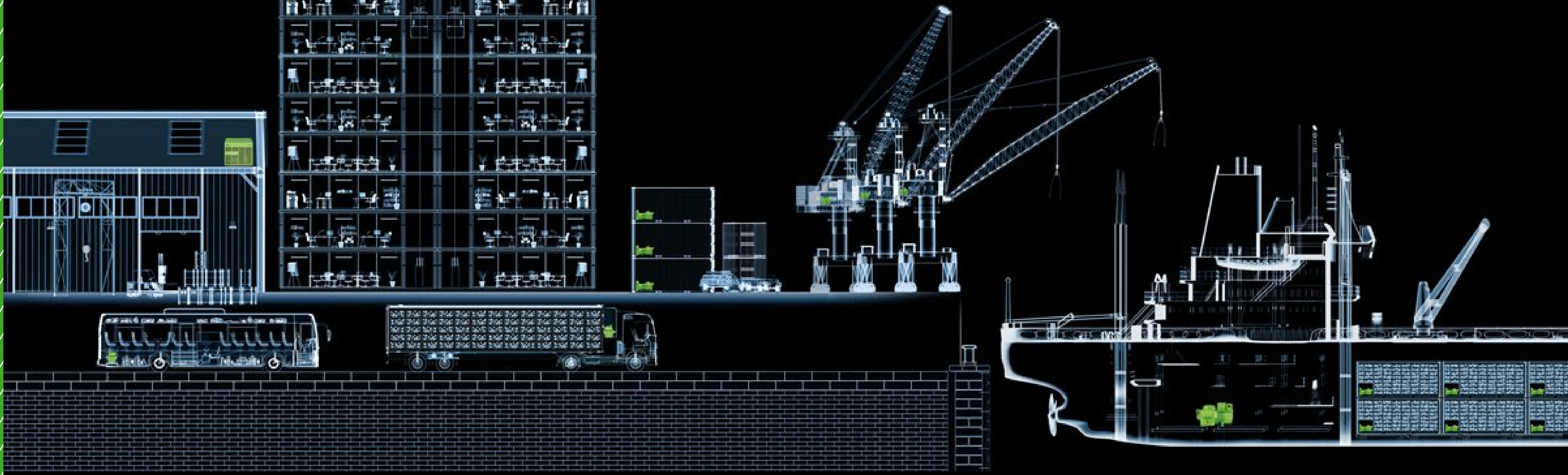
Digitalization of Refrigeration and Heat Pump Systems

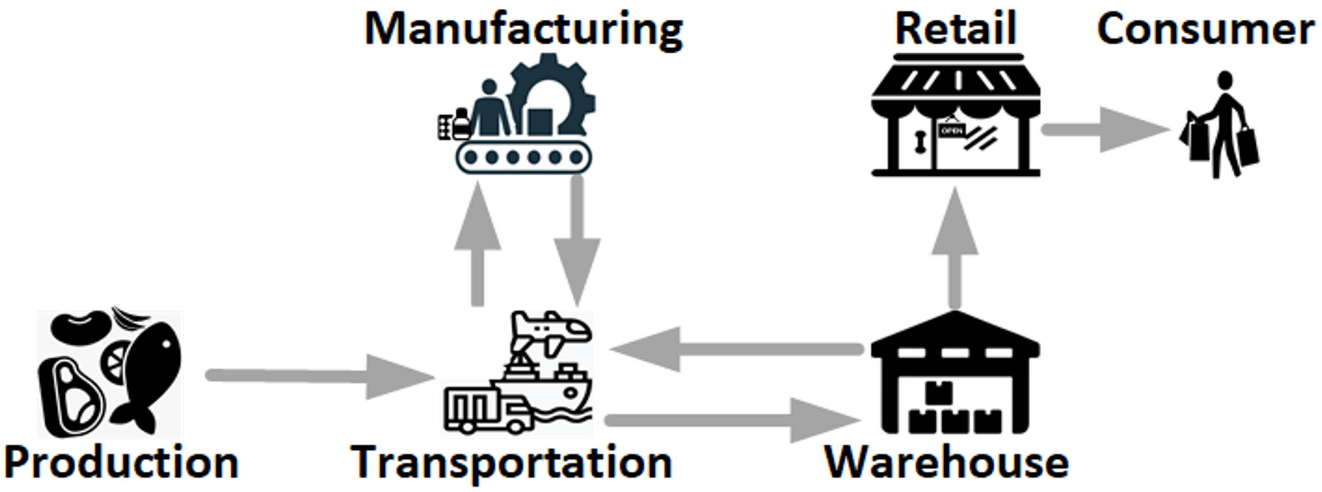


Automatic Fault Detection and Diagnosis in Refrigeration Systems -A Data-driven Approach-

- BITZER Electronics A/S ,collaboration with Aalborg university
- **July, 04 - 2024**

DAS HERZ DER FRISCHE

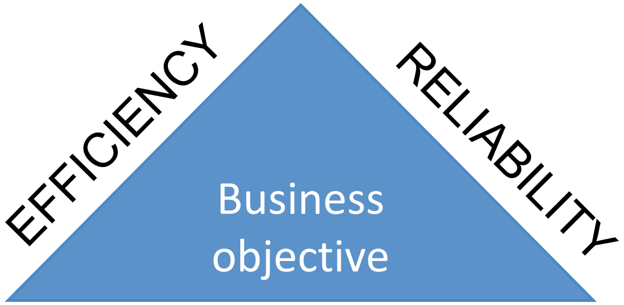
Refrigeration systems in cold chain



Refrigeration systems affect on:

- Medicine and food
- Human health
- Economy
- Global warming

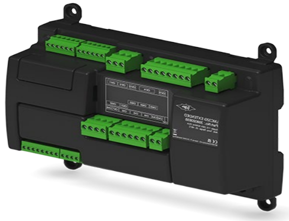
Bitzer, Green manufacturer



UPTIME

Important factors:

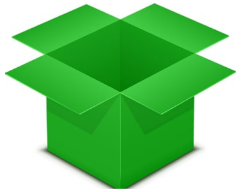
- Accuracy
- False positive rate
- Computation time
- Required amount of data and sample time
- Required variables (features)
- Ability to lower cost of human resources
- Robustness of the tool for distributed systems



