Machine Learning for Pattern Detection in Printhead Nozzle Logging

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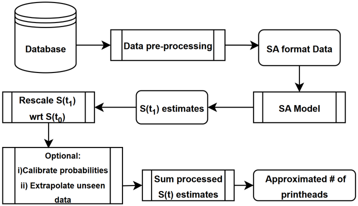
Context

- This research was conducted in collaboration with **Canon Production Printing (CPP)**, which specializes in **industrial-scale printers** used for commercial and production-grade applications.
- A core component of these systems is the **printhead**, responsible for jetting toner or ink.
- Ensuring accurate health assessment of these components is crucial for **maintenance scheduling**, **cost reduction**, and **customer satisfaction**.

Previous Work



- Our earlier work[1] **modeled printhead lifespan using survival analysis** on CPP's industrial data.
- We compared **classical and machine-learning survival models**.
- The study demonstrated that calibrated **survival models can reliably forecast failure timing**, establishing a foundation for deeper mechanism-level analysis in this follow-up work.

[1] D. Parii, E. Janssen, G. Tang, C. Kouzinopoulos and M. Pietrasik, "Predicting the Lifespan of Industrial Printheads with Survival Analysis," *2025 IEEE 8th International Conference on Industrial Cyber-Physical Systems (ICPS)*, 2025, pp. 1-6.

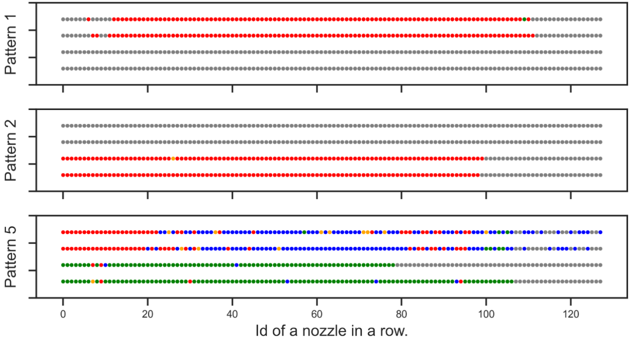
Objective

- Correctly **identifying printhead failure mechanisms** is essential for ensuring product quality and supporting effective corrective maintenance.
- Nozzle-level logs capture both **spatial** and **temporal** patterns of failures that can reveal distinct mechanisms.
- Traditional **rule-based systems** at CPP are effective but require manual updates and do not use full time-series information.

Goal

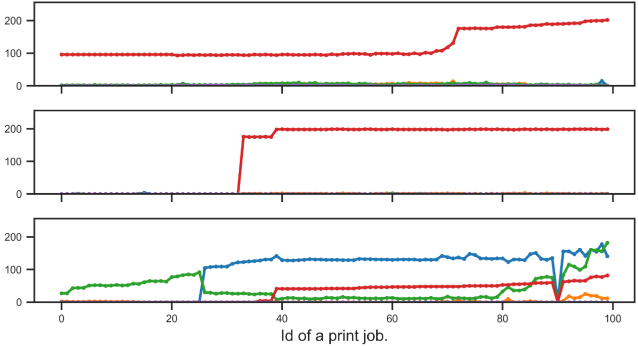
Given nozzle-logging data of nozzle failures in a nozzle grid over print jobs, learn a model that, at end-of-life, **classifies the printhead's underlying failure mechanism**.

Nozzle Logging Basics



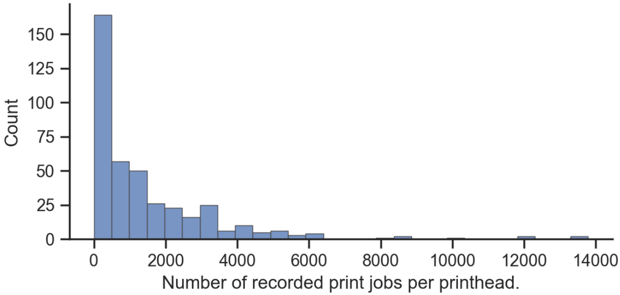
- Each log record captures the state of 512 nozzles arranged as a **4×128 grid**, with five possible failure statuses (NF1–NF5) or healthy.
- A log record can also be viewed as a **five-channel binary image**, which facilitates visual pattern analysis.

