AI solutions for predictive maintenance: Demonstrations from real-world use cases

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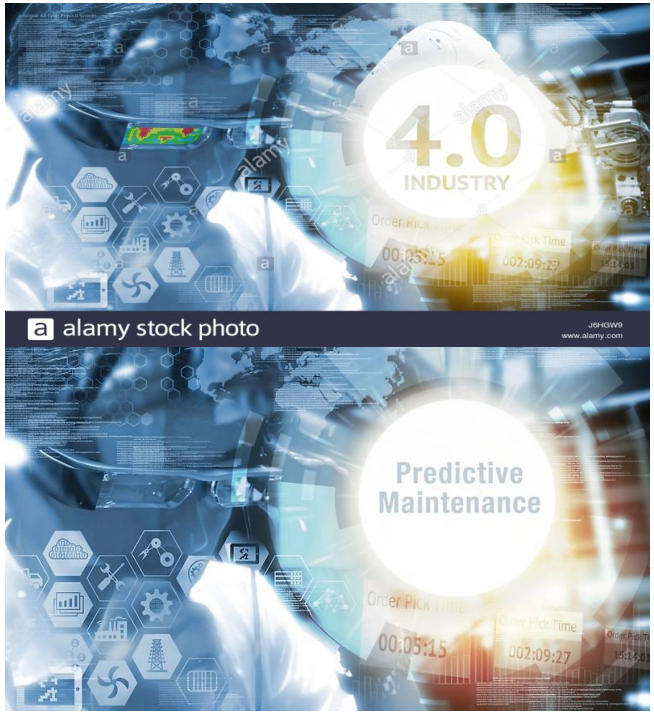
Agenda

- Maintenance needs in the digitalization era
  - An overview of Predictive Maintenance (PdM)
- Artificial Intelligence (AI) powered PdM
  - Key components of AI solutions for PdM
  - An overview of Machine Learning (ML) models for PdM
- Demonstration from real-world use cases in manufacturing
  - Use-case 1: Machine health index construction and monitoring
  - Use-case 2: Early fault (air leakage) detection in a pneumatic system
- Implementation considerations and challenges
- Conclusion



Maintenance needs in the digitalization era

- Increasing complexity,
- Growing cost pressure,
- Enhanced efficiency,
- Proactive maintenance and digitalization-driven maintenance strategies,
- Predictive Maintenance (PdM) has emerged as a solution to address maintenance needs proactively!

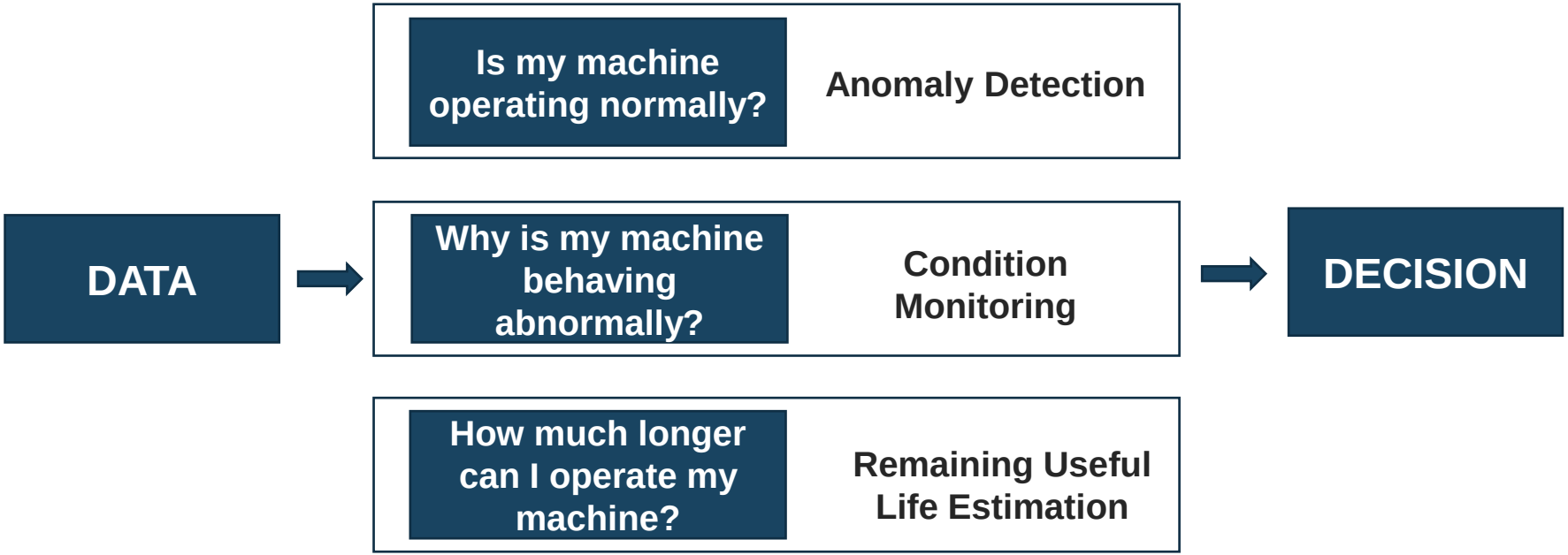
Maintenance needs in the digitalization era

