UNIVERSITÀ DEGLI STUDI DI NAPOLI FEDERICO II

Artificial Intelligence and Intelligent Systems
cini National Lab

PICUS lab
PATTERN ANALYSIS AND INTELLIGENT COMPUTATION FOR MULTIMEDIA SYSTEMS

Advanced AI-based approaches in Industry 4.0 of the University of Naples Federico II node of the CINI-AIIS Lab

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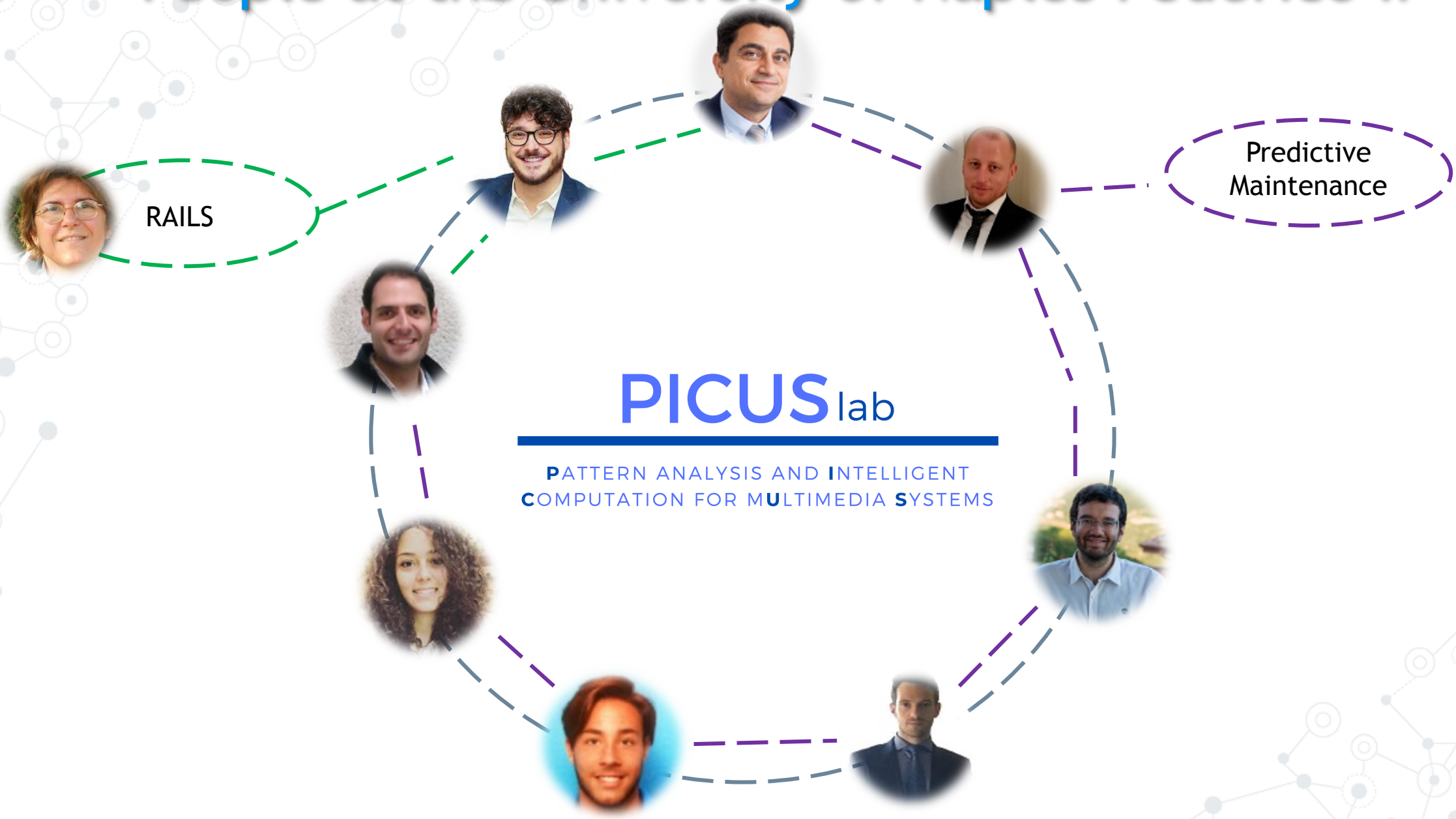
University of Naples Federico II