HVAC & R controllers

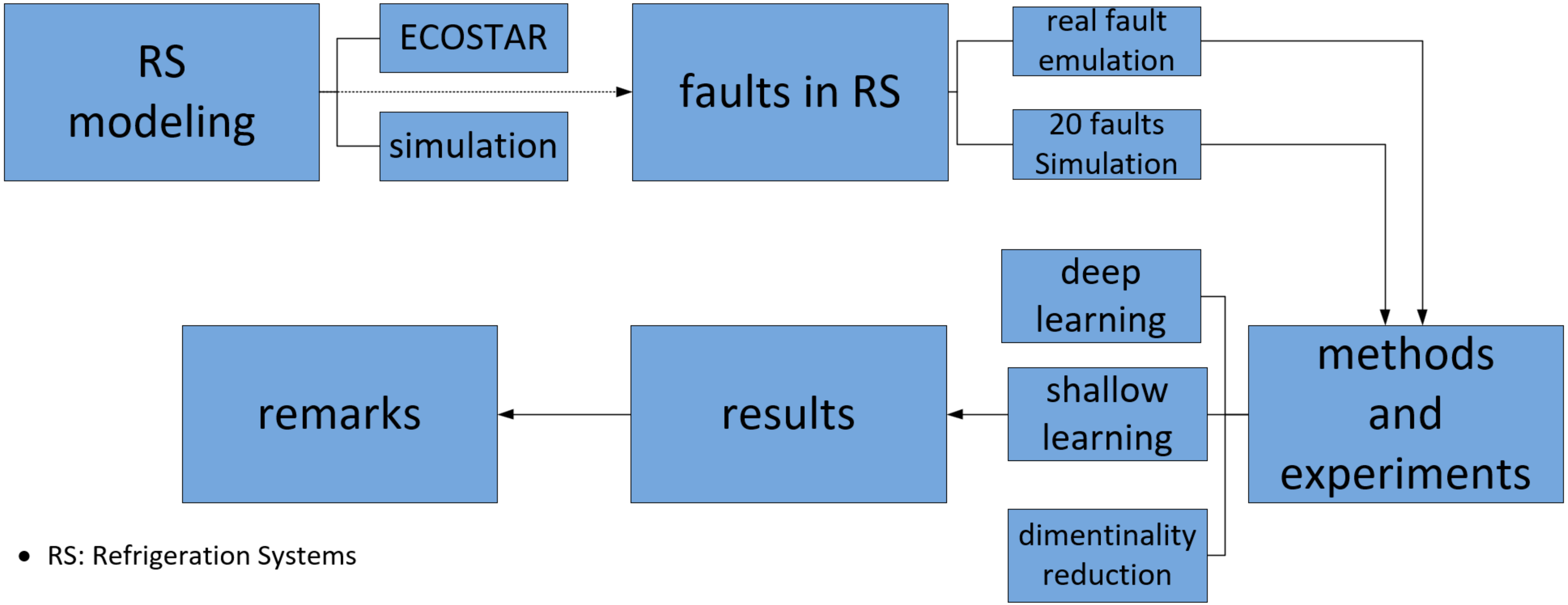
user panels
and
smart phone app

IQ
modules



and more products

Discussion points:

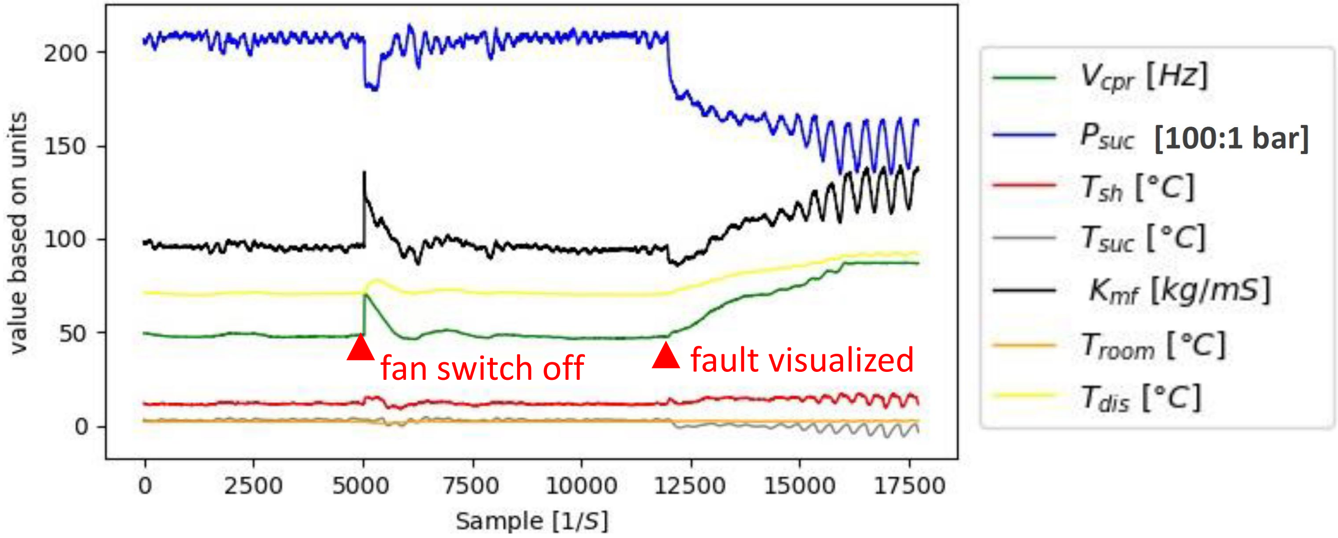


- RS: Refrigeration Systems

ECOSTAR Unit

Ecostar is a condensing unit for supermarket refrigeration systems

Evaporator fan fault

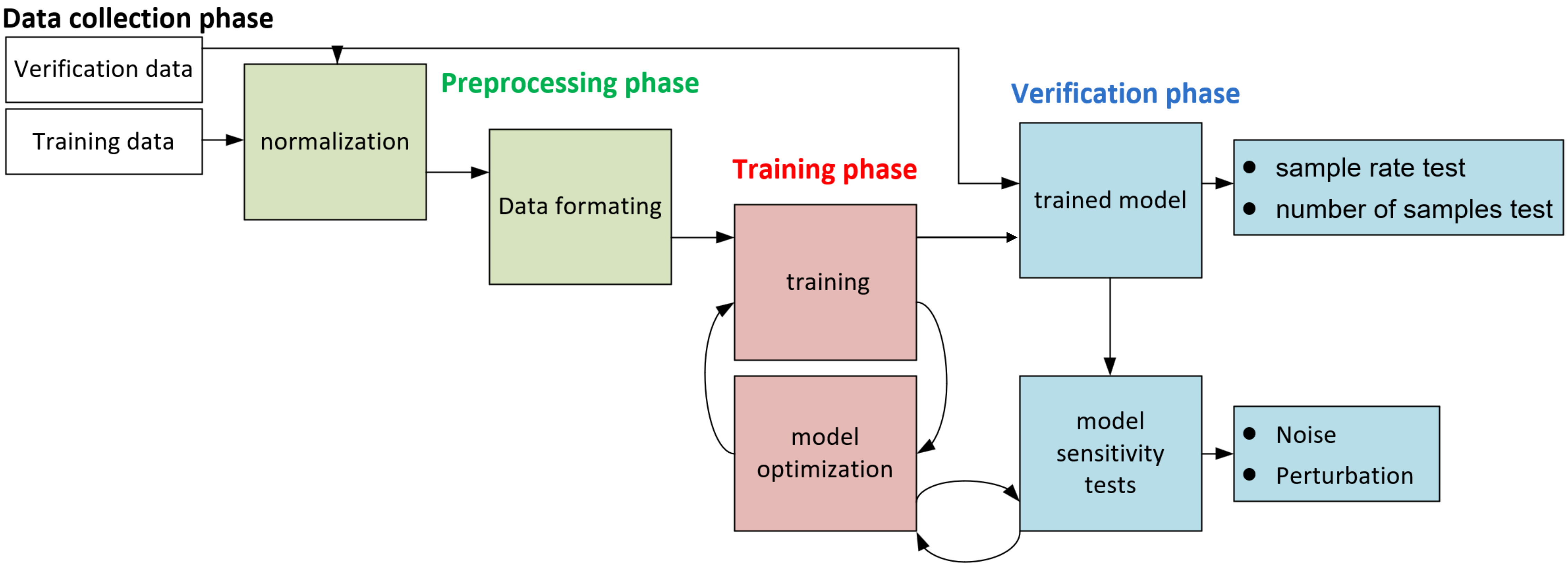


An example of datalog for fan fault detection. The fault happened in sample 5000 and it is obviously affected the data later.

Switch off for one of the evaporator fans

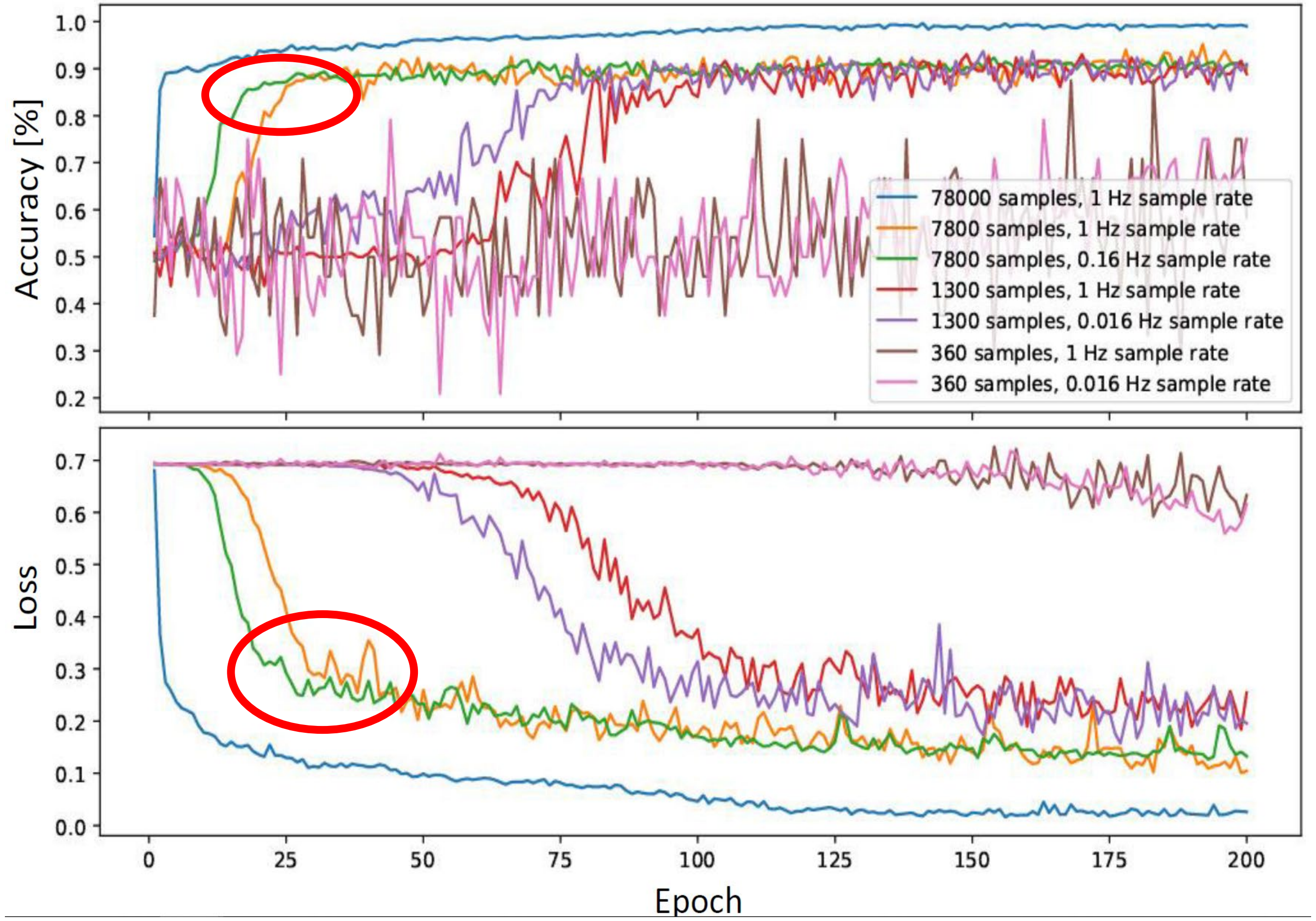
Ice accumulation on evaporator when one of the fan was off
defrost mode : off

CNN for Fan fault detection
Overview:



Lower resolution, faster convergence

- ✓ faster convergence
- ✓ same accuracy until 0.016 Hz



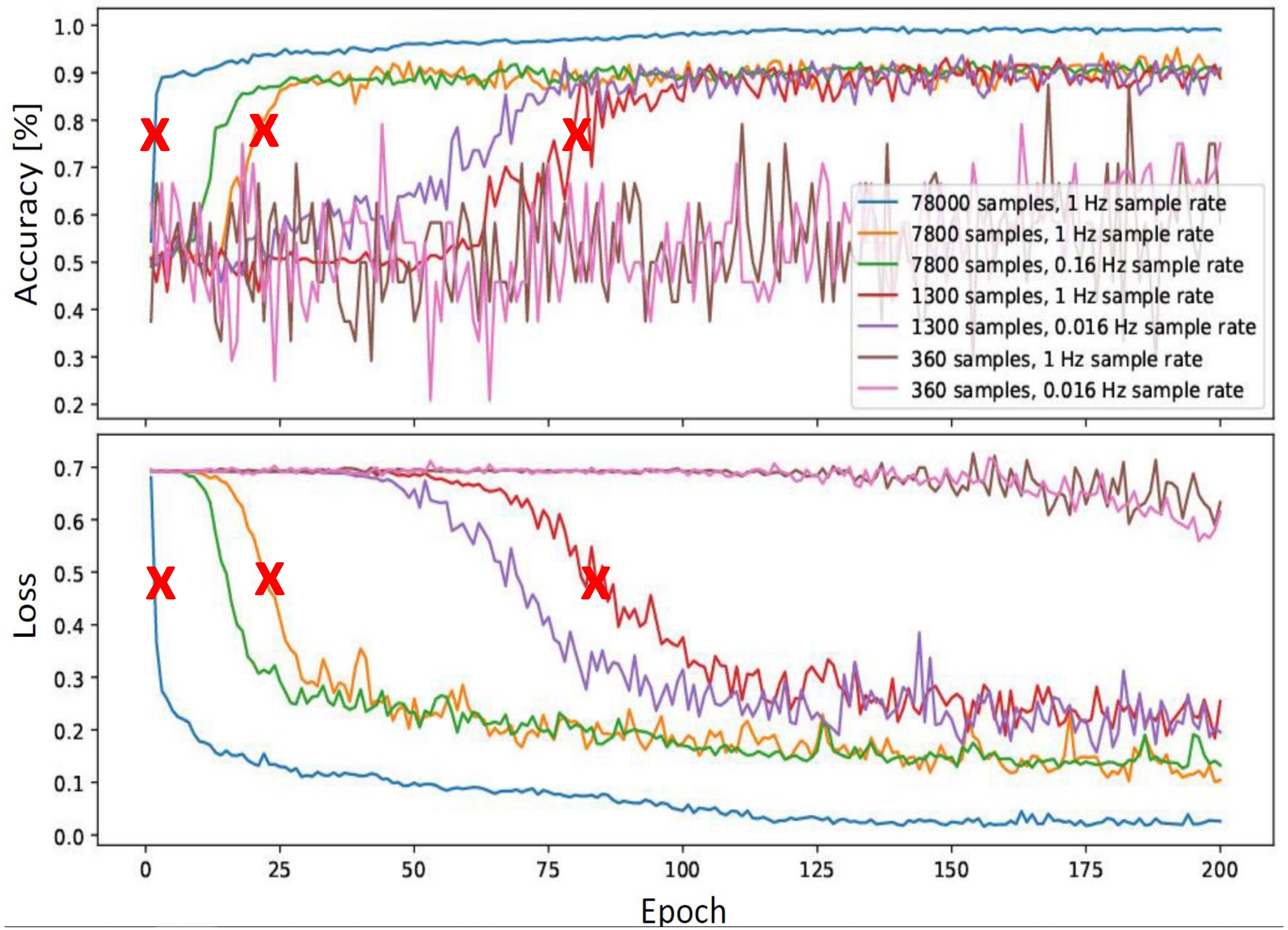
Evaluation of CNN training using data with different resolutions

Less number of samples, slower convergence

Less number of samples:

✓ lower accuracy

✓ Slower convergence

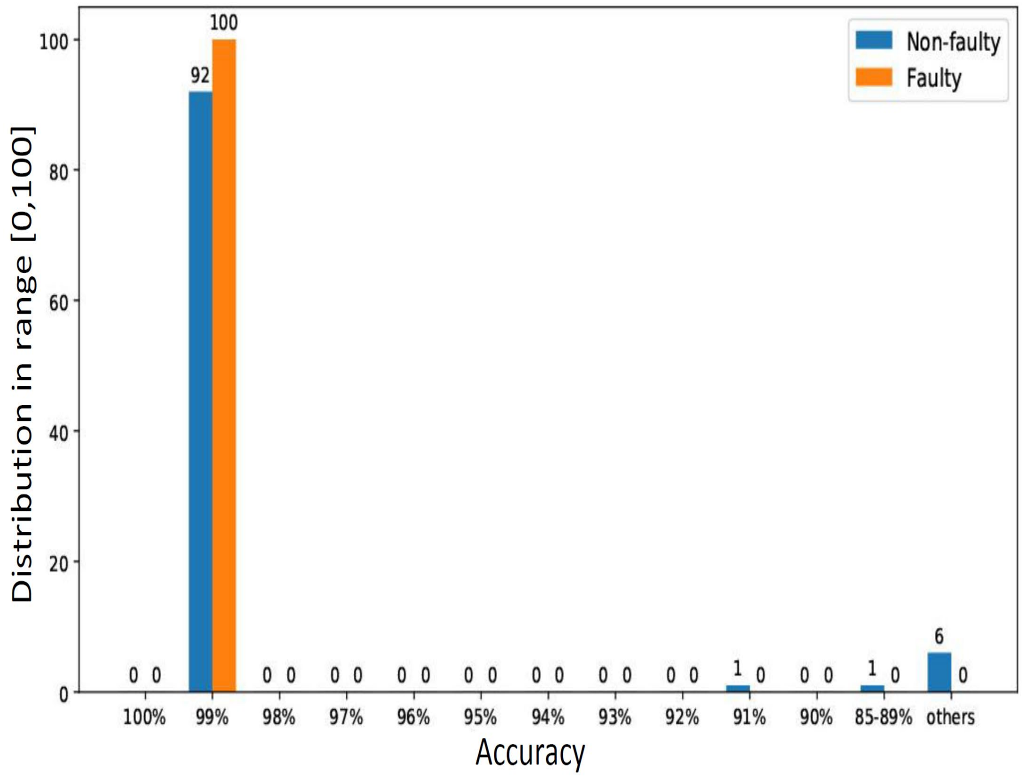


1. Evaluation of CNN training using data with different resolutions

Effect of perturbation & noise – CNN

- ***Perturbation test:***
- 1% false positive rate, reliable for 92% of the time

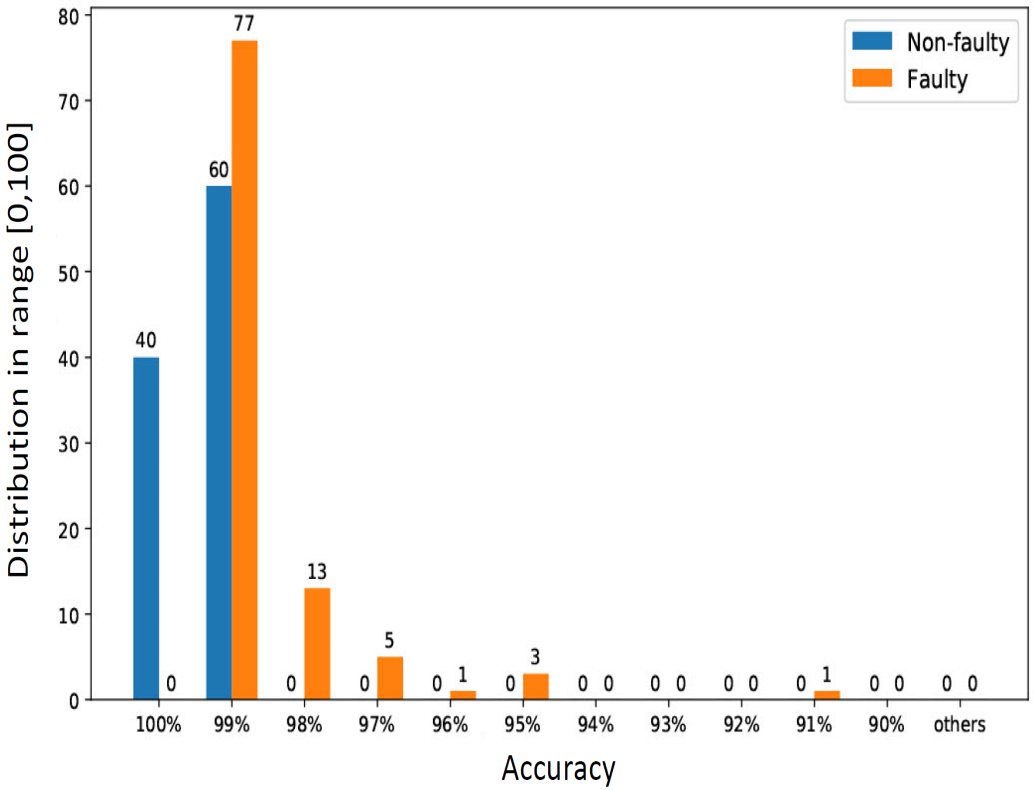
- 99% classification accuracy for detecting faulty condition