Nozzle Logging Basics



- Logs are collected frequently because nozzle states can change or recover, and they exhibit both spatial clustering and **temporal evolution**.

Dataset



- The dataset contains **411 failed printheads** labeled into **five main mechanisms** plus "Unknown" and "Outlier" categories.
- The number of nozzle logs per printheads **demonstrates high variability**.

Observed Failure Mechanisms

Failure Mechanism (Class label)	Count
Unknown	128
Pattern 1	121
Pattern 2	69
Pattern 3	30
Pattern 4	24
Pattern 5	23
Outlier	8
Pattern 1 & 2	6
Pattern 1 & 4	2

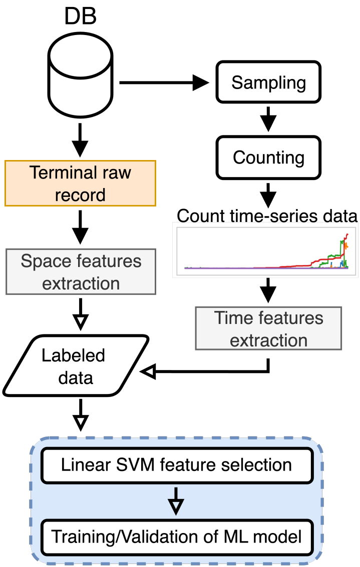
- Class distribution is **highly imbalanced**, and a few samples exhibit dual mechanisms such as "Pattern 1 & 2."
- Labels were produced by a rule-based model and then verified and corrected by **domain experts using logs and usage history**.

Observed Failure Mechanisms

- Domain experts observe **distinct patterns** such as scattered mixed failures and contiguous bands of neighboring failures, suggesting electrical issues.
- Limiting analysis to the last k records risks missing early signals because **different mechanisms can share similar terminal states but diverge in trajectory**.
- We therefore analyze the **full lifespan** while sampling at the first record of each print job to reduce redundancy and complexity.

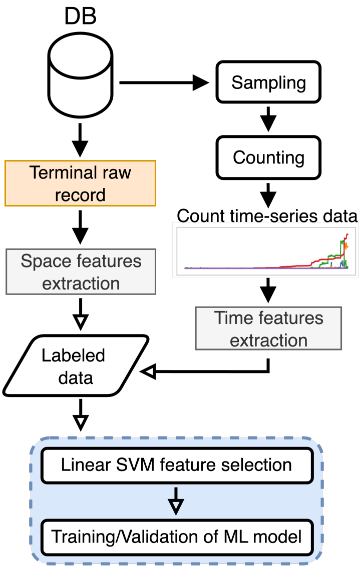
Feature Engineering: Temporal

- We extract **temporal features** using a curated subset of *tsfresh* functions guided by domain expertise.
    - We select 11 *tsfresh* functions capturing linear trends, autocorrelation, and other essential properties, and we add seven custom functions.
    - Custom features include first and second derivatives, last value, and maximum consecutive differences to detect abrupt shifts.



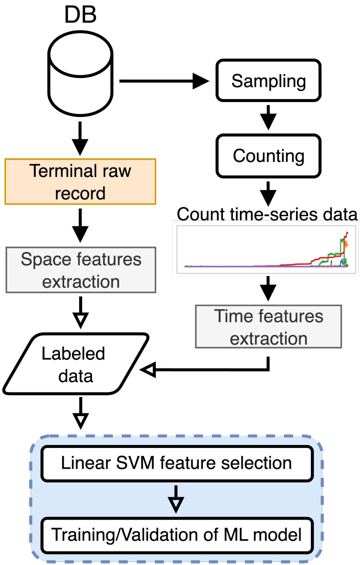
Feature Engineering: Spatial

- We extract **spatial features** from the final nozzle grid, including the average position of failures per class, and the number of consecutive NF4s from the edge.
    - These spatial descriptors help distinguish mechanisms characterized by edge-anchored bands or central clusters of failures.



