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ESCAPE

Predictive Maintenance in the Digital Era

Introduction

- A poor maintenance strategy can be catastrophic to an organisation.
- Predictive maintenance is popular as it enables the estimation of when maintenance is required.
- Industry 4.0 is transforming manufacturing environments into complex cyber-physical production systems.
- Predictive maintenance needs testing to ensure it is ready for the digital era.

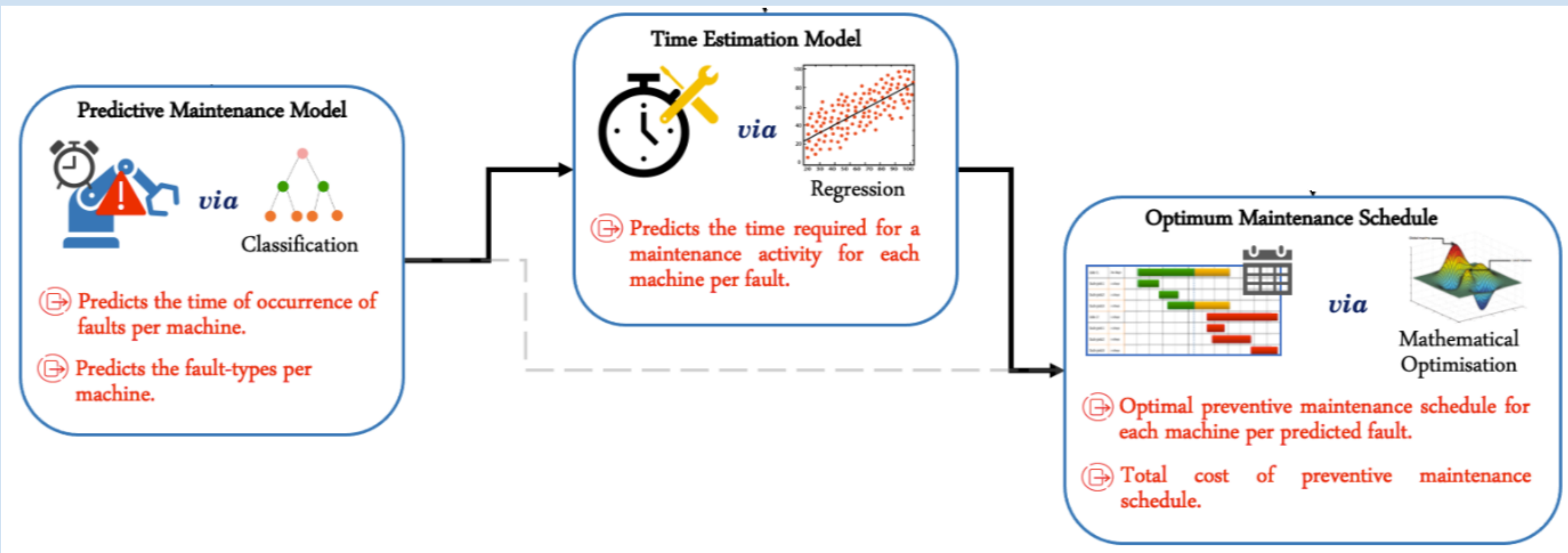
Objectives

- Investigate classification machine learning algorithms for predictive maintenance on a large cyber-physical production system.
- Apply a rigorous approach to compare and evaluate readily available classification models.
- Consider the importance of a predictive maintenance model and design a framework that uses the tool for maintenance in the digital era.

Data

A large Fischertechnik (FT) model factory (Klein and Bergmann, 2019) records sensor readings providing a **realistic** and **challenging** case study.

- Altogether **27,073** data points are simulated recording faults (such as driveshaft slippage in the conveyor) on 14 machines.
- The predictive maintenance uses **61** sensor readings to predict one of **15** classes (14 machine numbers and no fault).
- The data is split creating **23,303** training points and **3,770** test points.