An overview of Predictive Maintenance (PdM)

- PdM: Intelligent health monitoring of equipment
  - PdM helps avoid future equipment failure through intelligent monitoring.
  - Predicts failure time for optimal maintenance scheduling.
- Pinpointing problems in complex machinery
  - PdM identifies problems in complex machinery, aiding in efficient maintenance.
  - Helps identify specific parts that require fixing.
- PdM vision is failure-free production.

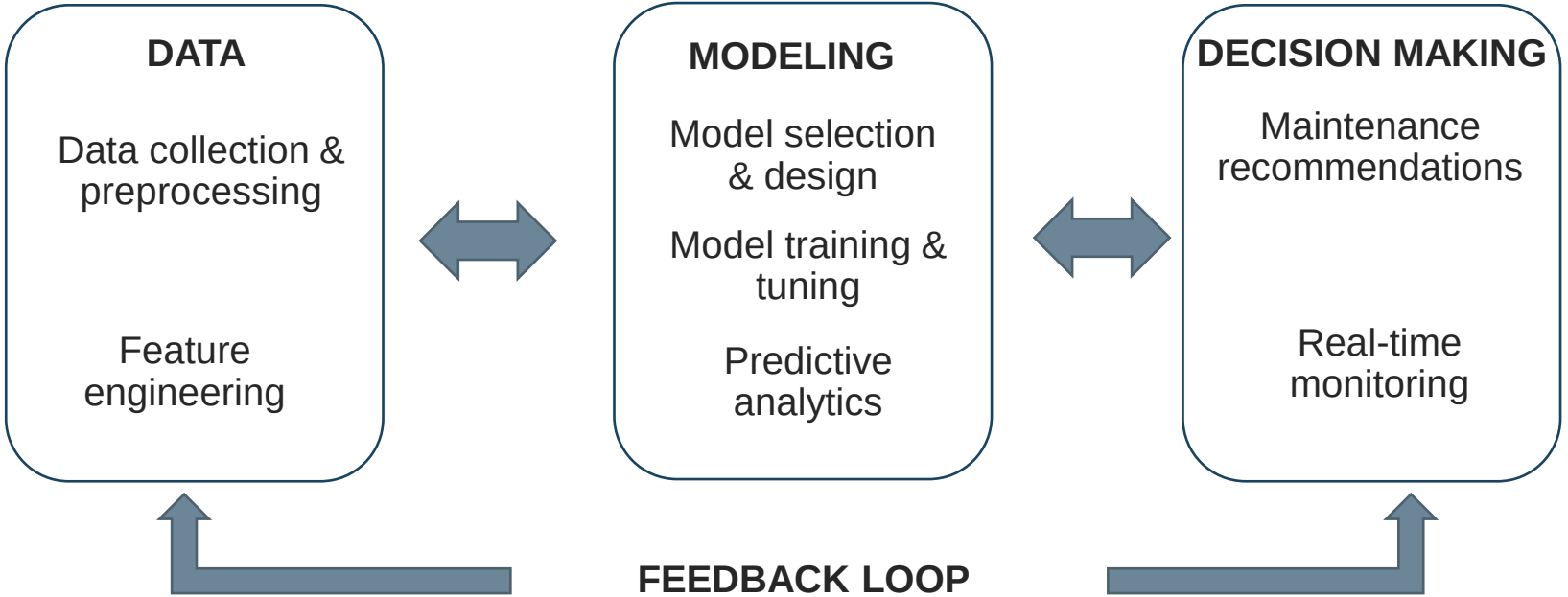
Maintenance needs in the digitalization era

What does a PdM do?



