Deep Learning Methods for Detecting Thermal Runaway Events in Battery Production Lines

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Overview

Context

- Project conducted in collaboration with **VDL Nedcar**, a Dutch automobile manufacturer.
- VDL Nedcar operates a modular **battery production demo line** designed for flexibility in assembling battery packs.
- Our work focuses on a critical safety issue in this environment: **thermal runaway detection**.

Context

Definition

Thermal Runaway: A self-reinforcing process in which rising temperature within a battery triggers exothermic reactions that further increase heat, potentially leading to fire, explosion, or system failure.

- **Errors in assembly** can trigger thermal runaway events in the manufacturing process.
- Once the event is underway, the battery must be exhausted in isolation.
- **Early detection** is of vital importance!

Context

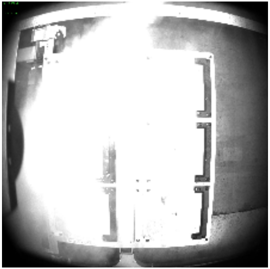
- Experiment conducted on the **first automated station** of VDL Nedcar's battery demo line.
- Battery packs are positioned and mounted using the **ABB IRB 6700-245/3.00** robotic arm.
- The robot is equipped with two overhead sensors:
  - **Cognex In-Sight 2800** optical camera.
  - **DIAS PYROVIEW 128LS** infrared camera.

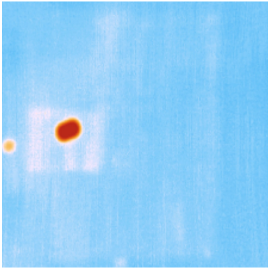
Objectives

- Develop an automated system for detecting **thermal runaway events** during battery assembly.
- Leverage **data fusion** of:
  - **Optical images** — to capture visible smoke emissions.
  - **Infrared images** — to detect heat buildup.
- Investigate whether **fusing both data modalities** improves classification performance compared to single-modality inputs.
- Use explainability techniques to validate that models focus on relevant features (smoke and heat).

Data Collection

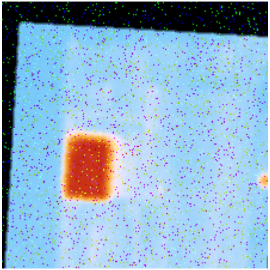
- Data collected from VDL Nedcar's battery demo line using a custom capture system.
- Each sample includes:
  - One **optical image**
  - One **infrared image**
- Two categories of samples:
  - **Baseline:** normal configurations with no anomalies.
  - **Simulated thermal runaway:** *smoke* (fog machine) and *heat* (resistance heaters).
- Total dataset: **832 samples** (412 baseline / 420 anomaly)





Data Processing

- The original dataset was **too small** for robust deep learning training.
- **Upsampling:** duplicated samples with replacement.
- **Image augmentation:** applied to increase diversity and reduce overfitting.
- Augmentation pipeline included:
  - Vertical flipping and rotation (up to 25°)
  - Affine transformations (scaling, shearing)
  - **Gaussian blur** and **salt-and-pepper noise**



Deep Learning Models

- We evaluated three deep learning architectures commonly used in computer vision:
  - **Convolutional Neural Network (CNN)** — A shallow custom-built architecture with two convolutional layers; serves as a baseline.
  - **Residual Neural Network (ResNet-50)** — A deeper, pre-trained CNN architecture that incorporates skip connections to improve gradient flow and accuracy.
  - **Vision Transformer (ViT)** — A transformer-based model adapted for image processing; leverages self-attention to capture global features.
- Models were trained on three input settings:
  - Optical-only images
  - Infrared-only images
  - Fused optical + infrared images (CNN/ResNet only)

Evaluation Procedure

- The dataset was randomly partitioned into:
  - **70%** training
  - **15%** validation
  - **15%** testing
- For each model:
  - Hyperparameters were optimized using a **grid search** on the validation set.
  - Best configuration retrained on training + validation sets.
  - Final performance assessed on the **held-out test set**.
- Evaluation metrics:
  - ROC-AUC (Receiver Operating Characteristic - Area Under Curve)
  - PR-AUC (Precision-Recall - Area Under Curve)
- Goal: Maximize both metrics to ensure high accuracy and reliability.

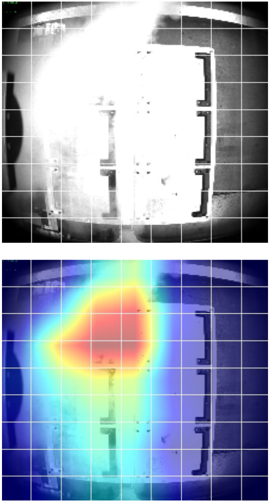
Results

	Dataset			Performance Metric	
Model	Type	Upsampled	Augmented	ROC-AUC	PR-AUC
CNN	Optical	No	No	1.00	1.00
CNN	Infrared	No	No	0.87	0.77
CNN	Fusion	No	No	1.00	1.00
CNN	Optical	Yes	Yes	0.72	0.38
CNN	Infrared	Yes	Yes	0.83	0.70
CNN	Fusion	Yes	Yes	1.00	1.00
ResNet	Optical	Yes	Yes	1.00	1.00
ResNet	Infrared	Yes	Yes	1.00	1.00
ResNet	Fusion	Yes	Yes	1.00	1.00
ViT	Optical	Yes	Yes	1.00	1.00
ViT	Infrared	Yes	Yes	1.00	1.00

- **All models** performed strongly in classifying thermal runaway vs. baseline events.
- **Best results:**
  - **ResNet-50 and ViT** achieved perfect scores: ROC-AUC $= 1.00$, PR-AUC $= 1.00$
  - **CNN** also reached perfect performance when trained on fused data.
- Data fusion improved CNN performance significantly.

Discussion

- **Explainability:**
  - Grad-CAM used for CNN and ResNet.
  - Attention heatmaps used for ViT.
  - Models correctly focused on smoke and heat regions.
- **Deployment potential:** Real-time inference speeds make integration into production systems feasible.
- **Limitations:** Current simulations reflect late-stage thermal runaway. Future work should simulate earlier indicators.



Conclusion

- **Deep learning is a viable solution** for detecting thermal runaway events in battery production lines.
- **Data fusion** of optical and infrared images enhances model performance, particularly in shallower architectures.
- **Future work** will focus on:
  - Detecting thermal runaway at earlier stages for proactive safety measures.
  - Investigating continuous learning for long-term deployment.
- Code and data available on **GitHub**.

Thank You!

Questions or Comments?

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