Ital-IA 2023: 3rd National Conference on Artificial Intelligence May 29--31, 2023, Pisa, Italy
Workshop: AI per l'industria

People at the University of Naples Federico II

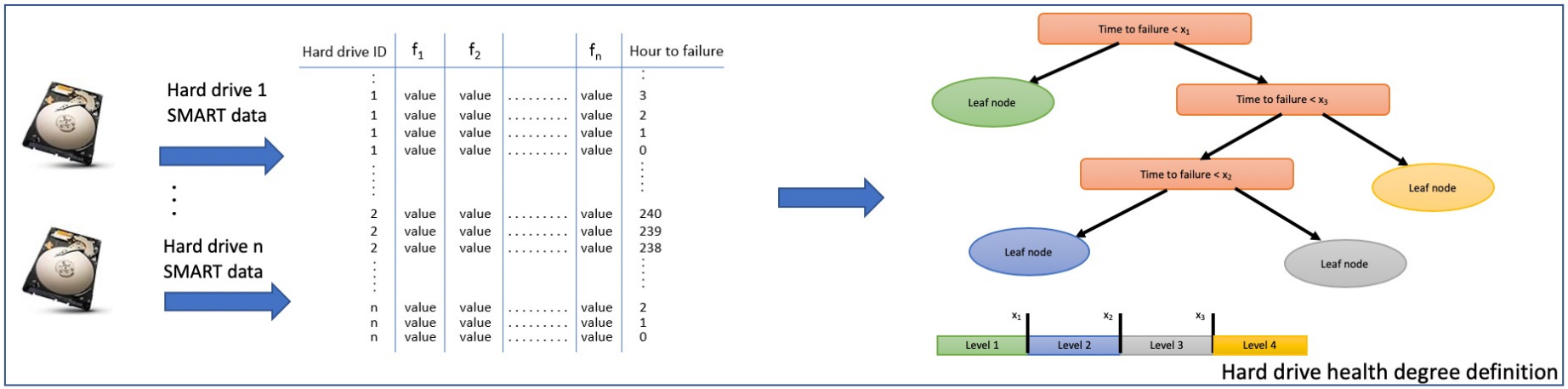


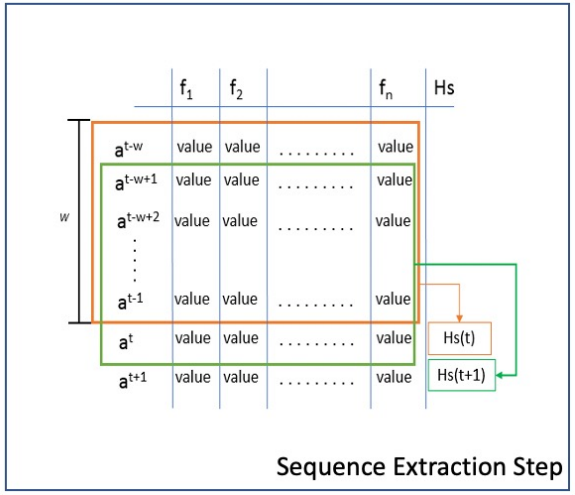
Industry 4.0 scenarios

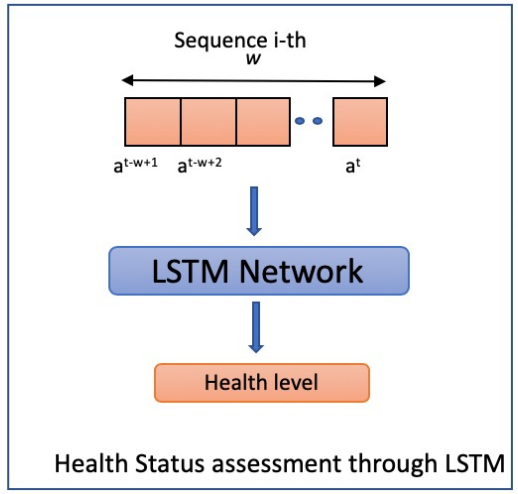
XAI - eXplainable Artificial Intelligence