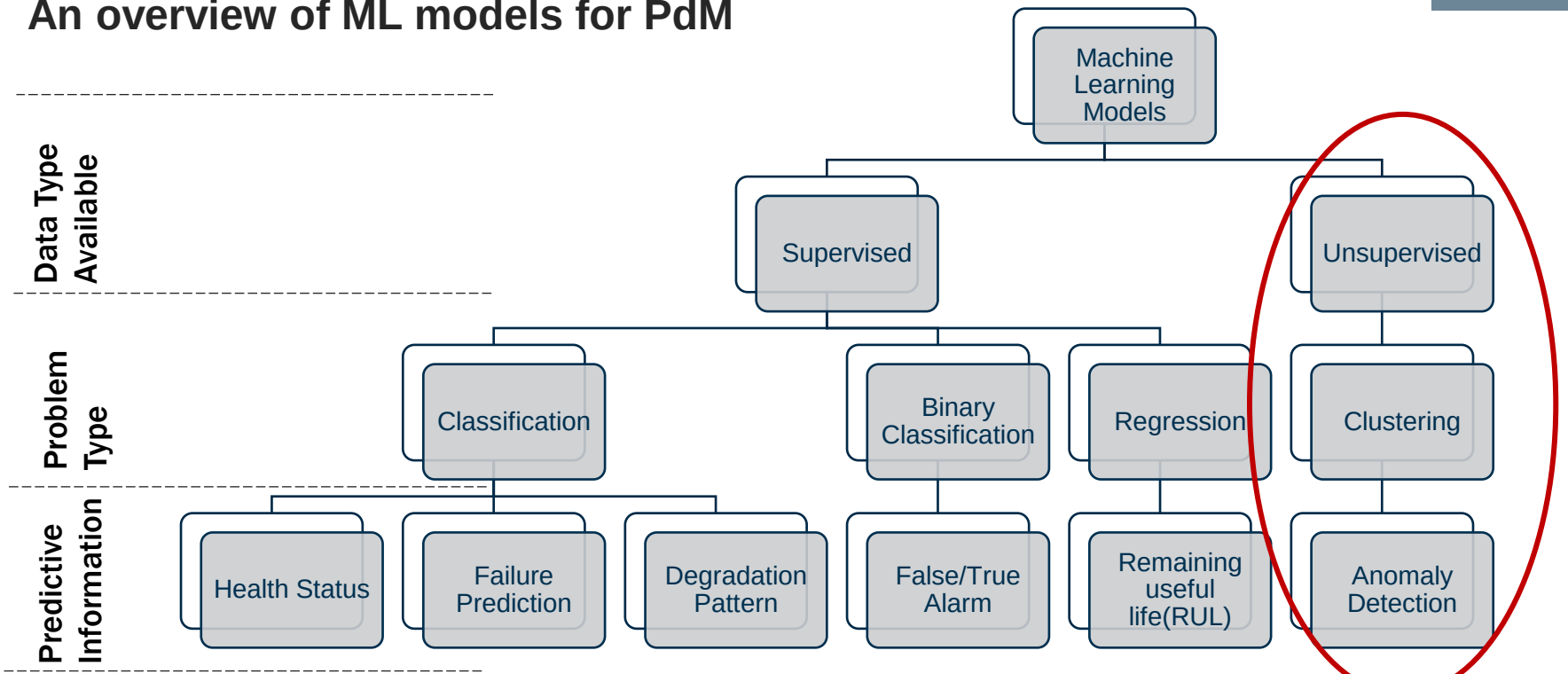
Artificial Intelligence (AI) powered PdM

Key components of AI solutions for PdM



Maintenance needs in the digitalization era

An overview of ML models for PdM



Source: An overview of various methods that can be chosen depending on what information is desired and to what extent data is available [1].