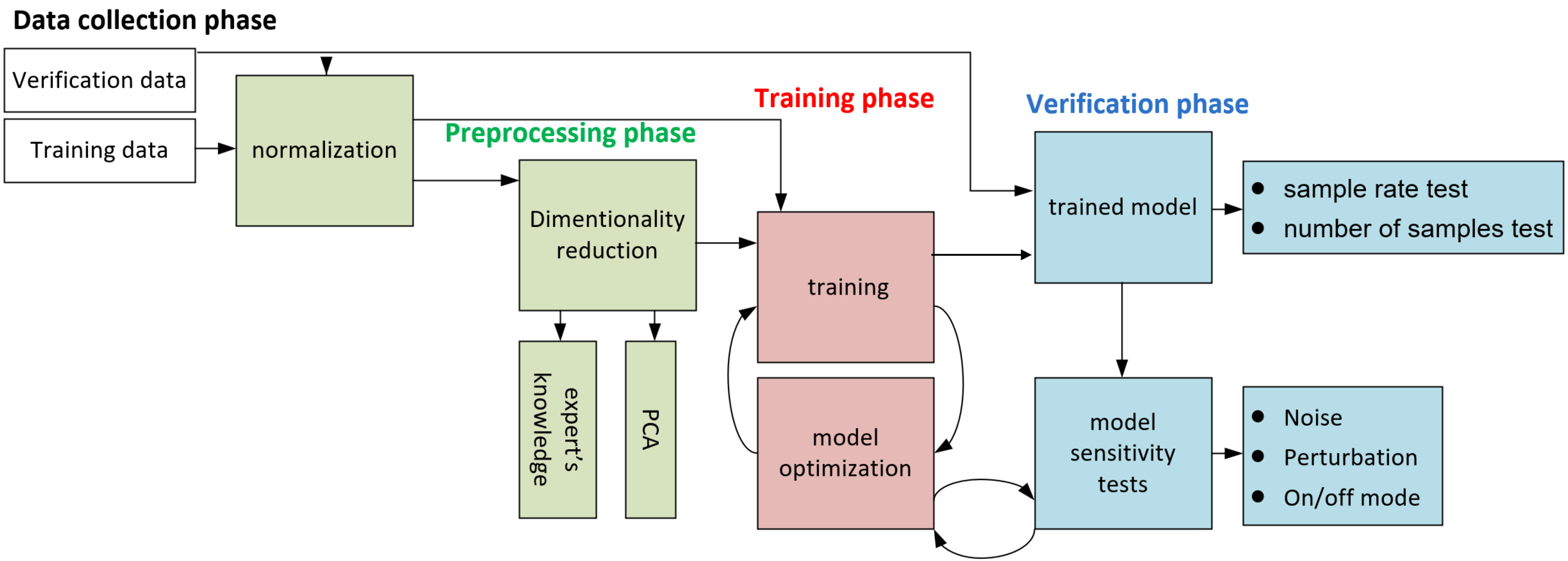
Noise test:

- < 1% false positive for all runs

- >95% fault classification accuracy for 99 runs out of 100



SVM for binary clssification: Overveiw



SVM sensitivity against data resolution and size

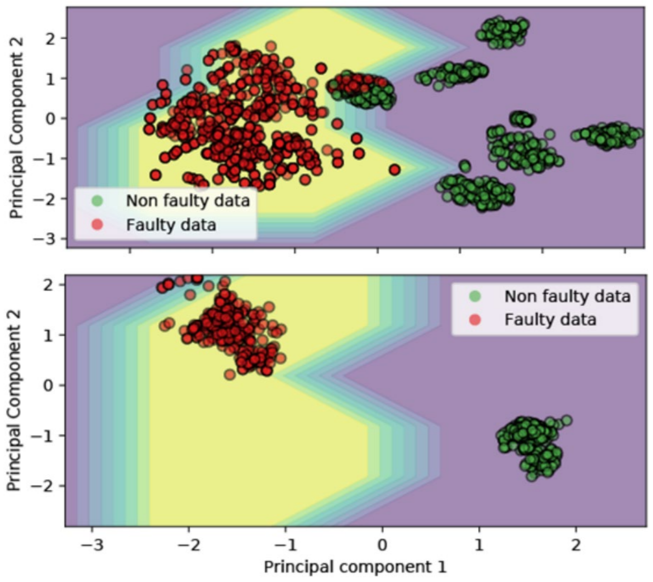
- Importance of data length selection for SVM training

- Result of the SVM training is independent to the sample rate, if data represents thermodynamical behavior of the systems

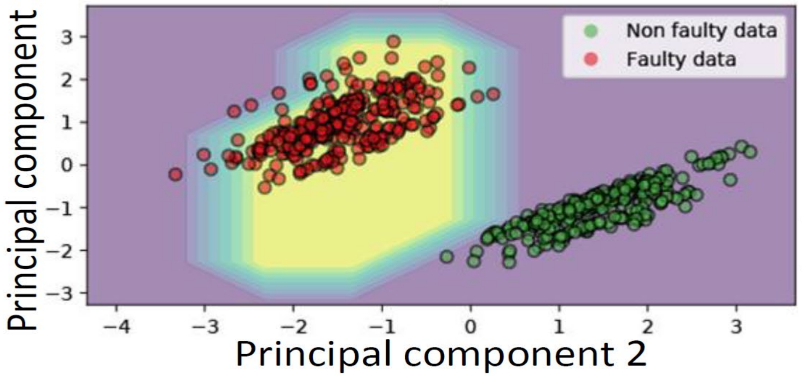
length	sample rate $[Hz]$	training time (s)	accuracy [%]
300	1	0.07	94
	0.1	0.08	94
	0.01	0.07	94
900	1	0.09	99
	0.1	0.09	99
	0.01	0.1	99
1800	1	0.57	93
	0.1	0.65	93
	0.01	0.63	93

