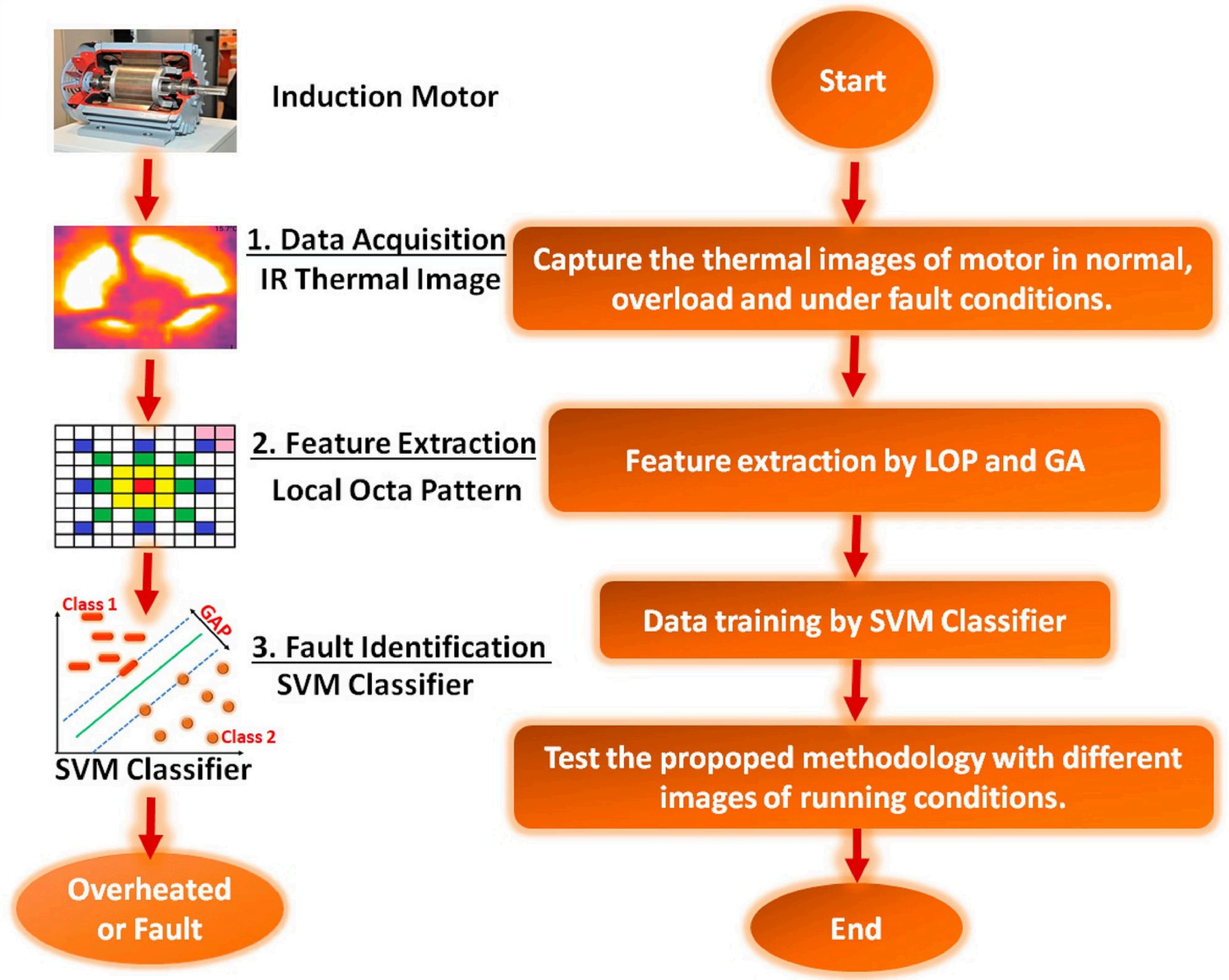
Induction Motor Thermal Fault Diagnosis using FP-CycleGAN



Thermal imaging3based condition monitoring of induction motors using advanced generative AI techniques.

Project Overview

Thermal Monitoring

Thermalimaging3basedcondition monitoring of induction motors.

