# Project - AI Thermal Fault Detection for Power Electronics

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***Abstract* -** Thermal behavior is a critical indicator of operating health and reliability in power electronic systems. Localized losses in semiconductor devices, passive components, and interconnects manifest as spatial temperature variations that can be observed through thermal imaging. This project presents a physics-informed artificial intelligence (AI) approach for detecting and classifying operating conditions in power electronics using synthetic thermal data. A controlled dataset of infrared-like thermal images was generated to represent normal operation, overheating conditions, and fault states. A convolutional neural network (CNN) using transfer learning was trained to classify these operating regimes based on spatial thermal patterns. The trained model achieved a test accuracy of 97.67%, demonstrating that physics-informed synthetic thermal data can effectively support AI-based fault detection in power electronic systems.

***Keywords:***

***Thermal Fault Detection -*** *The identification of abnormal operating conditions in electronic systems by analyzing spatial temperature patterns that indicate excessive losses or localized overheating.*

***Power Electronics -*** *The field of electrical engineering concerned with the conversion, control, and conditioning of electrical power using semiconductor switching devices.*

***Convolutional Neural Networks (CNNs) -*** *A class of deep learning models designed to automatically learn hierarchical spatial features from image data through convolutional filtering and nonlinear transformations.*

***Transfer Learning -*** *A machine learning technique in which a model pretrained on a large, general dataset is adapted to a related task, improving convergence speed and performance with limited domain-specific data.*

***Infrared Imaging -*** *A sensing technique that captures spatial temperature distributions by measuring emitted thermal radiation, commonly used for non-contact diagnostics and condition monitoring.*

***Predictive Maintenance -*** *A maintenance strategy that uses measured system indicators, such as thermal signatures, to anticipate failures and schedule interventions before catastrophic breakdown occurs.*

## I. INTRODUCTION

Power electronic systems operate under high current densities and switching frequencies, making them susceptible to thermal stress and localized overheating. Excessive junction temperatures accelerate device degradation, reduce efficiency, and increase the likelihood of catastrophic failure. As power density continues to increase in modern converters, traditional monitoring techniques based on electrical measurements alone may not fully capture emerging fault conditions.

Thermal imaging provides spatial insight into loss mechanisms by revealing temperature distributions across components and interconnects. Recent advances in machine learning have enabled automated interpretation of complex image data; however, the availability of labeled thermal fault data is often limited. This project explores the use of physics-informed synthetic thermal images combined with deep learning to enable reliable fault detection in power electronics without reliance on extensive real-world infrared datasets.

## II. PROBLEM STATEMENT

The objective of this project is to develop an AI-based system capable of classifying power electronic operating conditions, normal operation, overheating, and fault states, using spatial thermal patterns. The system must learn physically meaningful features from thermal data and generalize across operating regimes while remaining interpretable and reproducible.

## III. PHYSICS-INFORMED THERMAL DATA GENERATION

Thermal images were synthetically generated to represent infrared observations of a power electronic assembly. Heat sources corresponding to semiconductor switches, diodes, and passive components were modeled as localized Gaussian distributions, approximating thermal diffusion from concentrated loss regions. Operating conditions were defined as follows:

- **Normal:** Distributed, low-intensity thermal patterns corresponding to nominal losses
- **Overheating:** Elevated but spatially diffuse thermal signatures indicating increased losses
- **Fault:** Highly localized, high-intensity hotspots representing abnormal or failure conditions

Controlled noise, spatial variation, and intensity scaling were applied to improve realism while preserving class separability.