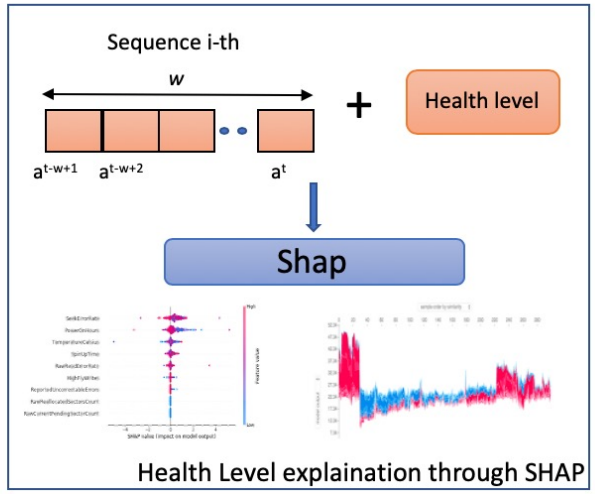
- Business Prespective
  - Blackbox AI creates business risk for Industry
- Model prespective
  - Debug (Mis-) Prediction
  - Improve ML model
  - Verify ML model
- Regularity prespective
  - Fairness
  - Privacy
  - Transparency

HDD health status assesment



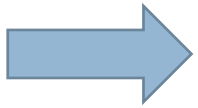


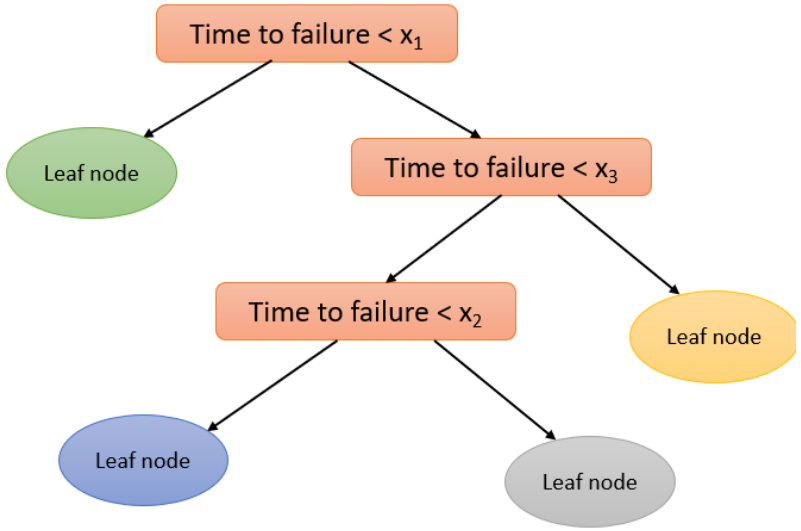


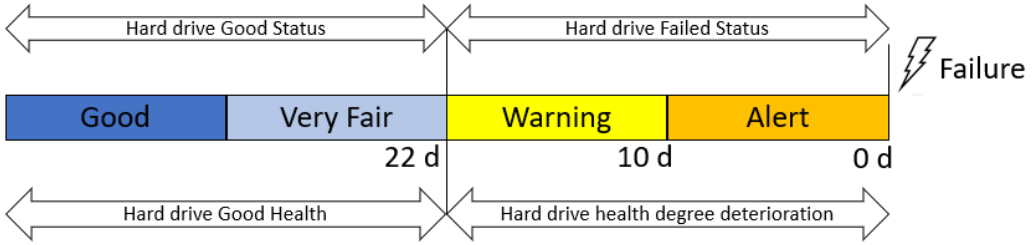


HDD health degree definition

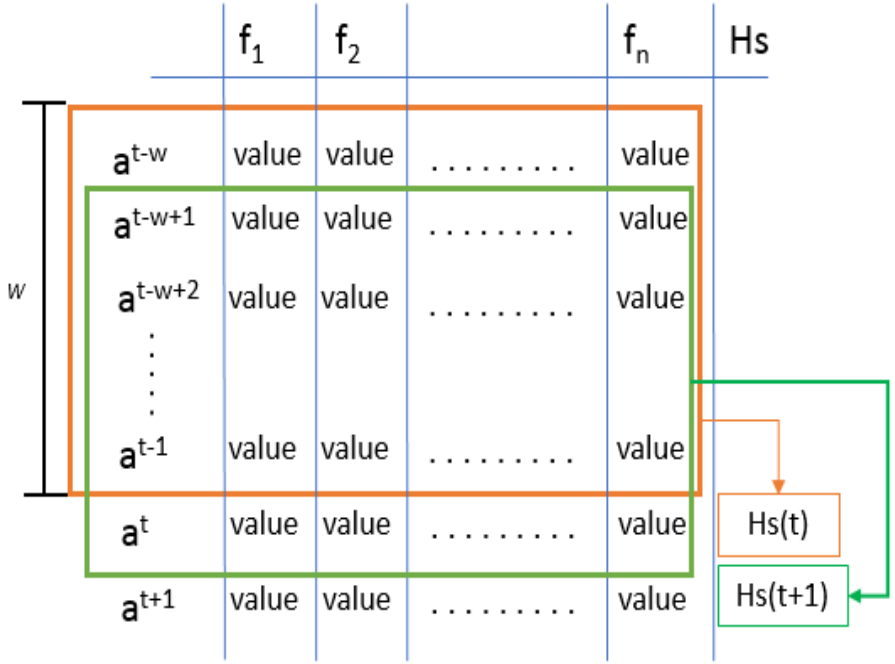
Hard drive ID	f_1	f_2		f_n	Hour to failure
⋮					⋮
1	value	value	.....	value	3
1	value	value	.....	value	2
1	value	value	.....	value	1
1	value	value	.....	value	0
⋮					⋮
2	value	value	.....	value	240