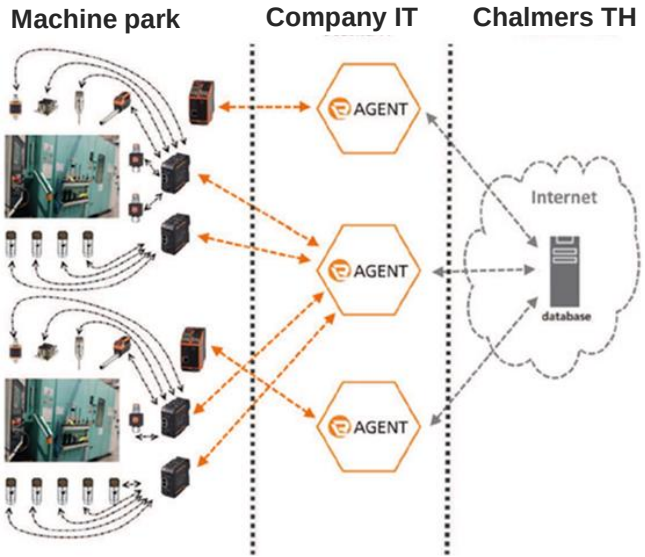
Demonstration from real-world use cases in manufacturing

Collaborative Research Projects

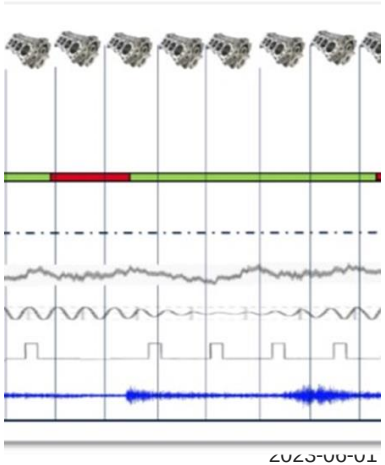
Project Name	Funder/Call	Duration/Funding	Role
SUstainability, sMart Maintenance and factory design Testbed (SUMMIT)	VINNOVA (National Sweden) SIP Produktion2030, Utlysning 7, Hösten 2017:1, Grant number: 2017-04773	11/2017 - 04/2021 8 MSEK	Project member
For details, https://produktion2030.se/en/projekt/summit-sustainability-smart-maintenance-and-factory-design-testbed/			
Predictive Maintenance using Advanced Cluster Analysis (PACA)	VINNOVA (National Sweden), SIP Produktion2030, utlysning 11, Grant number: 2019-00789	03/2019 - 08/2022 5 MSEK	Project leader
For details, https://produktion2030.se/en/projekt/predictive-maintenance-using-advanced-cluster-analysis-paca/			

Use-case 1: Machine health index construction and monitoring

Goal | Data | Approach | Results



The goal is to analyze vibration measurements for critical tooling machines on an engine component line for PdM implementation.



Multiple data sources

- External sensors (vibration data)
- Machine PLC (machine data)