Detection Goal

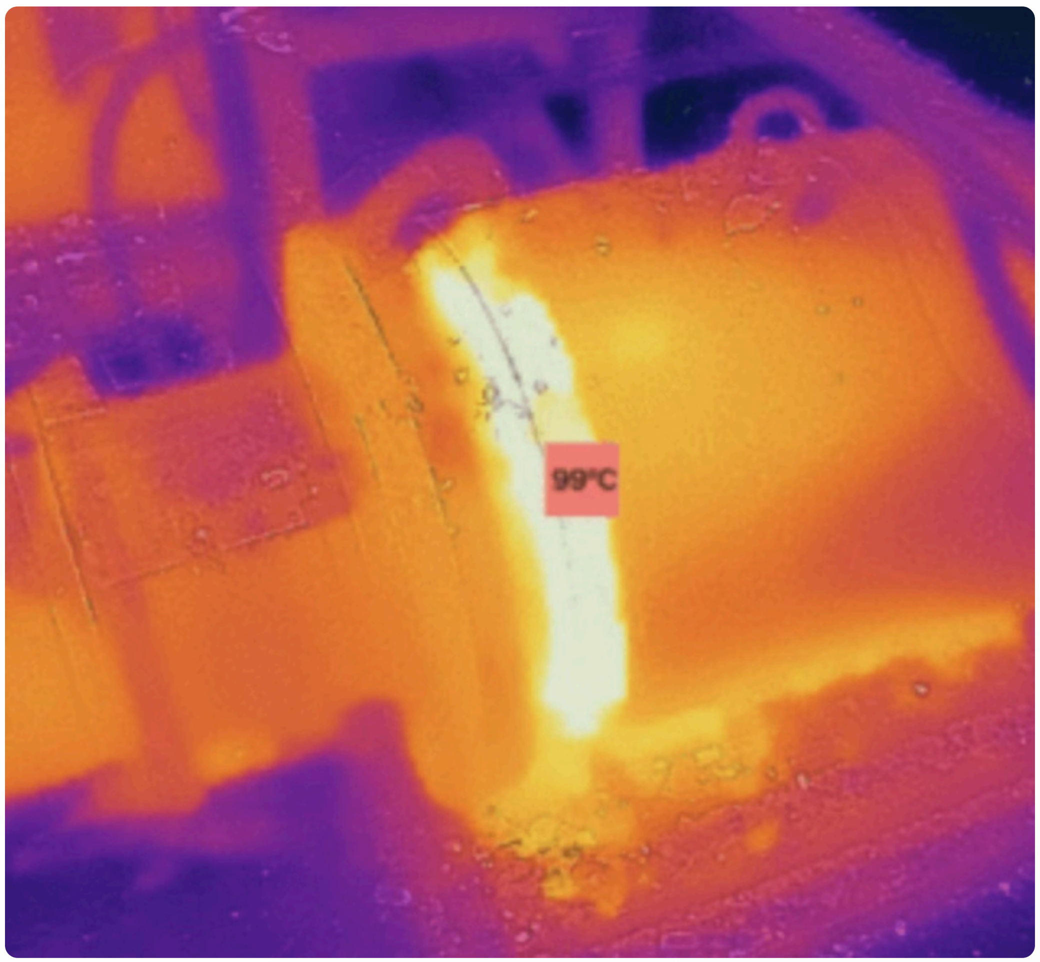
Detectfaultslikerotor, bearing, and stator defects.

Real Dataset

Datasetbuiltfrom real IR camera captures under various fault states.

Key Challenge

Smalldataset+class imbalance.



Healthy (Noload)

Faulty (A&B50)

Dataset Structure

Located in MyDrive/data/aug/

1

Total Classes

11folders(1healthy + 10 fault classes).

2

Images per Class

Eachfoldercontains~5503560 .bmp or .png images.

3

Healthy Class

Noload

4

Faulty Classes

A&B50,A&C&B10,A&C30, Fan, Rotor-0, etc.

Class Name	Image Count
Noload (Healthy)	~550
A&B50	~560
A&C&B10	~555
A&C30	~550
Fan	~560
Rotor-0	~555

Problem & Motivation

Why FP-CycleGAN?

Dataset Limitations

Smallandunbalanceddataset ³ poor classifier generalisation.