2	value	value	.....	value	239
2	value	value	.....	value	238
⋮					⋮
n	value	value	.....	value	2
n	value	value	.....	value	1
n	value	value	.....	value	0

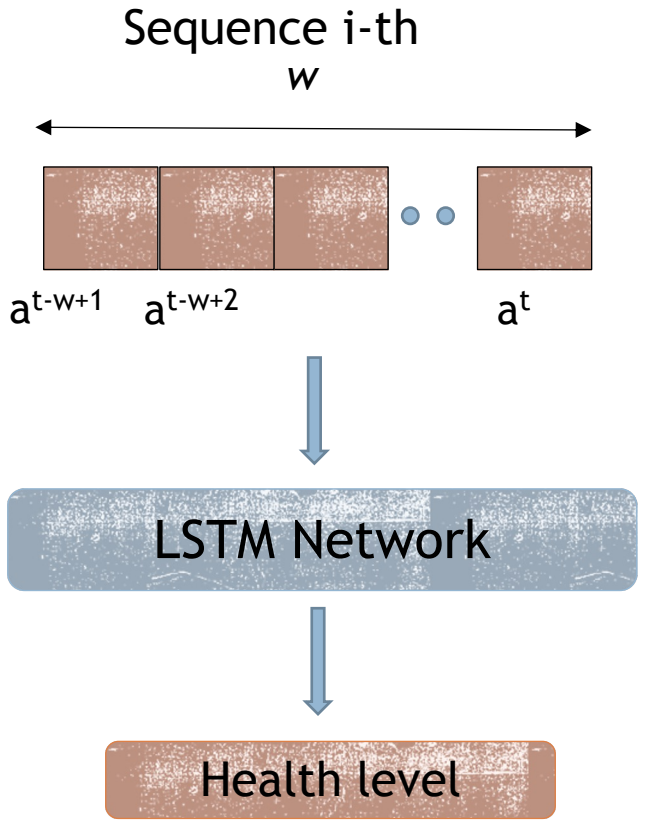






Health status assesment through LSTM





- the classification network is implemented as two stacked LSTM layers with 128 units, followed by a single dense layer with number of units equal to classes number, and softmax as a activation function

Results

Backblaze

Model	*Accuracy*	ACC_G	ACC_F	ACC_G^{TOL}	ACC_F^{TOL}	*FDR*	*FAR*
CT	83.80%	83.87%	56.31%	95.63%	88.46%	63.58%	4.69%
RF	85.77%	85.77%	**71.75%**	93.68%	**93.82%**	**80.66%**	6.49%
MNN	**96.17%**	**99.15%**	39.78%	**99.88%**	69.20%	85.75%	**0.95%**

