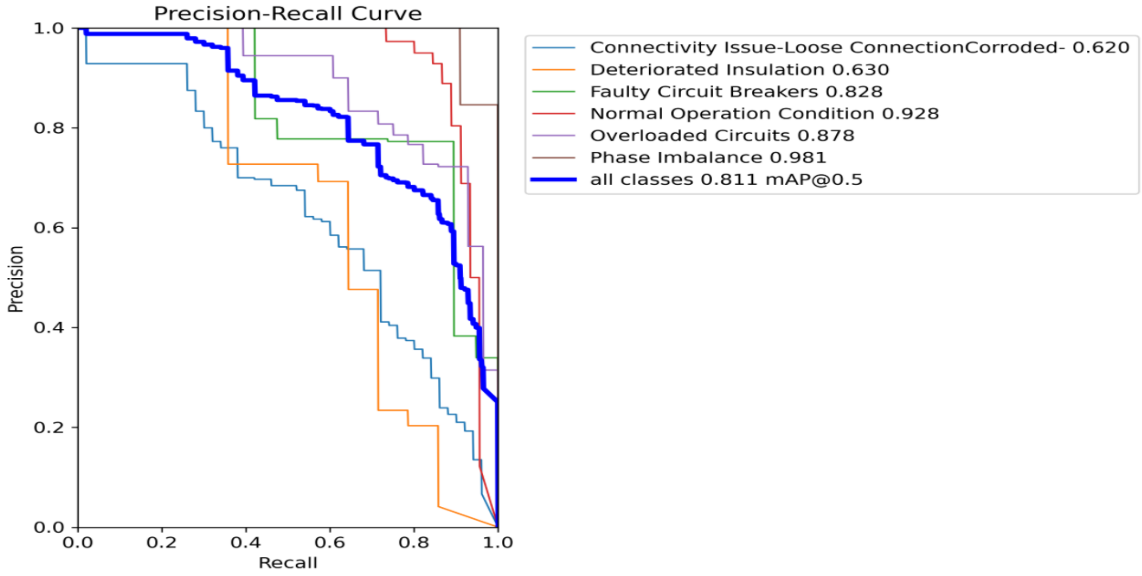
Ultralytics 8.3.54 🚀 Python-3.10.12 torch-2.5.1+cu121 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 168 layers, 3,006,818 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning /content/yolov8/Thermal Imaging.v6i.yolov8/valid/labels.cache... 102 images, 3
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 10
                   all        102        167      0.728      0.793      0.811      0.515
Connectivity Issue-Loose ConnectionCorroded-         37         50      0.573       0.62
Deteriorated Insulation         13         14      0.686       0.47       0.63      0.374
Faulty Circuit Breakers         12         19      0.689      0.895      0.828      0.526
Normal Operation Condition         35         45      0.937      0.844      0.928      0.677
   Overloaded Circuits         22         28      0.684      0.929      0.878      0.586
       Phase Imbalance          9         11      0.799          1      0.981      0.603
Speed: 0.4ms preprocess, 6.1ms inference, 0.0ms loss, 5.5ms postprocess per image
Results saved to runs/detect/train2
```

4.4 Performance Curve on Validation

The subsequent Precision-Recall Curve delineates the detection performance across various fault classes, emphasizing the trade-offs between precision and recall for each category. The mAP@0.5 score of 81.1% signifies the model's robust overall accuracy:

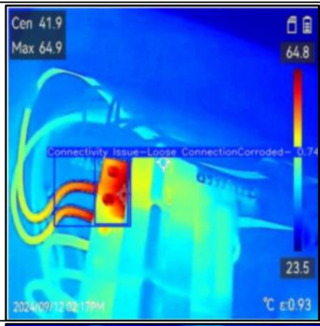
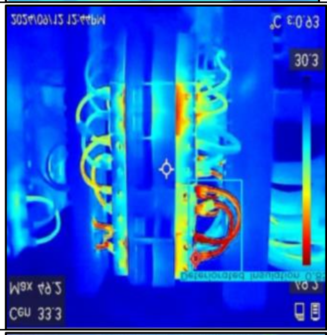
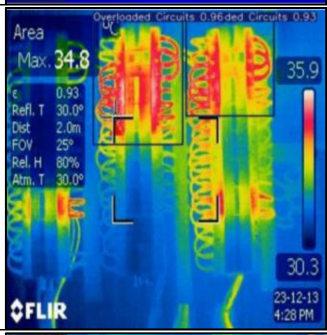
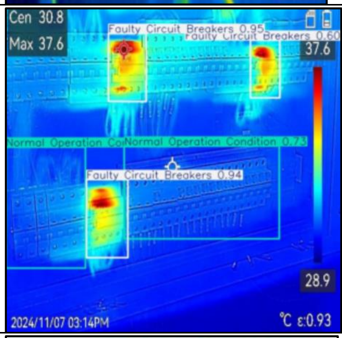
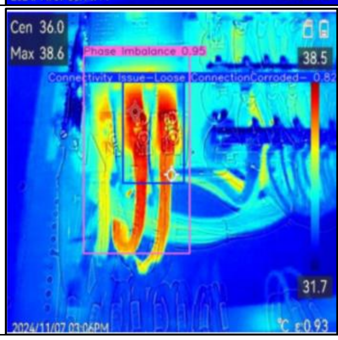


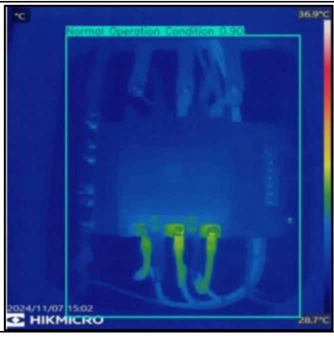
- Fault classes such as "Phase Imbalance" and "Overloaded Circuits" attain high precision and recall, which indicates the model's reliability in identifying these issues.

- the lower performance observed for "Connectivity Issue - Loose Connection" and "Deteriorated Insulation" suggests challenges that may arise because of subtle temperature variations or dataset imbalance.

- the graph showcases the model's ability to generalize across diverse fault types, it simultaneously maintains consistent detection accuracy. This dual capability is crucial for practical applications in real-world scenarios.

5. Results and Discussion

Fault Class	Predicted by Model
Connectivity Issue	
Deteriorated Insulation	
Overload Circuits	