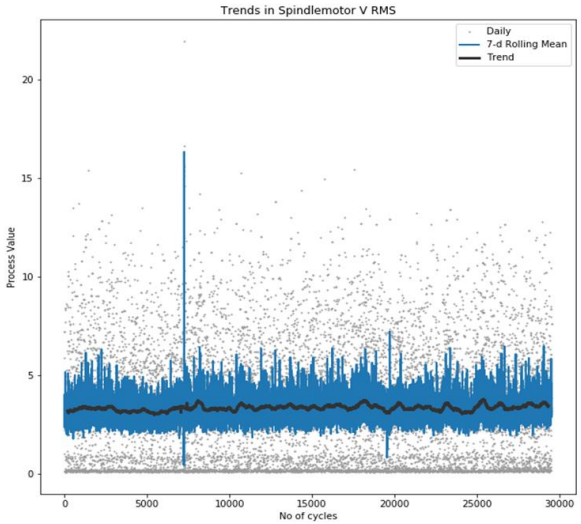
Different motor blocks

- 2,3,4 and 5

Use-case 1: Machine health index construction and monitoring

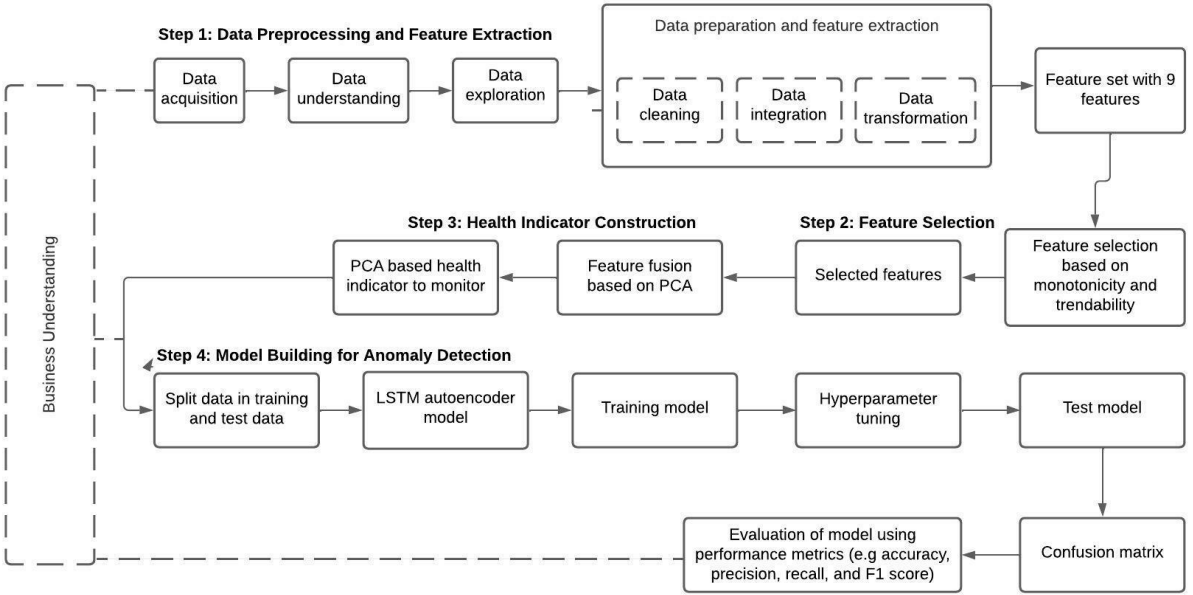
Goal | Data | Approach | Results

- Vibration measurements with 1s resolution from:
  - Spindle, spindle motor, table, and gearbox
- Time and frequency domain features:
  - Acceralation_RMS, Accelaration_peak, and Velocity_RMS
- Focus on the idle time of the machine. The spindle is ”spinning up”
  - 5 seconds before each new motor block



Use-case 1: Machine health index construction and monitoring

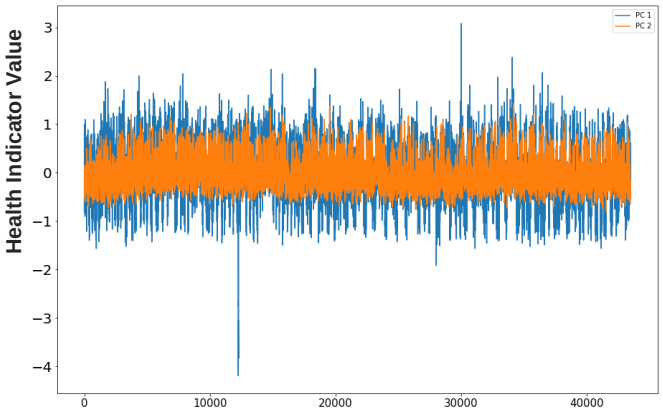
Goal | Data | Approach | Results



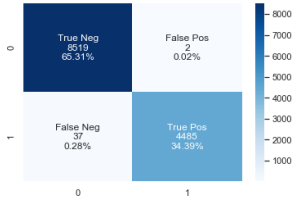
Use-case 1: Machine health index construction and monitoring

Goal | Data | Approach | Results

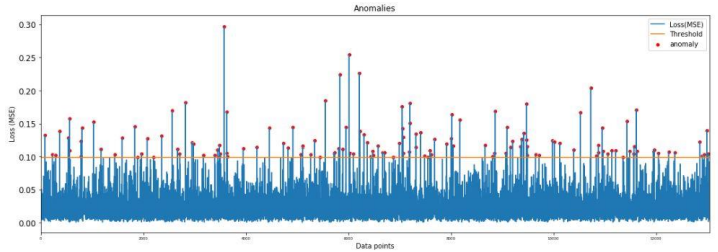
- Promising health indicators for easily monitoring the performance of the machines over time (cycles).



- Successfully identified anomalies with 99% validation accuracy.

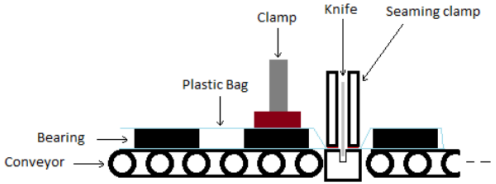


- Anomaly detection: Useful and diagnostic information!