Author	Methods	Accuracy	Precision	Recall
Zhang et al.[19]	LPAT+All	92.6%	89.3%	88.7%
Basak et al.[3]	LSTM	—	84.35	72.0%
Our Approach	LSTM	**98.45%**	**98.33%**	**98.34%**

Author	Methods	*FDR*	*FAR*
Shen et al.[15]	RF	94.89%	0.44%
Xiao et al.[17]	ORF	98.08%	0.66%
Our Approach	LSTM	**98.20%**	**0.20%**

Baidu

Model	*Accuracy*	ACC_G	ACC_F	ACC_G^{TOL}	ACC_F^{TOL}	*FDR*	*FAR*
CT	97.01%	97.01%	58.94%	99.09%	**85.77%**	84.16%	1.00%
RF	**98.13%**	98.13%	**59.44%**	**99.82%**	85.65%	**85.36%**	**0.40%**
MNN	96.24%	**98.57%**	38.99%	99.14%	69.59%	73.03%	1.20%

Author	Methods	ACC_G	ACC_F	ACC_G^{TOL}	ACC_F^{TOL}
Xu et al. [4]	Multiclass NN	99.19%	16.01%	99.40%	43.34%
Xu et al. [4]	CRF	99.57%	28.51%	99.59%	61.30%
Xu et al. [4]	RNN	99.73%	41.05%	**99.93%**	64.86%
Our Approach	LSTM	**99.83%**	**93.17%**	99.89%	**98.31%**

Author	Methods	*FDR*	*FAR*
Xu et al.[4]	Multiclass NN	83.21%	0.60%
Xu et al.[4]	CRF	85.50%	0.22%
Xu et al.[4]	RNN	87.79%	**0.004%**
Li et al.[11]	CT	95.49%	0.09%
Zhu et al.[12]	BP NN	94.62%	0.48%
Shen et al.[3]	RF	97.67%	0.017%
Our Approach	LSTM	**98.20%**	0.20%

[19]Zhang, J., Wang, J., He, L., Li, Z., Philip, S.Y.: Layerwise perturbation-based adversarial training for hard drive health degree prediction. In: 2018 IEEE ICDM. pp. 1428–1433. IEEE (2018)
[3]Basak, S., Sengupta, S., Dubey, A.: Mechanisms for integrated feature normalization and remaining useful life estimation using lstms applied to hard-disks. In: 2019 IEEE SMARTCOMP
[15]Shen,J.,Wan,J.,Lim,S.J.,Yu,L.:Random-forest-based failure prediction for hard disk drives. International Journal of Distributed Sensor Networks 14(11) (2018)
[17]Xiao, J., Xiong, Z., Wu, S., Yi, Y., Jin, H., Hu, K.: Disk failure prediction in data centers via online learning. In: Proceedings of the 47th ICPP. p. 35. ACM (2018)
[4]C. Xu, G. Wang, X. Liu, D. Guo, and T.-Y. Liu, "Health status assessment and failure prediction for hard drives with recurrent neural networks," IEEE Transactions on Computers
[11]J. Li, X. Ji, Y. Jia, B. Zhu, G. Wang, Z. Li, and X. Liu, "Hard drive failure prediction using classification and regression trees," in International Conference on Dependable Systems and Networks.
[12]SheB. Zhu, G. Wang, X. Liu, D. Hu, S. Lin, and J. Ma, "Proactive drive failure prediction for large scale storage systems," in 2013 IEEE 29˚ Symposium on Mass Storage Systems and Technologies

The RAILS Project

Roadmaps for AI integration in the raiL Sector

Partners:

cini consorzio interuniversitario nazionale per l'informatica

UNIVERSITY OF LEEDS

Linnæus University

TU Delft

Objective:

Investigate the potential of Artificial Intelligence (AI) approaches in the rail sector and contribute to the definition of roadmaps for future research in **train safety and automation**, **assets maintenance and inspection**, and traffic planning and management.

