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Probabilistic Uncertainty-Aware Decision Fusion of Neural Network for Bearing Fault Diagnosis

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Introduction

Condition monitoring is a system constructed from many parts
Sensors, measurement devices, CM algorithms, operators …

Importance of reliability of the condition monitoring systems
False diagnosis is costly and reduces the trust of operators in CMS

Uncertainty and Reliability
Uncertainty can undermine the predictability of the model

Objective of study
Mitigating uncertainty by fusion

Methodology
Bayesian model averaging for an uncertainty aware decision fusion

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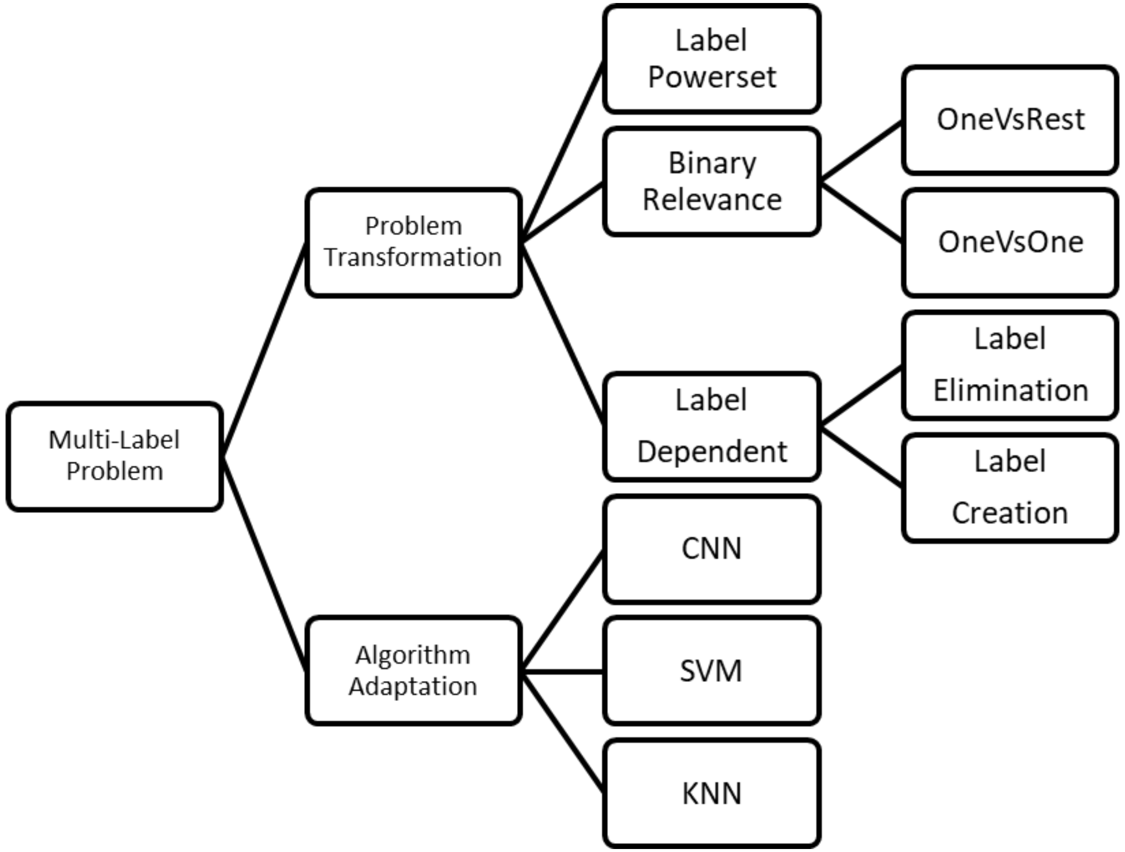
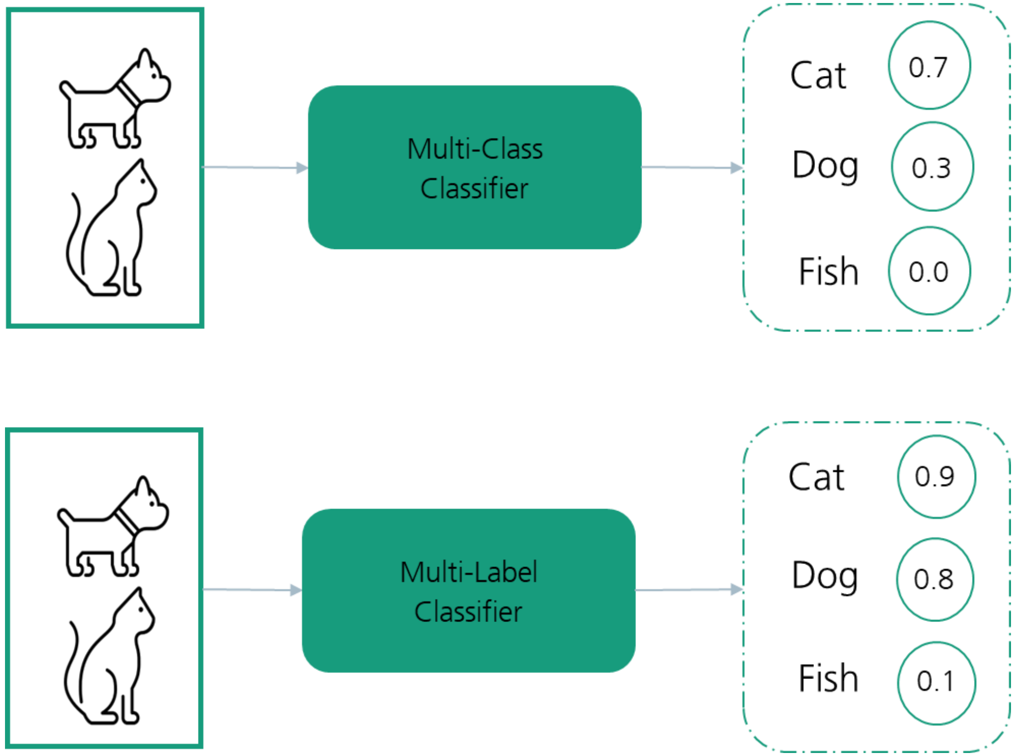
Methodology