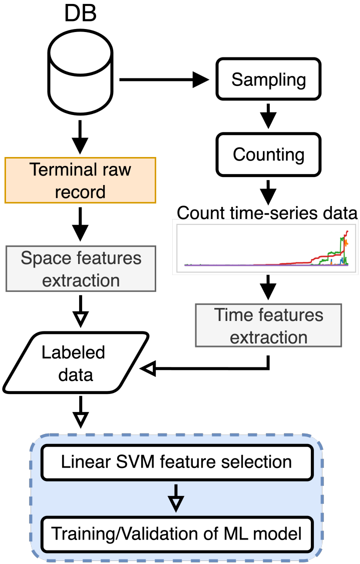
Modeling Pipeline

- We evaluate **several classic models** with imputation, scaling, and model-based feature selection using a linear-kernel SVM to improve generalization.
  - We consider Random Forests (RF), Logistic Regression (LR), Extremely Randomized Trees (ET), Decision Trees (DT), *k*-nearest neighbours (KNN), and support vector machines (RBF-SVM).
- Because some printheads show two mechanisms at end-of-life, we use a **One-vs-Rest (OVR)** setup that can predict multiple labels.



Evaluation

- Given small per-class counts, we use **leave-one-out cross-validation** for final evaluation.
- We report precision, recall, and F1, and we leverage **weighted averages** to account for differing class supports.



Results

- After hyperparameter tuning, **RF achieves the best weighted F1 and recall**, while ET slightly lead in precision.
- LR and RBF-SVM perform competitively, whereas **DT and KNN underperform** due to overfitting and generalization issues.

Model	**Prec.**	**Rec.**	**F1**
RF	0.9318	0.9513	0.9410
LR	0.9201	0.9294	0.9242
KNN	0.8366	0.8394	0.8369
DT	0.8077	0.8881	0.8428
ET	0.9355	0.9440	0.9392
SVM	0.9170	0.9367	0.9266

Results

	Model	Prec.	Rec.	F1	Support
Pattern 1	Baseline	0.93	0.98	0.95	127
	OVR-RF	0.90	0.96	0.93	
Pattern 2	Baseline	0.80	0.99	0.89	75
	OVR-RF	0.95	0.93	0.94	
Pattern 3	Baseline	1.0	1.0	1.0	30
	OVR-RF	0.80	0.93	0.86	
Pattern 4	Baseline	0.76	0.73	0.75	26
	OVR-RF	1.00	0.85	0.92	
Pattern 5	Baseline	0.92	0.52	0.67	23
	OVR-RF	0.95	0.87	0.91	
Other	Baseline	0.97	1.00	0.99	136
	OVR-RF	0.96	0.93	0.94	
Weighted average	Baseline	0.91	0.95	0.93	417
	OVR-RF	0.93	0.93	0.93	

- **OVR-RF achieves a weighted F1 of 0.93**, same as the rule-based baseline.
  - The RF model substantially improves F1 for Patterns 2, 4, and 5, but trails the baseline on Pattern 3.

Results

Baseline (rows: True Class; columns: Predicted Class)

True Class	Pattern 1	Pattern 2	Pattern 3	Pattern 4	Pattern 5	Other
Pattern 1	124	12	0	0	1	0
Pattern 2	2	74	0	0	0	0
Pattern 3	0	0	30	0	0	0
Pattern 4	6	4	0	19	0	1
Pattern 5	2	2	0	6	12	3
Other	0	0	0	0	0	136

Predicted Class

OVR RF (rows: True Class; columns: Predicted Class)

True Class	Pattern 1	Pattern 2	Pattern 3	Pattern 4	Pattern 5	Other
Pattern 1	122	3	1	0	0	2
Pattern 2	3	70	0	0	0	0
Pattern 3	1	0	28	0	0	3
Pattern 4	4	1	0	22	0	0
Pattern 5	3	0	0	0	20	0
Other	3	0	6	0	1	126

Predicted Class

- **OVR-RF outperformed baseline** on separation between “Pattern 1” and “Pattern 2.”
  - Poor performance on “Other” class.
- The RF model is **can be used by CPP engineers** for classifying failure mechanisms.

Conclusion and Future Work

- Proposed a **data-driven approach** that fuses time-series dynamics with spatial signatures that can reliably classify printhead failure mechanisms.
- The OVR-RF **performs at the level of a production rule-based baseline** and can be used by CPP engineers.
- Future work will investigate adapting the methodology to **other types of CPP printheads and printers**.

Thank You!

Questions or Comments?

This work was conducted in collaboration with Canon Production Printing.