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Trends, Advances, and Challenges of Industrial Physical AI in Smart Manufacturing

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Outline

- Trends of AI and AI Industry Transformation
- Industrial AI, Physical AI, and Industrial Physical AI
- Recent Advances and Challenges
- New Breed of AI Manufacturing Talents

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Evolving Role of AI from Algorithm to Platform to Agent

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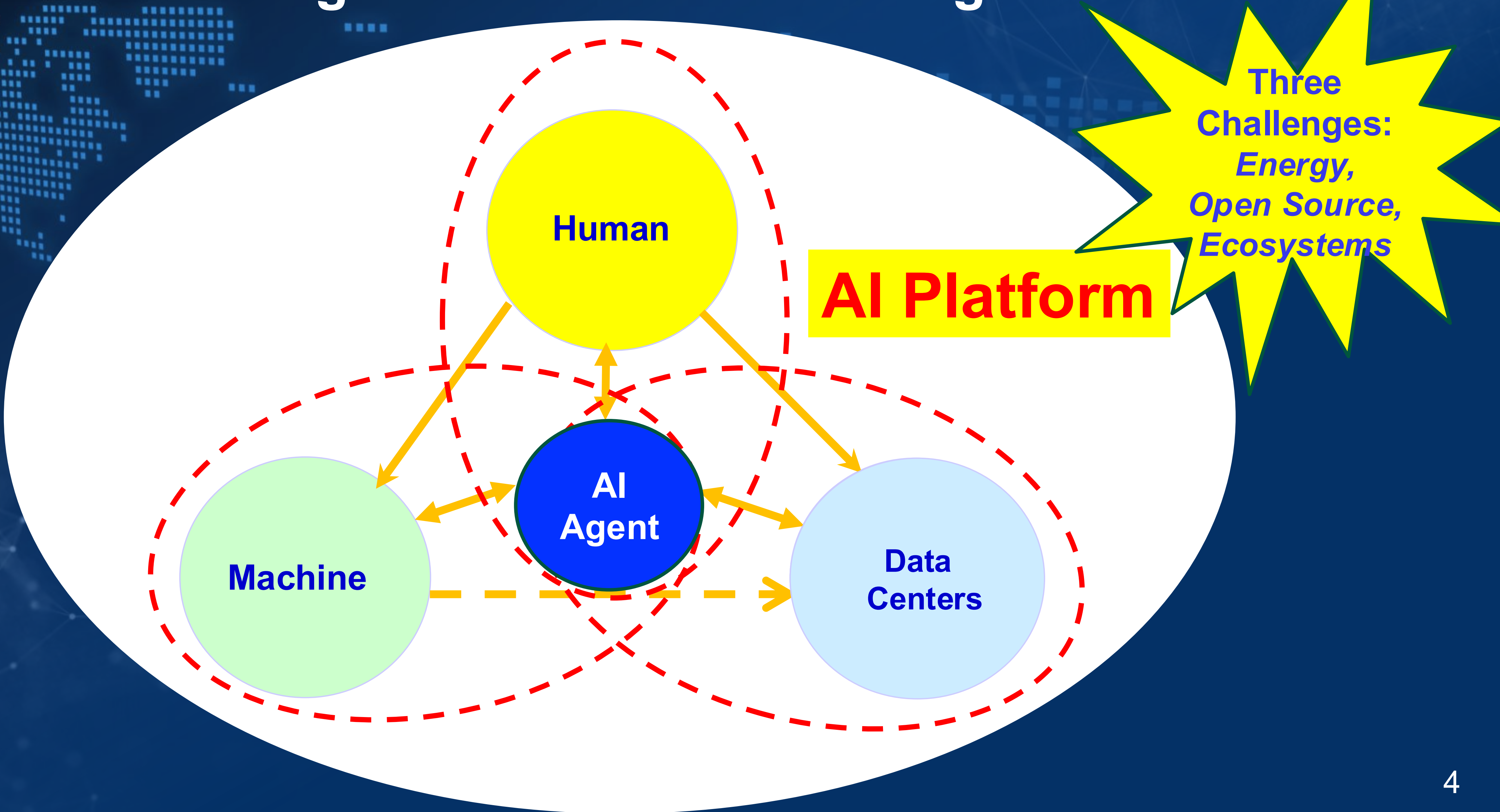

AI Industry ABCDE Transformation Paths

A. Algorithm
B. Big Data
C. Compute
D. Data Center
E. Electricity

AI Infrastructure

A. Algorithm
B. Big Data
C. Compute
D. Device
E. Edge

AI Products

A. Algorithm
B. Big Data
C. Compute
D. Domain
E. Ecosystem

Domain AI (Industrial AI)