Multi-Label Classifier

- **Multi-Label classification**
- **One-against-all multi-label classifier**
- **Algorithm adaptation**





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Methodology

Bayesian model averaging

- Selecting one model vs. Bayesian Model averaging
- Considering Uncertainty of each model with BMA
- Models' prior probability represented as a weight: non-negative and sum up to one

$$\pi(\theta_l|Y, M_l) = \frac{L(Y|\theta_l, M_l)\pi(\theta_l|M_l)}{\int L\,(Y|\theta_l, M_l)\pi(\theta_l|M_l)d\theta_l}$$

$$BF_{lm} = \frac{\pi(M_l|Y)}{\pi(M_m|Y)}$$

$$\pi(\Delta|Y) = \Sigma_{l=1}^{k}\pi(\Delta|M_l, Y)\pi(M_l|Y)$$

Prior Estimation: Log Likelihood Maximization

“Maximum likelihood estimator is the value of the parameter vector that maximizes the likelihood function, that is, the value of the parameter vector under which the observed data were most likely to have been observed”

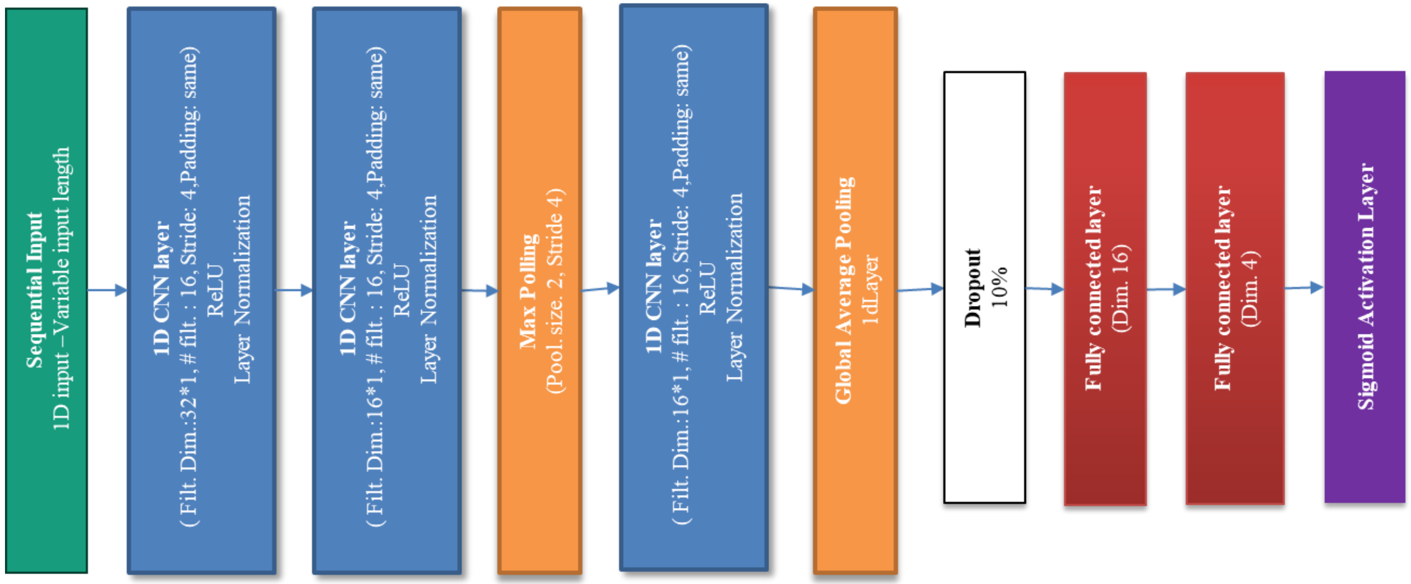
$$L(w_k|Y) = \Sigma_t \Sigma_{k=1}^{k} \log \pi(\Delta|M_l, Y)\, w_k$$

Model

1D Multi-Label CNN

- Reduction of computational complexity by 1D CNN
- Architecture and cost function difference
- Lightweight model and suitable for real-time
- No preprocessing step needed
- Two similar 1D multi-label CNNs for two different accelerometers

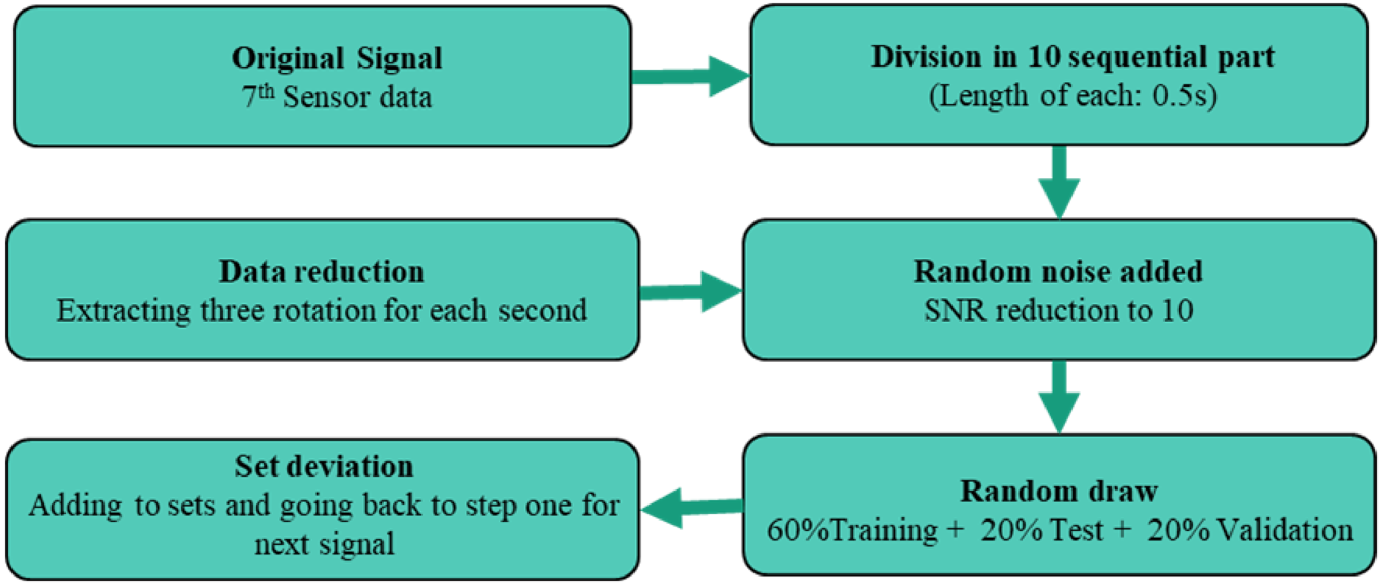
Hyperparameter	Value
Mini batch size	25
Max epoch	50
Network selection (early stoppage)	Minimum validation loss
optimizer	Adam
Learning rate	0.001
Loss Function	Binary cross-entropy
Padding	“Same”
Software	MATLAB