PCA-SVM sensitivity tests

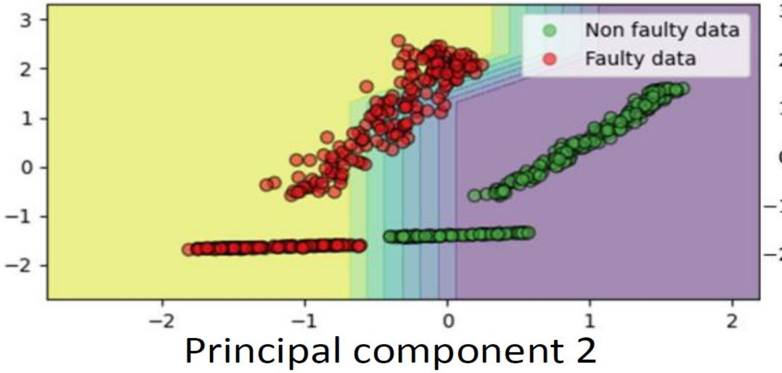
Training and test result for PCA-SVM



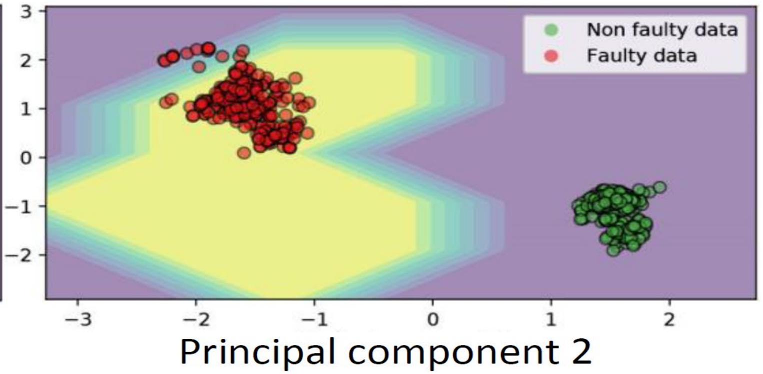
Result for noisy validation data



Result for validation data in On/OFF mode



Result for perturbed validation data



PCA-SVM better than the others

- **4D SVM** and **2D PCA-SVM** obtained very similar results
- PCA-SVM performs better in fault detection in On/Off experiment
- PCA-SVM is more robust and efficient as it automatically select the dimensions

	Algorithm	Non faulty[%]	Faulty[%]
Noisy	14D SVM	98.5 -99.6	98 -99.4
	4D SVM	98 -100	98 -99.4
	PCA-SVM	98 -100	98 -99.6
Perturbed	14D SVM	89-100	97-100
	4D SVM	99.2-100	99-100
	PCA-SVM	100	100
On/Off	14D SVM	50-60	53-60.5
	4D SVM	55-60	54-61
	PCA-SVM	85-86	95.5-96.4

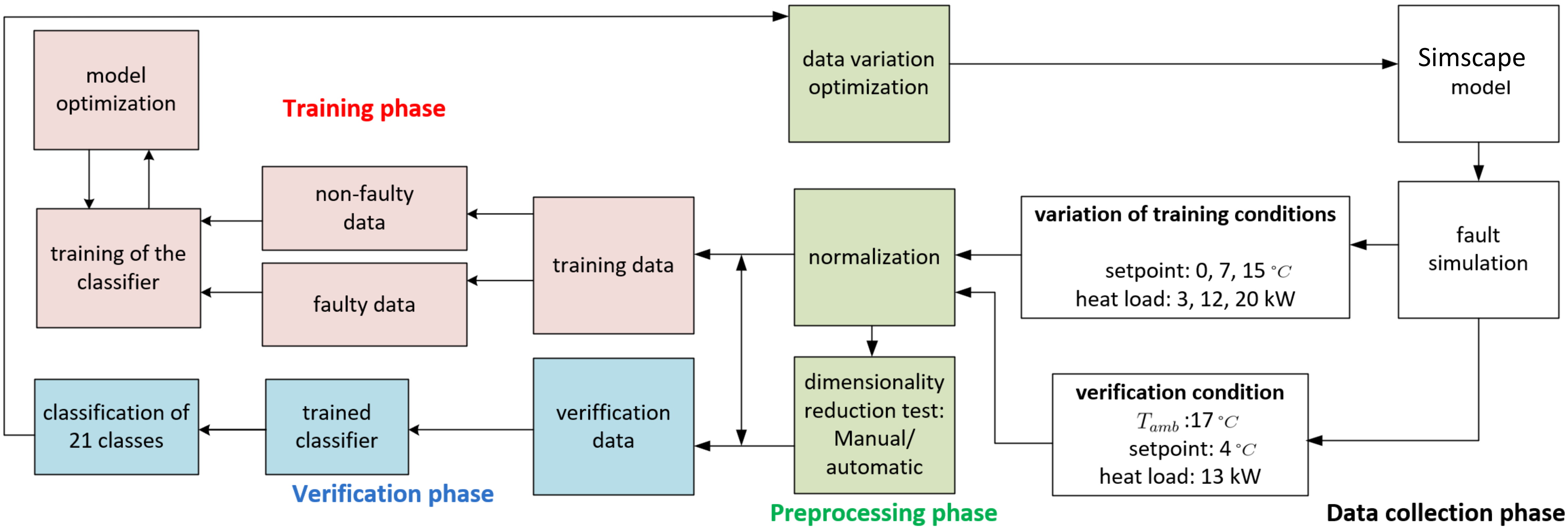
PCA-SVM obtained the best result for the experiments above