Links:

https://rails-project.eu/

RAILS S2R Project

@project_rails

https://www.researchgate.net/project/RAILS-Roadmaps-for-AI-integration-in-the-raiL-Sector-EU-Horizon-2020-Shift2Rail-JU

Horizon 2020
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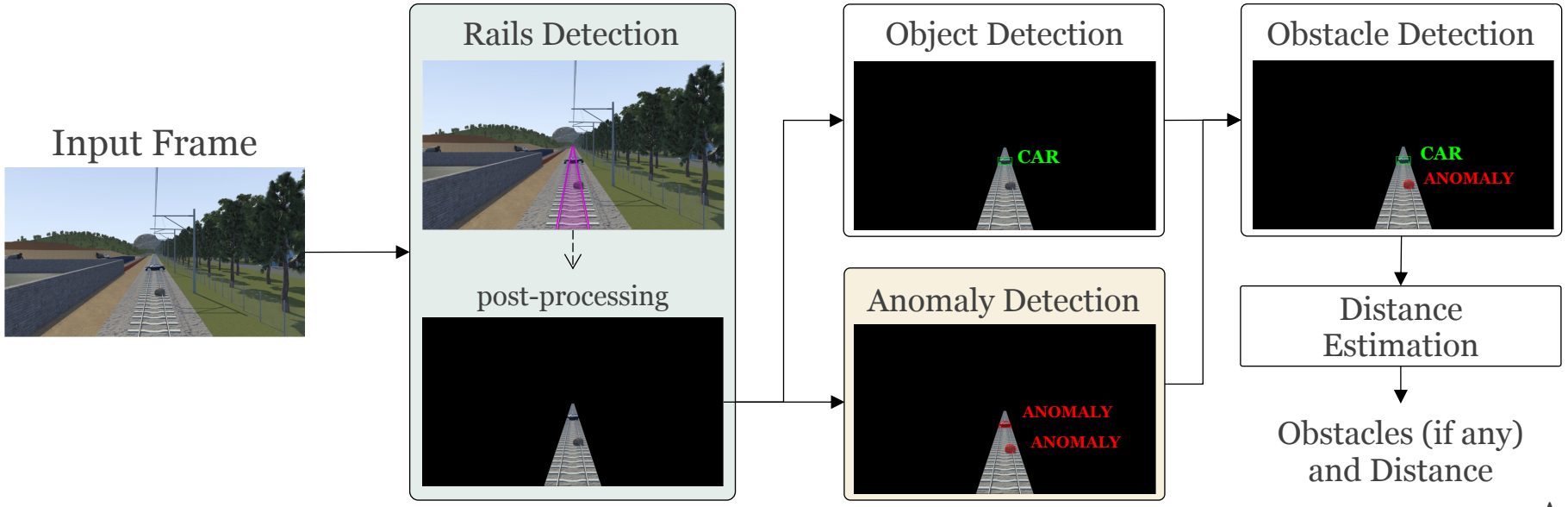
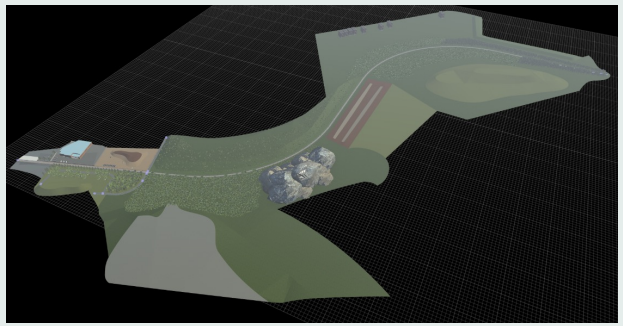
Vision-Based Obstacle Detection on Rail Tracks

Understand to what extent it would be possible to adopt a single *RGB camera* (as the easiest, yet challenging, possible scenario) and Deep Learning to detect *any kind of obstacles* on rail tracks.



Rails Detection

RoadRunner Scenario



RoadRunner / Augmentations (9600 samples)