Mathematical Background

This work compares five supervised classification techniques using the Python library, Scikit Learn (Pedregosa et al., 2011):

1. Decision Tree (DT)
2. Random Forest (RF)
3. Neural Network (NN)
4. AdaBoost (AB)
5. Quadratic Discriminant Analysis (QDA)

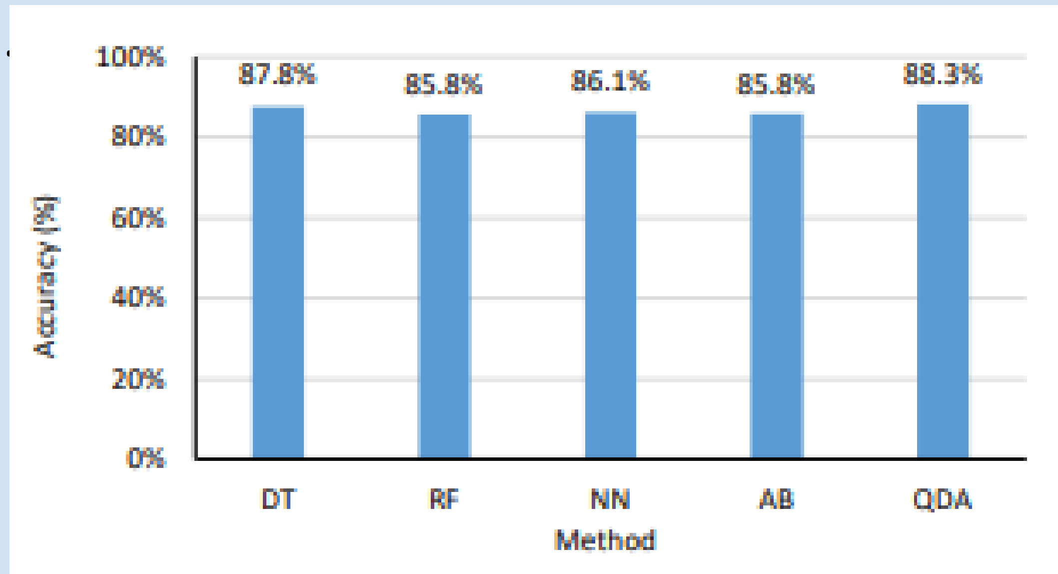
Each classification method has to be tested robustly. To do this, more than one error metric should be calculated and compared. It is important to analyse how the predictive maintenance models have performed with regards to the predicted labels in comparison to the truly observed labels.

For example, predictions on the class "Fault on Machine 1" fall into four possible outcomes:

True Positive (TP) - **Actual Observation: There's a fault on machine 1.** - **Prediction: Fault on machine 1.** - **Maintenance correctly predicted for machine 1.**	**False Positive (FP)** - **Actual Observation: There's no fault on machine 1.** - **Prediction: Fault on machine 1.** - **Maintenance in-correctly predicted for machine 1.**
False Negative (FN) - **Actual Observation: There's a fault on machine 1.** - **Prediction: No fault on machine 1.** - **Maintenance is not predicted on machine 1 and it leads to failure.**	**True Negative (NP)** - **Actual Observation: There's no fault on machine 1.** - **Prediction: No fault on machine 1.** - **Maintenance correctly no predicted for machine 1.**

Results

Accuracy



Accuracy:

$$\frac{Tp+Tn}{Tp+Tn+Fp+Fn}$$

Precision:

$$P=\frac{Tp}{Tp+Fp}$$

Recall:

$$P=\frac{Tp}{Tp+Fn}$$

F1-Score:

$$F1=2\frac{PR}{P+R}$$

Resulting Diagnostics

	Precision	Recall	F1 Score
DT	0.839	0.878	0.838
RF	0.735	0.858	0.792
NN	0.788	0.861	0.799
AB	0.736	0.858	0.793
QDA	0.880	0.883	0.877

Confusion Matrix

		True Label		
		No Fault	Fault	Total
QDA Predicted Label	No Fault	3086	95	3181
	Fault	147	442	589
	Total	3233	537	3770

Conclusion

The technical contributions can be summarised as:

- Results showed that the machine learning methods adopted were accurate in predicting faults, and suitable for predictive maintenance in the digital era.

Together, the integration of **predictive maintenance**, **maintenance time estimation** and **schedule optimisation** can be used to produce an optimal maintenance schedule (Yeardley et al., 2022).

P. Klein, R. Bergmann, 2019. Generation of complex data for AI-based predictive maintenance research with a physical factory model. ICINCO 2019 - Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics 1 (September), 40–50.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12, 2825–2830.

A. S. Yeardley, J. O. Ejeh, L. Allen, S. F. Brown and J. Cordiner , 2022. Integrating Machine Learning Techniques into Optimal Maintenance Scheduling. Manuscript submitted for publication.