Realistic Augmentation

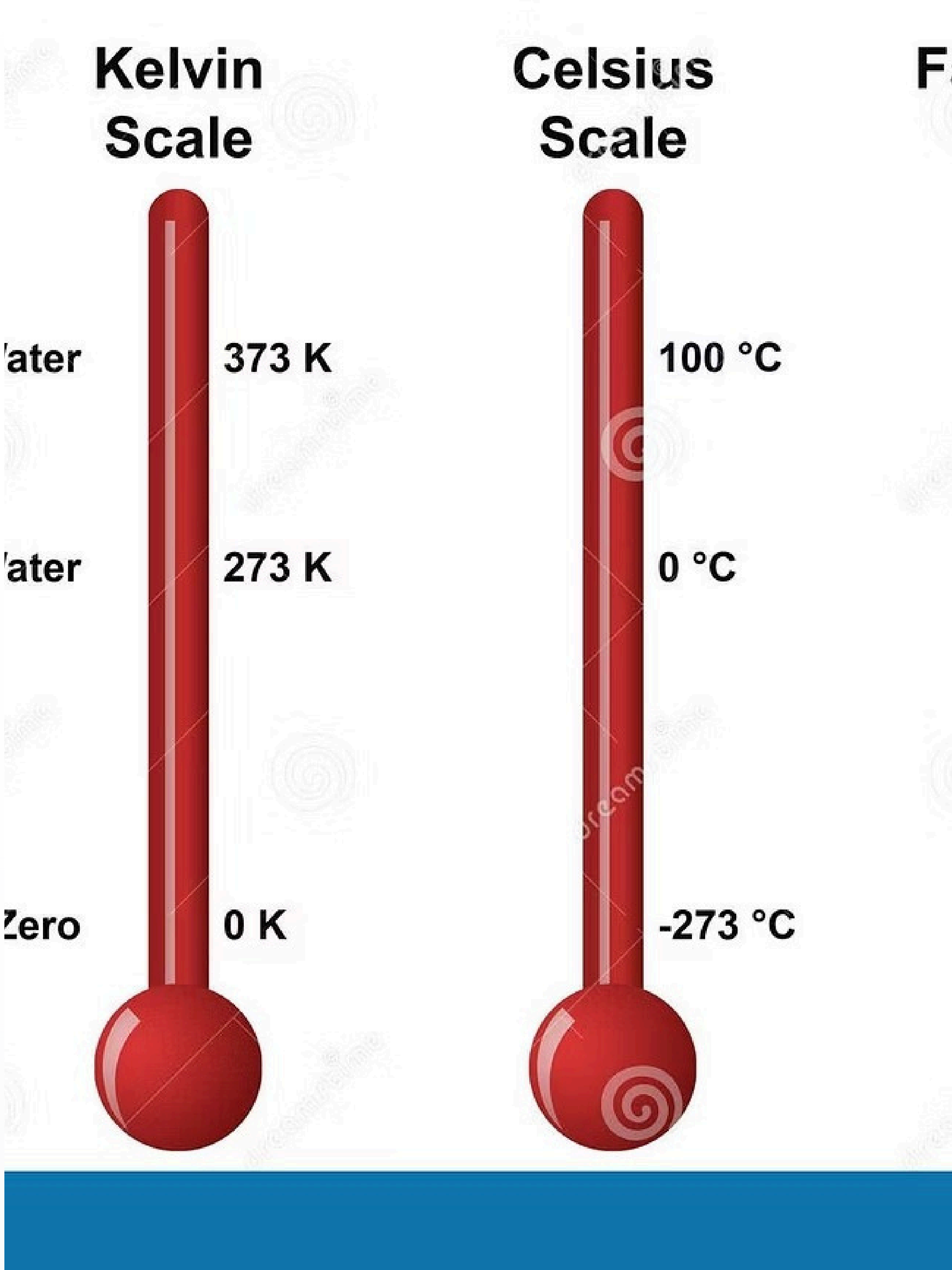
Needrealisticaugmentationwithout losing thermal characteristics.

Feature Preservation

FP-CycleGANadds**feature-preserving loss** for domain consistency.

Synthetic Generation

Generatessyntheticfaultyimages from healthy ones.



Configuration Summary

Medium-VersionHyperparameters

Source Class

A-class (source): **Noload**

Batch Sizes

8 (GAN), 32 (CLS)

Training Epochs

12 (GAN), 12 (classifier)

Classifier Runs

5 classifier runs (ResNet18×5)

Learning Rates

2e-4 (GAN), 3e-4 (ResNet18)

Training Duration

j 5 hours (on T4 GPU)

FP-CycleGAN Architecture

Network Components

Generator

UNet+ConvNeXt hybrid for spatial + contextual features.