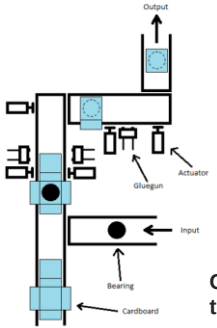


Use-case 2: Early fault (air leakage) detection in a pneumatic system

Goal | Data | Approach | Results



Conceptual model representing the wrapping process



Conceptual model representing the packaging process

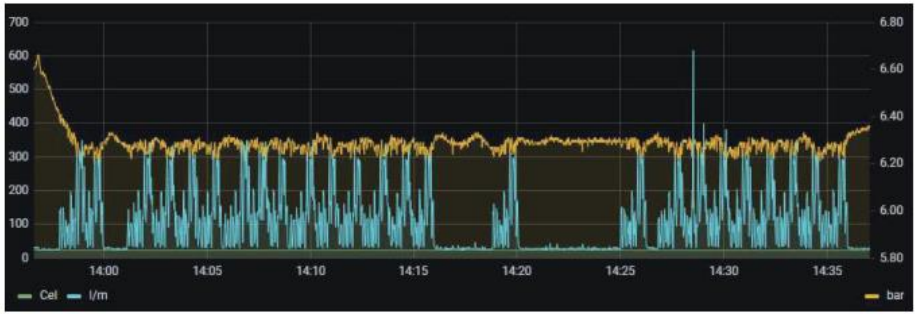
Goal: Develop a data-driven detection method for predicting future failures in the pneumatic system.

- Objective: Detect the early leakage stage as a precursor to potential failures.
- Focus on identifying early signs of leakage in the pneumatic system.
- Data-driven approach: Utilize data analysis techniques and ML algorithms.

Use-case 2: Early fault (air leakage) detection in a pneumatic system

Goal | Data | Approach | Results

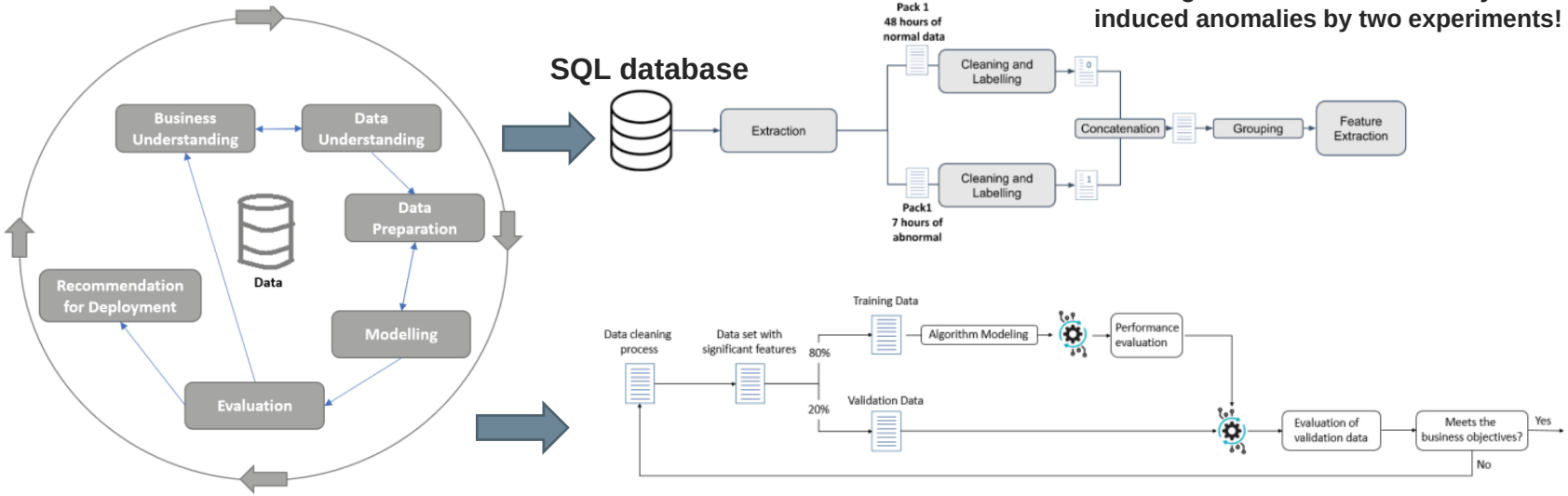
- The continuous measurement of IoT sensors data, including
  - Pressure (Bar)
  - Airflow (l/m)
  - Temperature (Cel)
- The behavior of airflow is easy to distinguish the state of the machine:
  - The cyclical pattern when the machine is working
  - A flat non-cyclical pattern when the machine is idle.
- Lack of failure data



Visualized data of packaging machine using Grafana.
The orange line shows the pressure, the blue line shows the airflow and the green line shows the temperature.