Faults description

- Temperature offset 2 ^{0}C
- Psuc offset 0.2 bar
- Pdis offset 1 bar

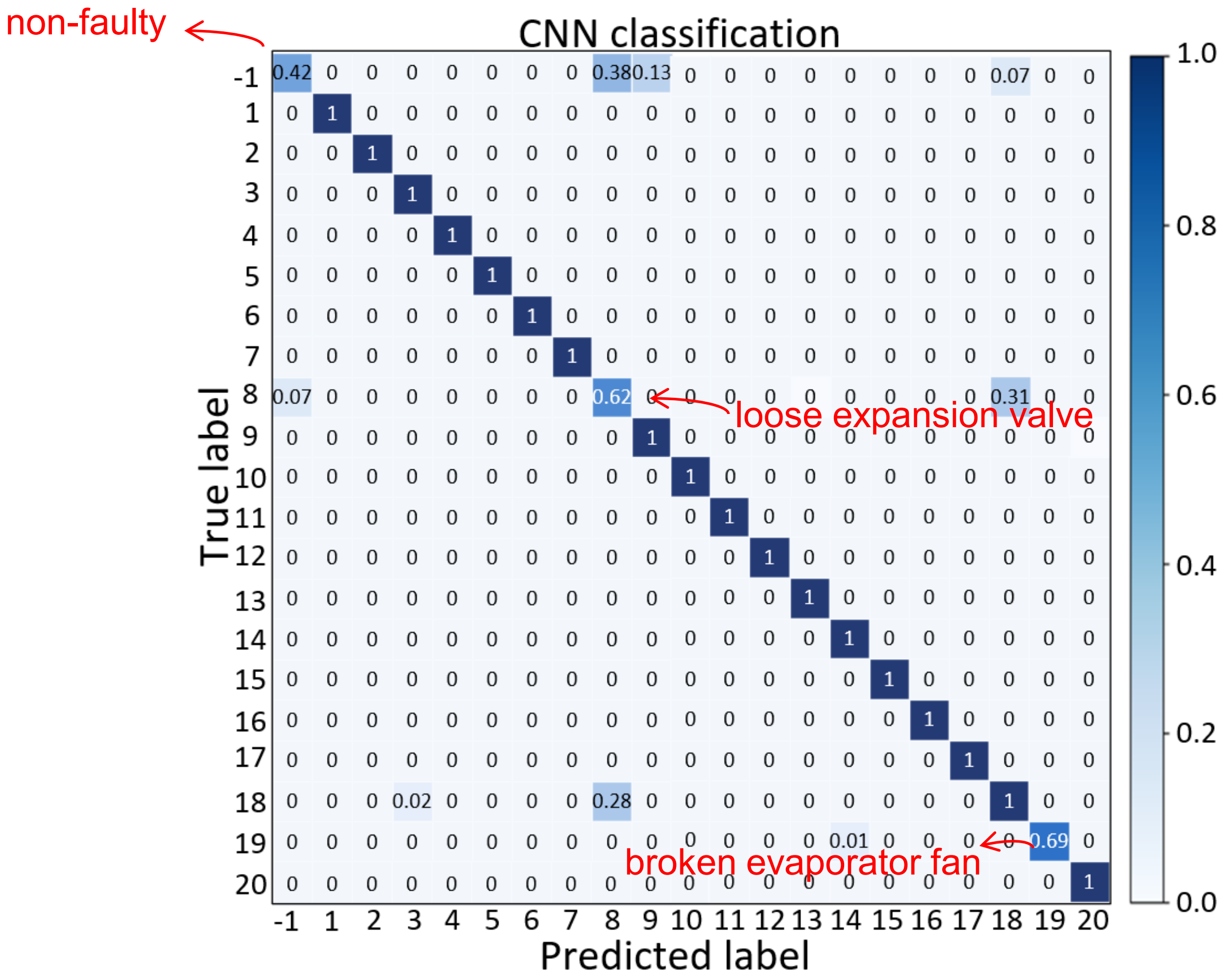
Label	Fault
1	T_{suc} sensors positive offset
2	T_{sup} sensors positive offset
3	T_{ret} sensors positive offset
4	T_{dis} sensors positive offset
5	P_{dis} sensor positive offset
6	P_{suc} sensor positive offset
7	Compressor poor performance
8	Losse expansion valve
9	Evaporator fan poor performance
10	Condenser fan poor performance
11	T_{suc} sensors negative offset
12	T_{sup} sensors negative offset
13	T_{ret} sensors negative offset
14	T_{dis} sensors negative offset
15	P_{dis} sensor negative offset
16	P_{suc} sensor negative offset
17	Broken compressor
18	Blocked expansion valve
19	Broken evaporator fan
20	Blocked condenser fan

Multi-class classification
Overview



CNN for multi-class classification

- Can classify most of the classes
- Total accuracy: 94%
- 58% false positive

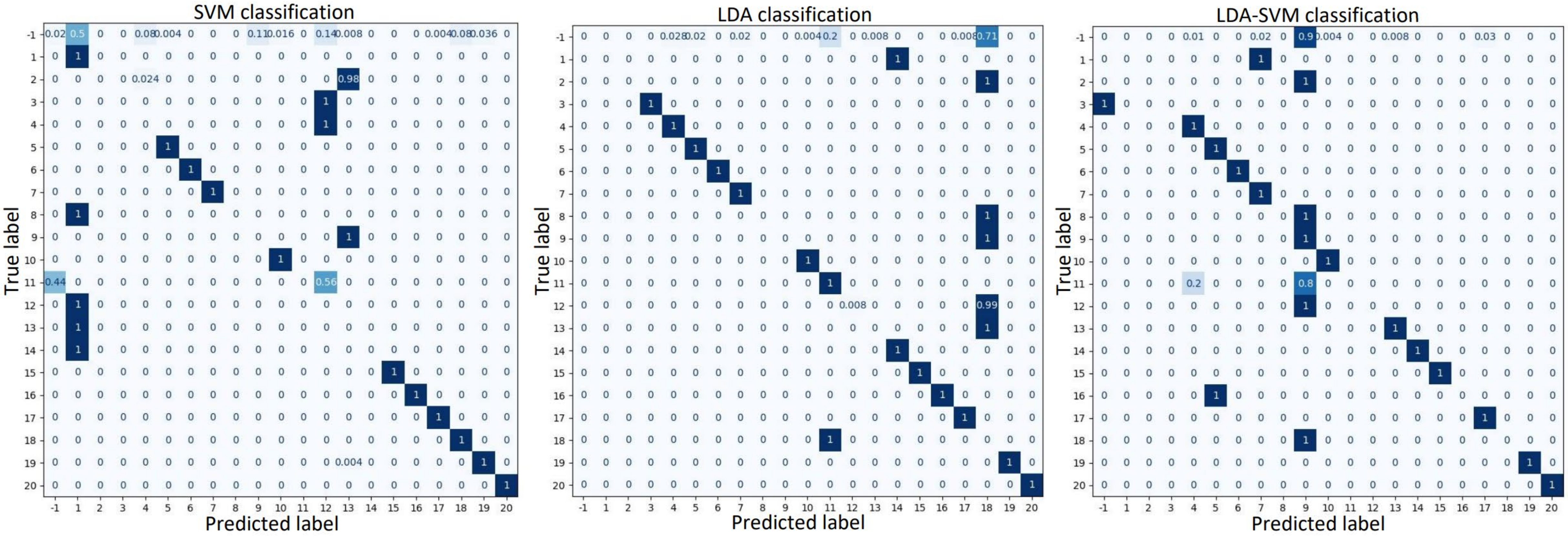


Models comparison: training/test results

model	accuracy	false positive	training time	prediction time
SVM	99.6%	0%	1.1 s	1 s
LDA	99.8%	0%	3.2 s	0.3 s
CNN	94%	68%	112.5 s	0.1 s
PCA-SVM	55.4%	24%	7.2 s	5.6 s
LDA-SVM	96.6%	18%	1 s	1.1 s