Discriminator

PatchGAN for local realism.

DAB (Domain Aware Block)

Classifier to preserve healthy vs faulty domain features.

Losses:

GAN loss (realism)

Cycle loss (reconstruction)

Identity loss (consistency)

Classification loss (feature preservation)

FP-CycleGAN Training Process

Per-Class GAN Training

Input

Healthyimages (Domain A).

Training

Train aseparate FP-CycleGAN for each fault class.

Output

Fault-simulated images (Domain B).

Each epoch updates G, D, and DAB losses.

Results saved under `/fp_cyclegan_medium/fp_cyclegan/`.

Generated Image Examples

Synthetic Fault Image Generation

- Generator G_ABproducesrealistic faultythermal images.
- Preserves geometry and key heat regions.
- Slight hue/contrast variations simulate domain changes.
- Stored under /fp_cyclegan_medium/generated/<fault_class>/

Amplified Dataset Creation

Real + Synthetic Data Fusion

Data Combination

Combined300real+350generated samples per class.

Balanced Dataset

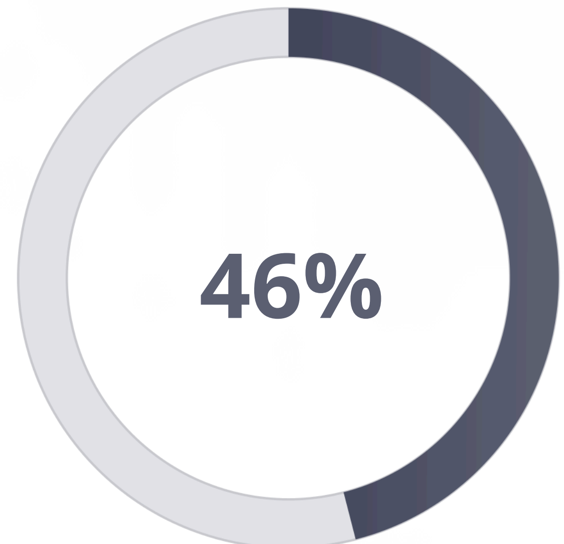
Total j 650images/class ^{3} balanced dataset.

Test Set Integrity

Testsetusesonlyrealdata for fairness.

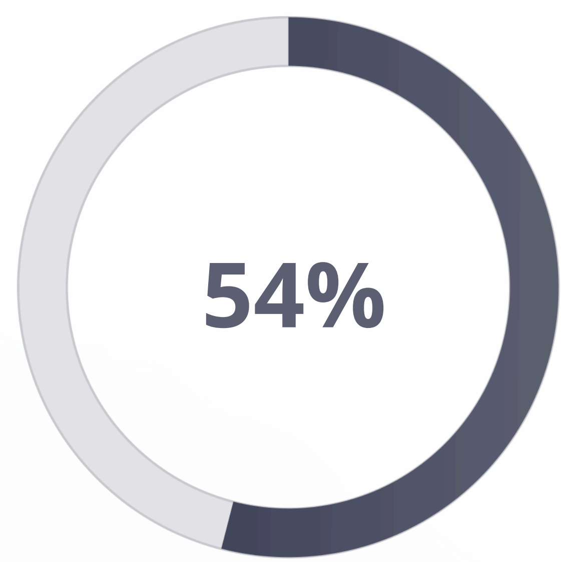
Data Storage

Train/testlistssaved as TSV files.