Faulty Circuit Breakers	
Phase Imbalance	

Normal Operation Condition	

5.1 Key Findings

- The model illustrated strong capabilities in fault detection for typical electrical problems.
- Real-time processing features underscore its practical applicability in preventive maintenance.
- Rare faults showed decreased detection accuracy because of dataset imbalance.
- Automating fault detection not only reduces reliance on trained personnel but also expedites inspections, thereby enhancing scalability for large facilities.
- AI integration enhances thermography by identifying subtle patterns or anomalies that could be overlooked during manual inspections, although this can be challenging at times.

5.2 Limitations

- Dataset limitations: Predominantly focused on medium- and low-voltage systems, with limited data for rare faults.

- Environmental factors: inconsistent temperature evaluations, which significantly impacted certain readings.

6. Practical Applications

The combination of AI and thermography is proving to be a game-changer for spotting faults, with several key applications:

- Preventive Maintenance: Using thermal cameras for real-time fault detection helps cut down on downtime and maintenance expenses.
- Scalability and Efficiency: Automating inspections allows for large facilities to be monitored without needing a lot of manpower.
- Enhanced Safety Systems: Automated alerts notify operators about possible hazards, which helps lower the risks tied to electrical failures.
- Standardized Inspections: This approach ensures consistency and adherence to industry standards, reducing the inconsistencies often found in manual assessments.

7. Future Work

- Broaden the dataset to cover high-voltage systems and uncommon fault types.
- Boost the accuracy of fault categorization and detection using advanced augmentation techniques.
- Look into integrating with wider electrical diagnostic systems for more thorough monitoring.

8. Conclusion

This project has effectively showcased how deep learning can be combined with thermography for detecting electrical faults. The YOLOv8 model achieved precise and real-time fault localization, tackling significant challenges faced by traditional methods. Moving forward, we aim to strengthen the model's reliability and expand its range of applications, making it a crucial asset for diagnosing and maintaining electrical systems.