- LDA, SVM, LDA-SVM obtained the most accuracy, respectivly
- False positive in LDA and SVM are perfect (training/test phase)
- Prediction time of LDA is comperatively lower than the others
- Training time is too slow in CNN and false positive is too high
- Total accuracy for PCA-SVM is too low

No satisfatory results

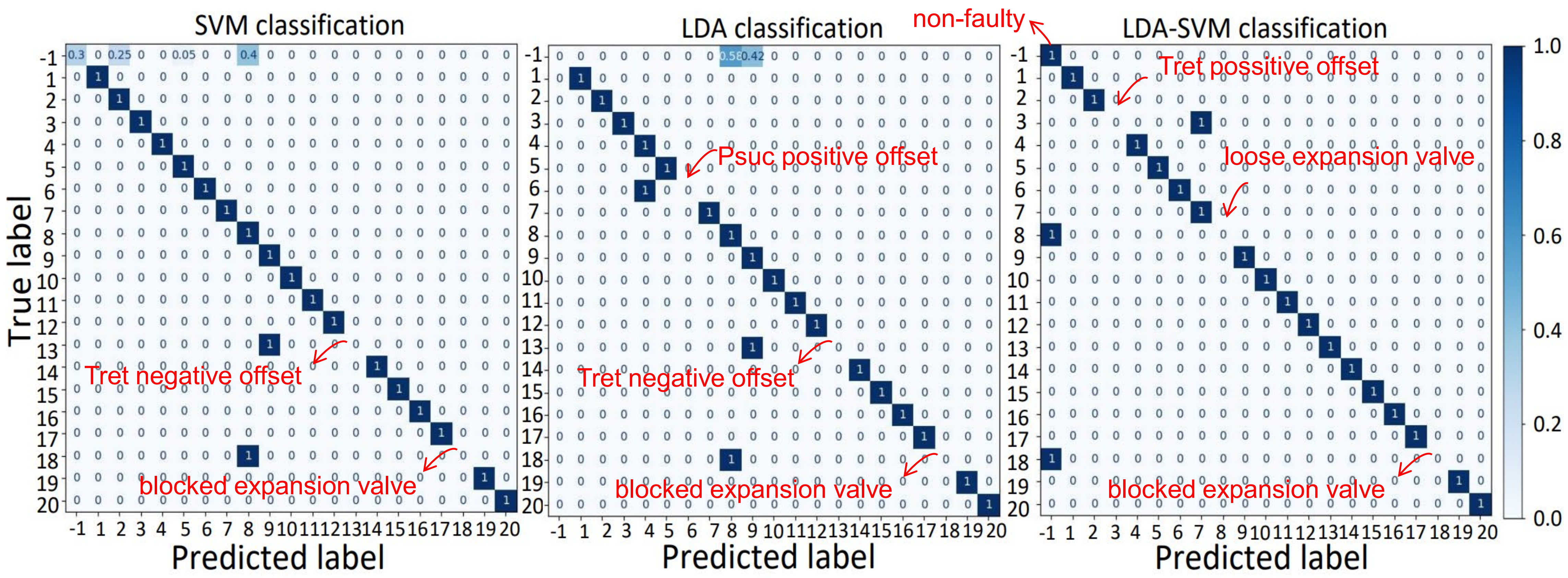


Verification data in different operation conditions than training

- Non-faulty data is **not** identified
- Faulty data are **not** classified satisfactorily

models with more data variation

Adding variation of ambient temperature and setpoint to the data features



- density, and power consumption of the compressor are removed.

LDA-SVM for fault detection

model	accuracy	false positive	prediction time
SVM	87%	70%	0.4 s
LDA	81%	100%	0.3 s
LDA-SVM	86%	0%	1.5 s

Reseach remarks

- PCA Vs LDA   (binary classification or multi-class classification)?

- Data resolution is not important when using SVM until it preserve dynamic of the systems
- Careful selection of data size when using SVM.

- Best model selection: a trade-off among a high accuracy, low computation, and low false positive

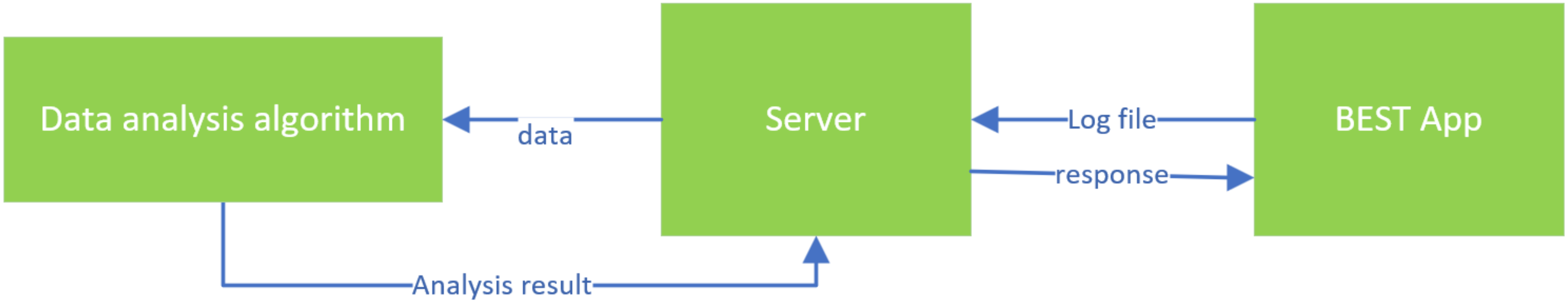
    LDA-SVM, a reliable model for fault detection with a 0% false positive

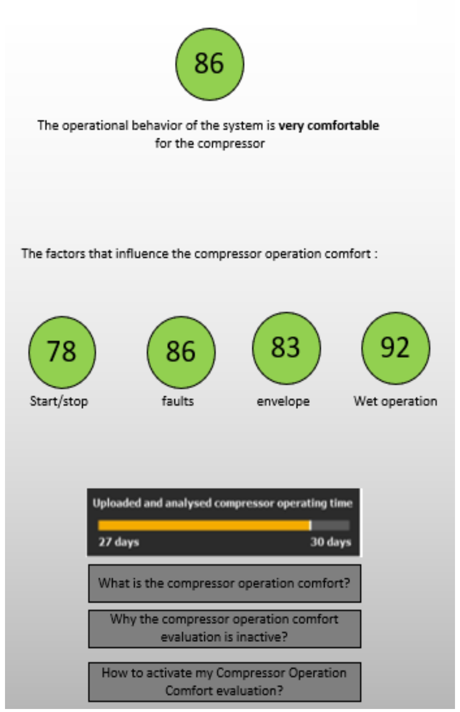
    SVM, the most accurate model for fault diagnosis

    LDA quick at prediction

- Careful selection of input data

Smart solution for performance monitoring





Zahra Soltani
zahra.soltani@bitzerdk.com
Bitzer Electronics
Sønderborg