Real Images

300perclass



Synthetic Images

350perclass

Classification & Performance

Classification Stage

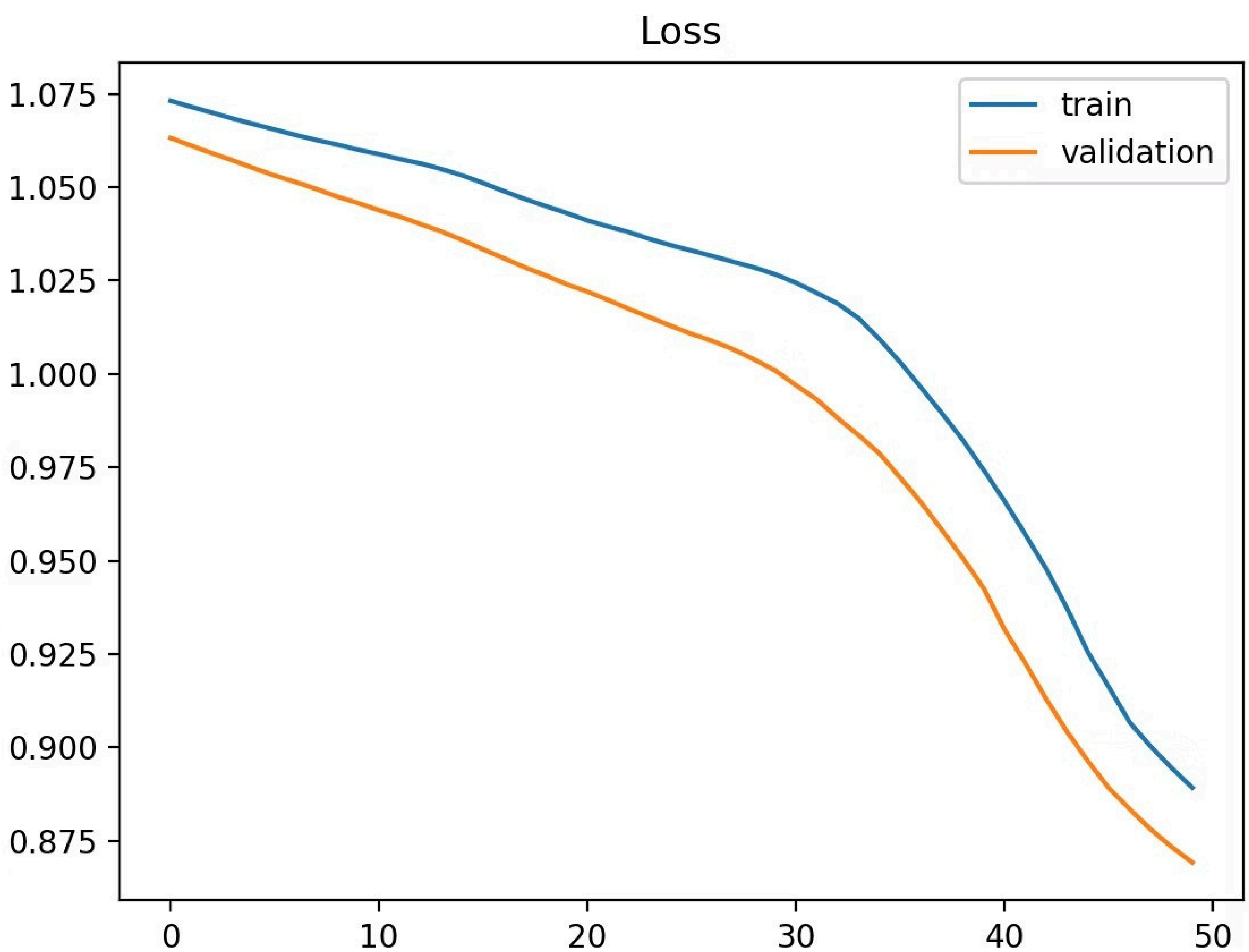
ResNet18-Based Fault Classification

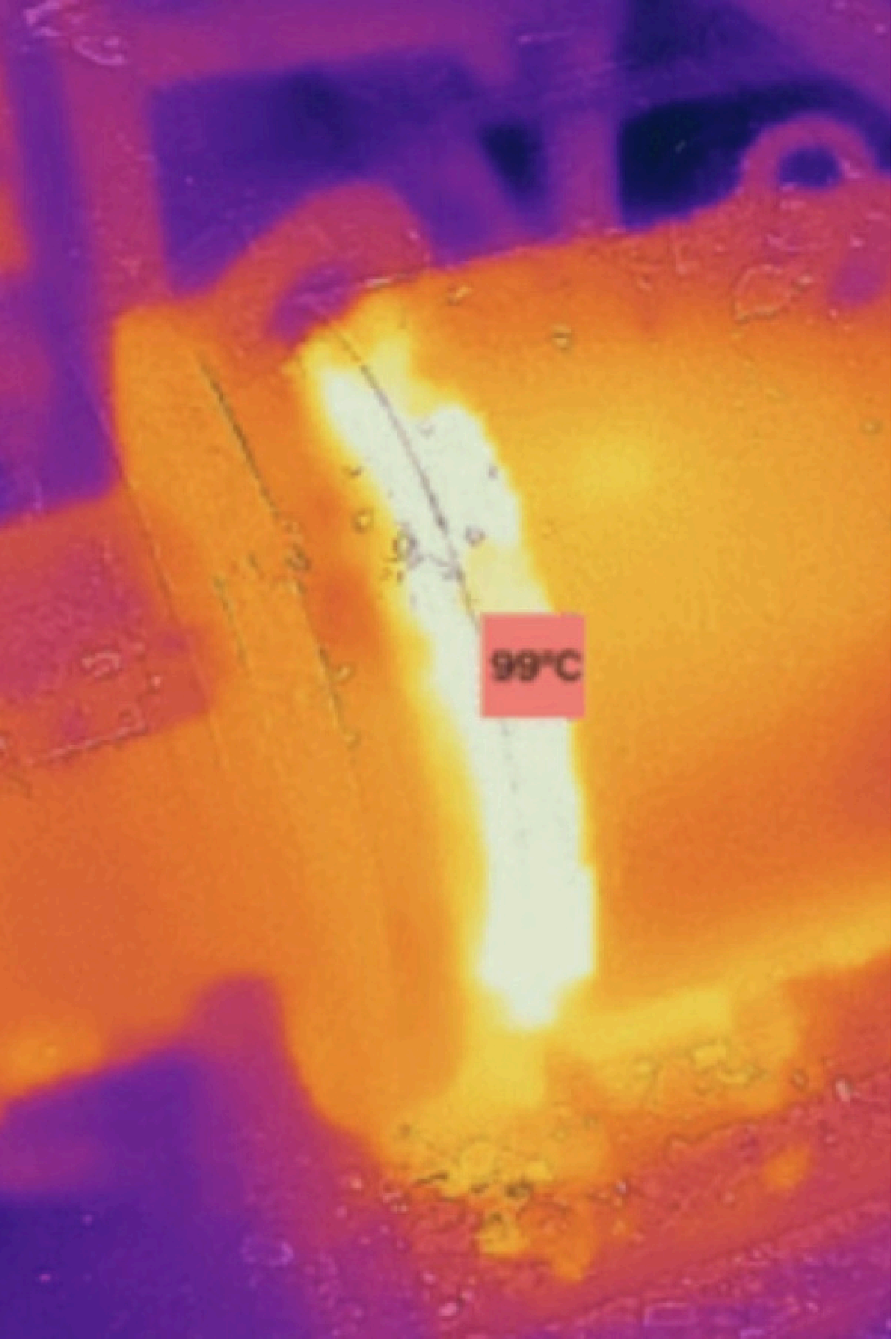
- Model: ResNet18 (ImageNet pretrained).
- Optimiser: AdamW, LR = 3e-4.
- 5 independent runs (different random seeds).
- Metrics: Accuracy, Precision, Recall, F1-score per class.

Performance Evaluation

Accuracy and Metrics

- Aggregatedresultssaved as CSV (resnet18_medium_5runs.csv).
- Mean accuracy computed across 5 runs.
- Performance plot saved as acc_5x_medium.png.
- Expect balanced recall for all fault types.





Generated Image Validation

Computational Requirements

Runtime Summary

Stage	Duration (T4 GPU)
FP-CycleGAN (per class)	20325 min
Generation	30 min
ResNet18 (×5 runs)	~45350 min
Total Runtime	**j 5 hours**

- **Thermal contrast variations are visible (purple hue ³ simulated fault)**
- **Motor shape preserved 4 structural fidelity maintained**
- **Confirms successful *feature-preserving* augmentation**
- **Augmented images used for classifier training**

Summary of Deliverables

Final Outcome

FP-CycleGAN + ResNet18 pipeline fully implemented in Colab

Dataset amplified and balanced

Synthetic images verified visually and statistically

Accuracy improvements expected over baseline models

Artifacts saved under /content/fp_cyclegan_medium/

Research Insights

Key Takeaways

FP-CycleGAN successfully generates realistic thermal faults

Domain-aware training ensures feature consistency

Augmented dataset yields higher classifier accuracy

Medium configuration offers good balance of performance and time

Future Improvements

Future Work

Experiment with ViT or ConvNeXt classifiers

Explore FP-CycleGAN++ (multi-domain translation)

Deploy on embedded edge hardware

Evaluate with real motor lab test data