Dataset and Data handling

MAFAULDA Open Dataset

- Test bench: SpectraQuest
- Bearings: two ABVT 8 rolling ball bearings
- RMP range: 700 – 3600 rpm
- Sensors:
  - Tachometer
  - Two tridimensional accelerometers
  - Microphone
- Sampling Frequency: 50 KHz
- Measurement duration: 5s
- Outer/Inner/cage fault scenarios



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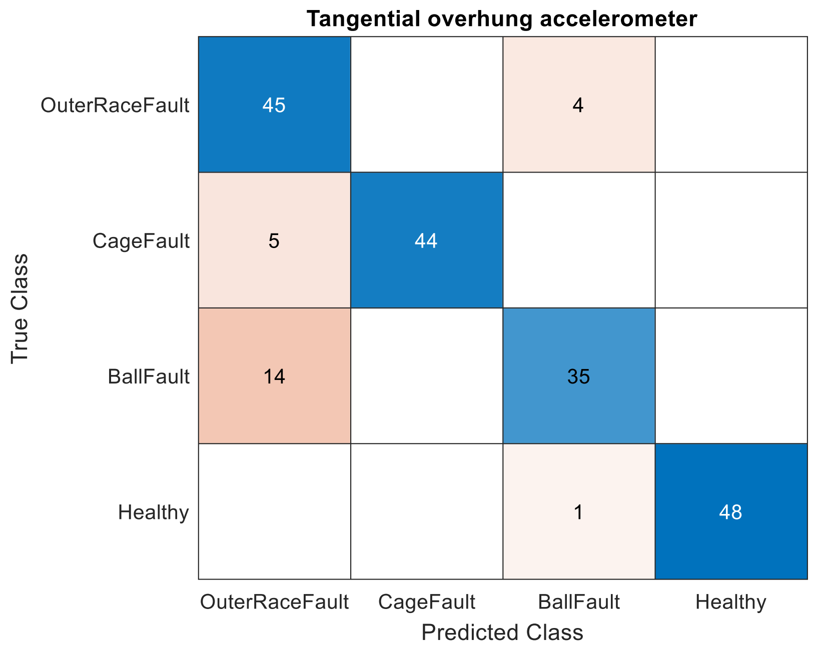
Result