U-Net

Pre-training on RailSem19

Dice Score: 0.9993

Anomaly Detection

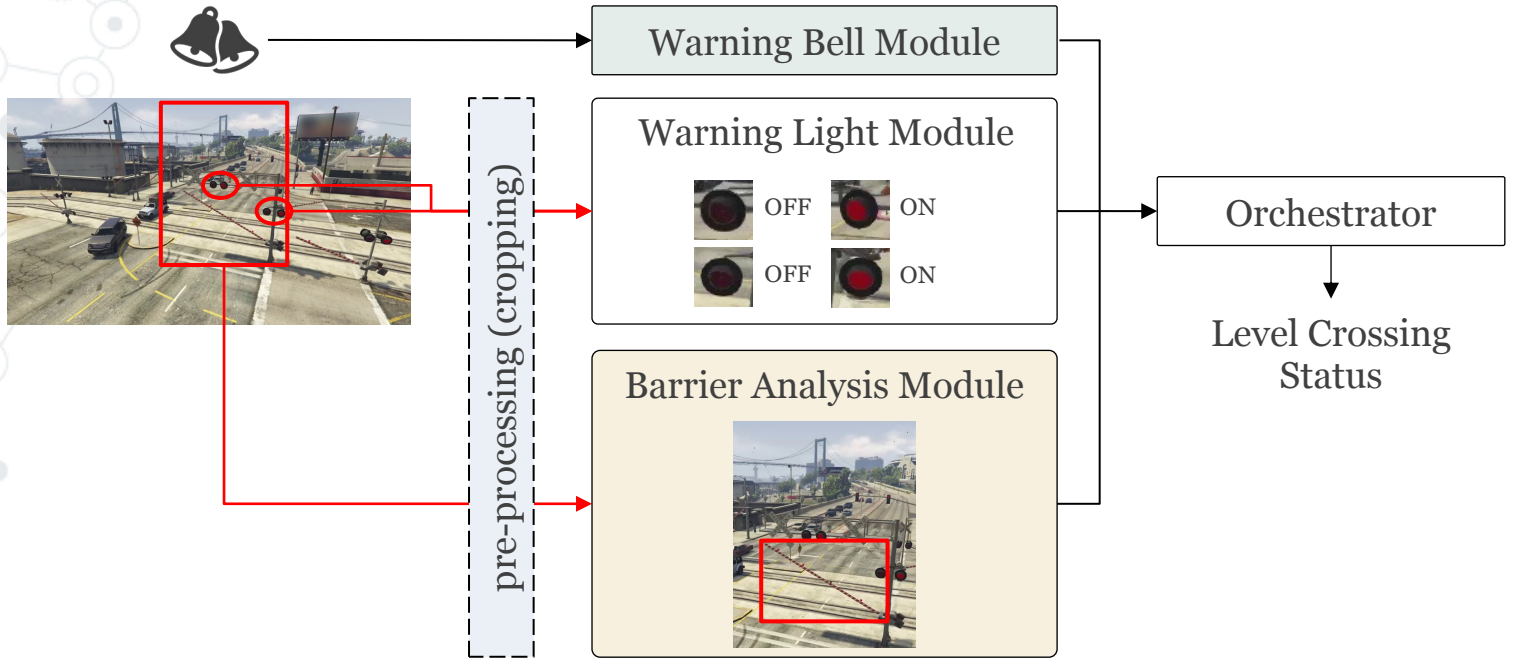
Rails Detection's Output + Augmentation (9000 frames)

SSIM-VQ-VAE

Reconstruction (SSIM) Score: 0.9887
maskMSE: 0.0346 (max 0.1852)
Detection Distance: 70m

Smart Maintenance at Level Crossings

Migrate from scheduled-based inspections and corrective maintenance to continuous monitoring and predictive maintenance of Level Crossings while leveraging *cost-effective* and *non-intrusive* sensors.

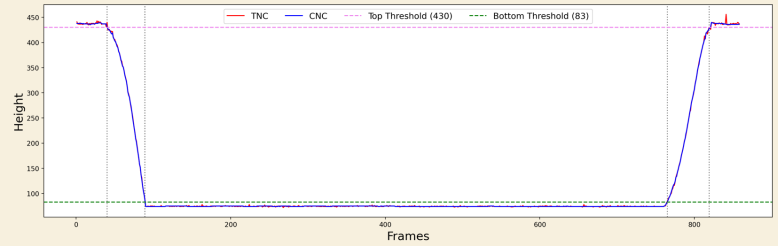


Warning Bell Module

- AudioSet / YouTube (1180 samples)
- VGGish CNN
- VGGish's weights (on YouTube8M)
- Frame-Level Accuracy: 92.48%
  Audio-Level Accuracy: 97.37%

Barrier Analysis Module

- GTA V / Augmentations (17760 samples)
- YOLOv5s
- YOLOv5s' pre-trained weights
- mAP@.5:.95: 0.98738
  Miss-detection Rate: < 0.8 %



Thank you for your attention!