Use-case 2: Early fault (air leakage) detection in a pneumatic system

Goal | Data | Approach | Results



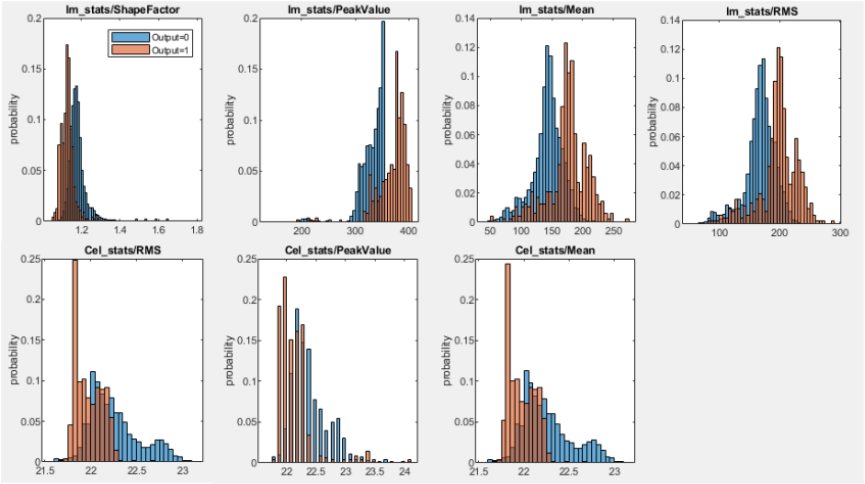
Labeling was done with artificially induced anomalies by two experiments!

Source: CRISP-DM methodology [2].

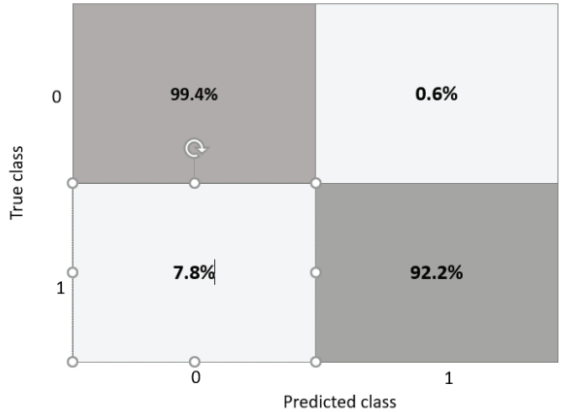
Use-case 2: Early fault (air leakage) detection in a pneumatic system