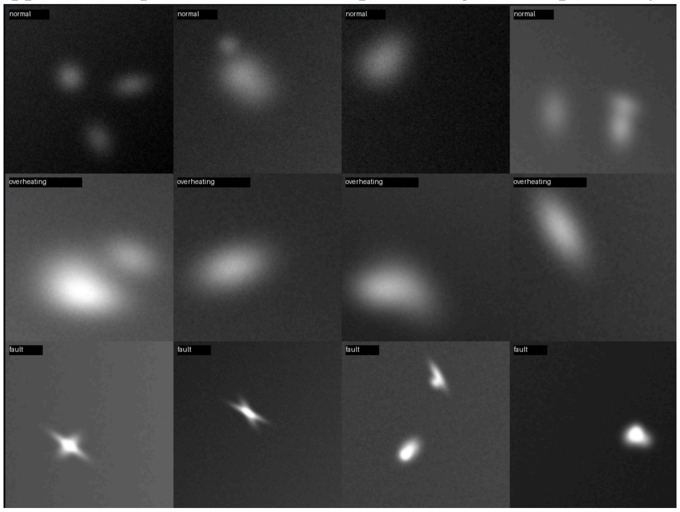


**Figure 1.** Synthetic thermal dataset montage (normal, overheating, fault)

## IV. MODEL ARCHITECTURE AND TRAINING

A ResNet18 convolutional neural network architecture was selected due to its proven effectiveness in learning hierarchical spatial features. Transfer learning was employed by initializing the model with pretrained ImageNet weights and adapting the classifier head for three-class thermal fault classification.

The dataset was split into training, validation, and test sets to ensure unbiased evaluation. Training was performed in two phases: initial training with a frozen backbone to stabilize feature extraction, followed by fine-tuning of deeper layers using a reduced learning rate. Model performance was monitored using accuracy and loss metrics across epochs.

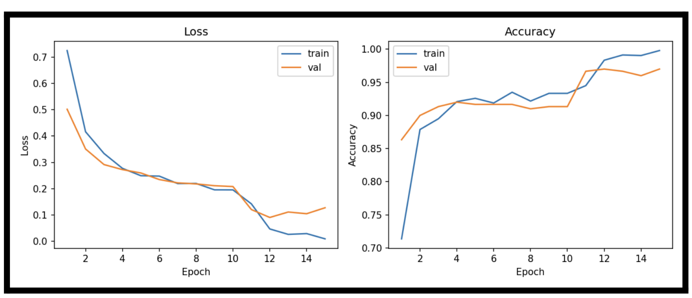


**Figure 2.** Training and Validation Loss/Accuracy Curves

## V. RESULTS

The trained baseline model achieved a test accuracy of 97.67% on the held-out dataset. The confusion matrix shows perfect classification of fault conditions, with all fault samples correctly identified. Limited confusion occurred between the normal and overheating classes, consistent with the gradual thermal transition between these operating regimes.

Per-class evaluation metrics indicate a precision and recall of 1.00 for the fault class, confirming robust detection of localized thermal anomalies. Normal and overheating classes maintained high F1-scores (> 0.96), demonstrating reliable classification of distributed thermal patterns.

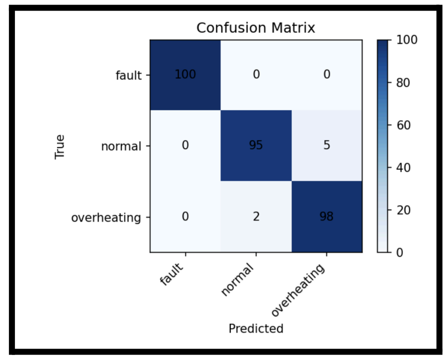


**Figure 3.** Confusion Matrix for Dataset Classification

## VI. DISCUSSION

The results demonstrate that physics-informed synthetic thermal data can encode meaningful features for AI-based fault detection in power electronics. Perfect fault classification reflects the strong spatial distinctiveness of localized thermal anomalies, while minor overlap between normal and overheating classes aligns with physical expectations. These findings suggest that the proposed approach is well-suited for early fault detection and predictive maintenance applications, where thermal trends provide valuable insight into system health.

## VII. CONCLUSION AND NEXT STEPS

This project successfully established a reproducible pipeline for thermal fault detection using physics-informed data generation and deep learning. The high baseline performance validates the effectiveness of combining physical intuition with AI-based classification. Future work will focus on incorporating real infrared measurements, improving data realism, and applying explainability techniques such as saliency mapping to enhance interpretability and deployment readiness.

## VIII. ACKNOWLEDGEMENT


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