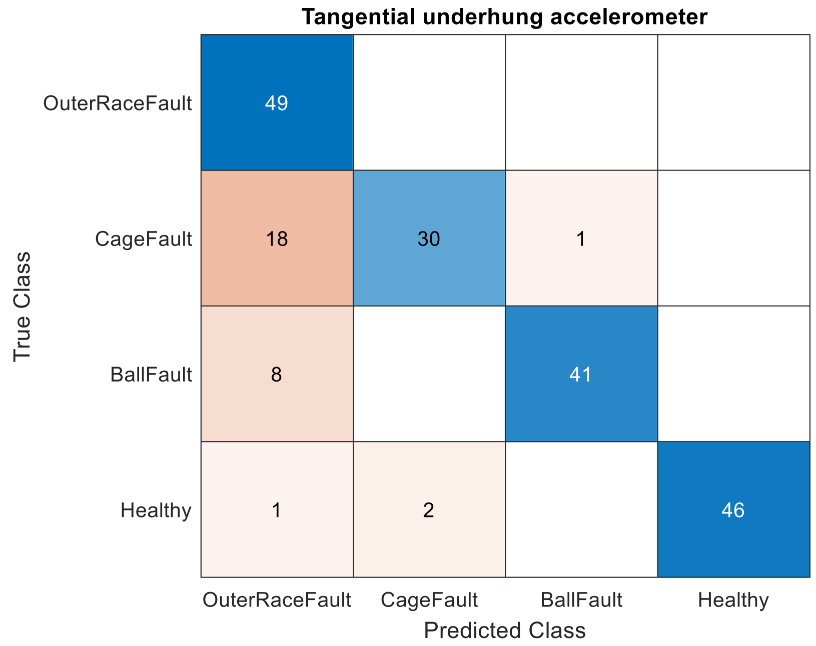
Single model result

* Acceptance threshold = 0.5

Model	Accuracy (%)
Overhang accelerometer	87.76
Underhung accelerometer	84.69



Tangential overhung accelerometer



Tangential underhung accelerometer

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Result

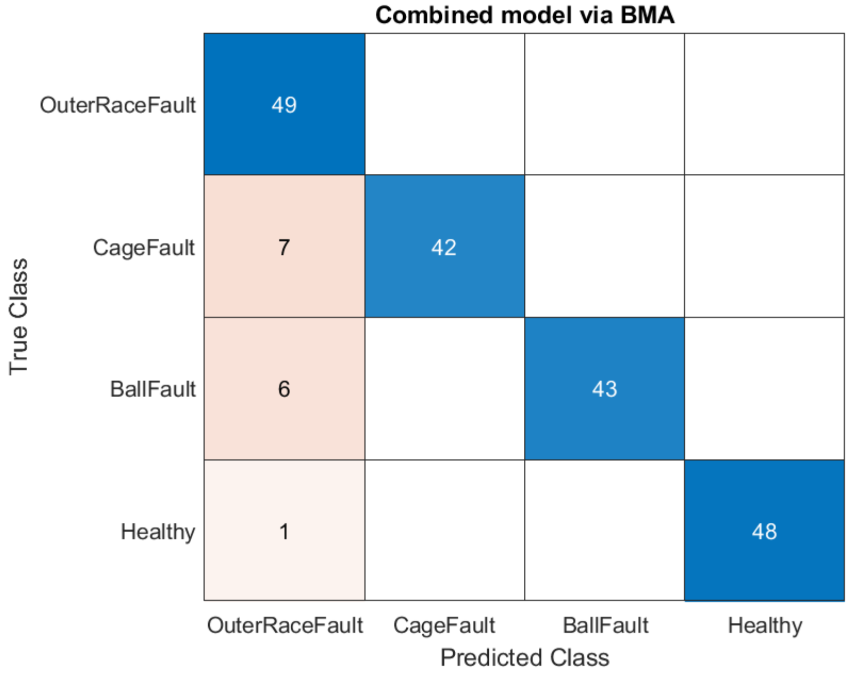
Bayesian Model averaging

* Acceptance threshold = 0.5

Model	Accuracy (%)
Overhang accelerometer	87.76
Underhung accelerometer	84.69
Combined Model	91.84

Posterior probability of overhang model (%)	Posterior probability of underhung model (%)
37.28	62.72

	Case A			Case B		
	Overhang	Underhung	Combined	Overhang	Underhung	Combined
Outer race fault	0.04	0.59	0.39	0.46	0.78	0.66
Cage fault	1.00	0.24	0.52	0.01	0.2	0.13
Ball fault	0.00	0.05	0.03	0.54	0.02	0.21
Healthy	0.00	0.00	0.00	0.00	0.00	0.00
True label	Cage Fault			Outer Race Fault		



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Conclusion

Uncertainty-Aware Fusion Algorithm

Implementing an uncertainty-aware fusion algorithm helps differentiate between high and low-quality information

Bayesian odel Averaging

Bayesian model averaging serves as both a model selector and an uncertainty-aware decision fusion algorithm

Benefits of the Suggested Methodology

- Simplicity
- Lightweight
- Increased Accuracy

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Thank You!

Questions?

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