Goal | Data | Approach | Results

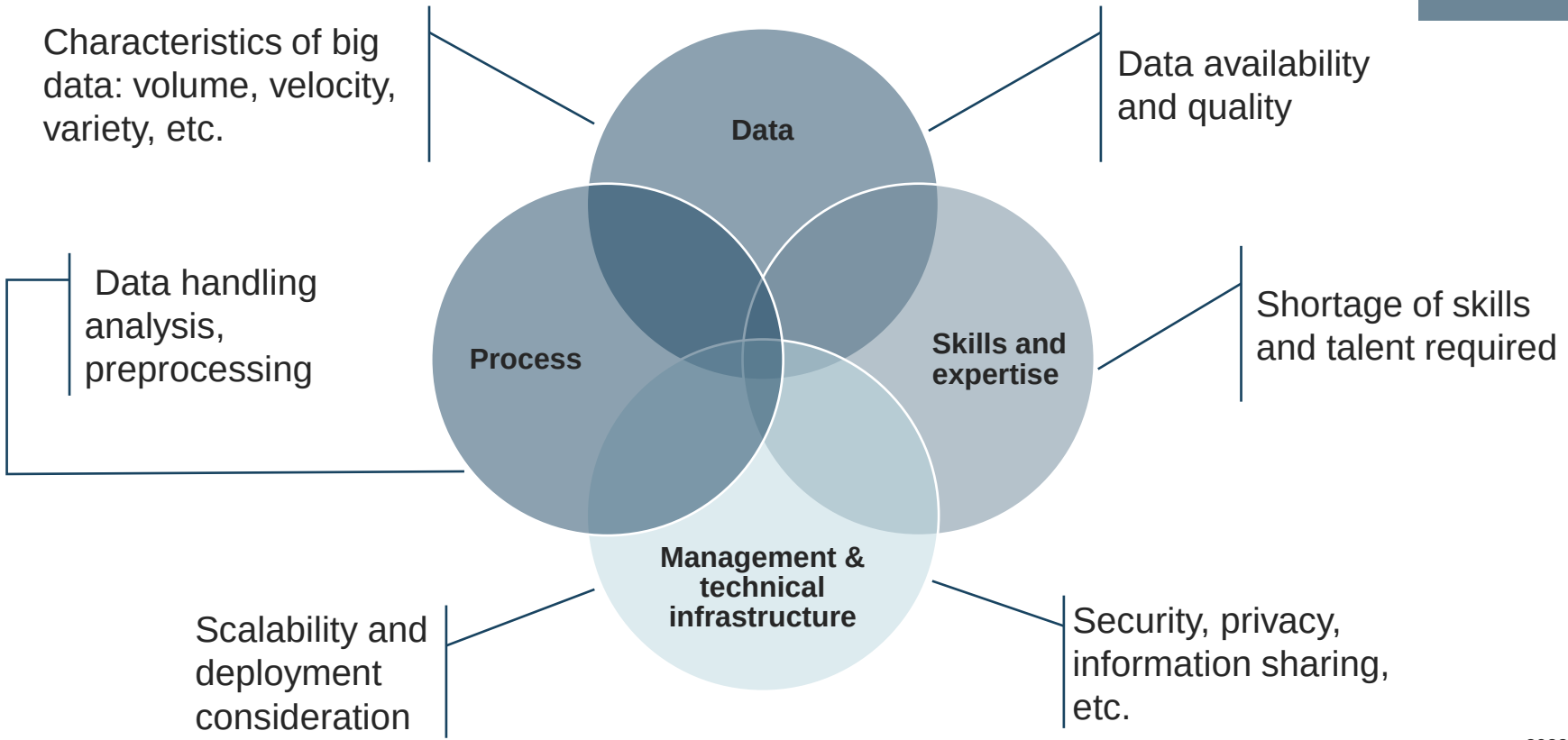
- Identification of the most significant features.



- The RUSboosted model successfully detects air leakage with 98.73% validation accuracy.

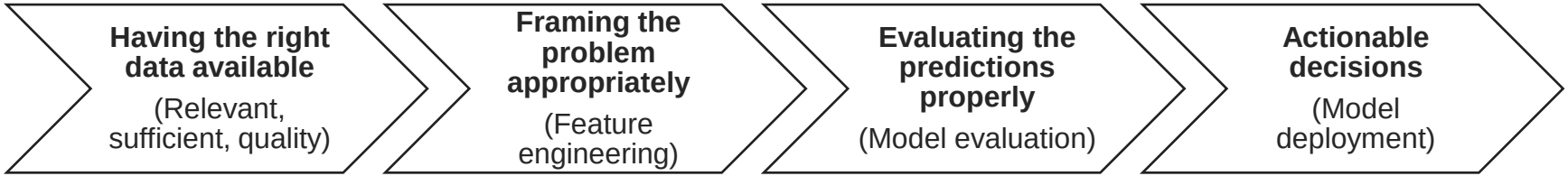


Implementation considerations and challenges



Conclusion

Success in PdM = Domain expertise powered AI



Effective data management using appropriate expertise and secure infrastructure to develop trustworthy PdM

Sources used in the presentation

- [1] Fausing Olesen, J., & Shaker, H. R. (2020). Predictive Maintenance for Pump Systems and Thermal Power Plants: State-of-the-Art Review, Trends and Challenges. Sensors, 20(8), 2425.
- [2] Wirth, R., & Hipp, J. (2000, April). CRISP-DM: Towards a standard process model for data mining. In Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining (Vol. 1, pp. 29-39).
- **The published conference paper related to Use-case 1:** https://link.springer.com/chapter/10.1007/978-3-030-85906-0_65
- **The published conference paper related to Use-case 2:** https://ieeexplore.ieee.org/abstract/document/9612973
- **The published MSc thesis related to Use-case 2:** https://odr.chalmers.se/server/api/core/bitstreams/a6bdf293-e070-4d98-ada5-d7559b4594d4/content

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- Graduated MSc students who contributed to the PACA project!
- Production Area of Advance at Chalmers University of Technology!

Thank you all for your listening! Any questions & reflections?

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