Jay Lee, Engineering artificial intelligence: framework, challenges, and future direction, Machine Learning: Engineering, Volume 1, Number 1, DOI 10.1088/3049-4761/adce0d

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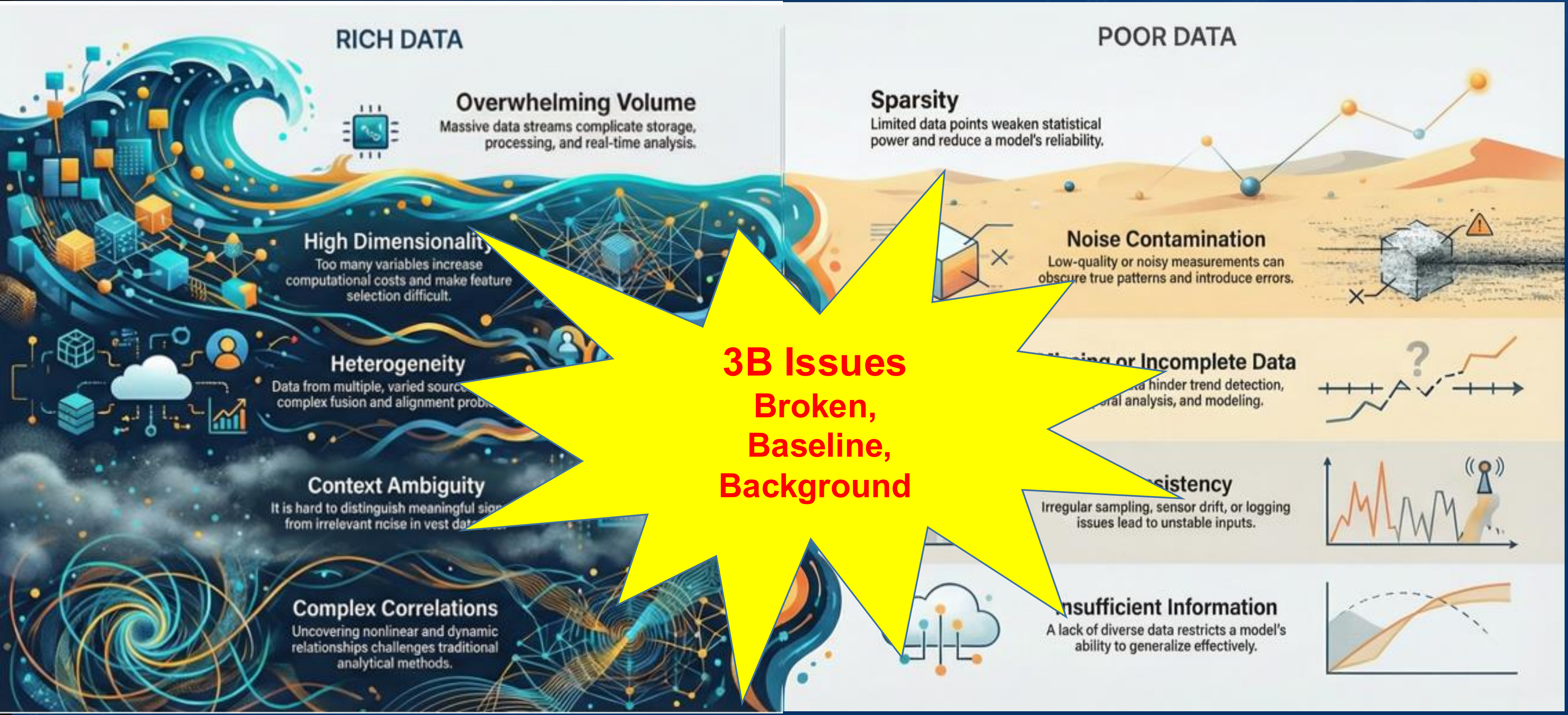
Industrial AI and Data-Centric Metrology for Highly Connected and Complex Industrial System @ Univ. of Maryland

Value of AI and Industrial Productivity Transformation

	Visible	Invisible
Avoid	Utilize New Knowledge/ Technologies For Value-added Improvement	Value Creation using Smarter Information For Unknown Knowledge
Solve	Problem Solving Through Continuous Improvement and Standard Work	Utilize New Methods/ Techniques to Solve The Unknown Problems

Jay Lee, Industrial AI, Springer (2020)

Data Issues and Challenges for Machine Learning

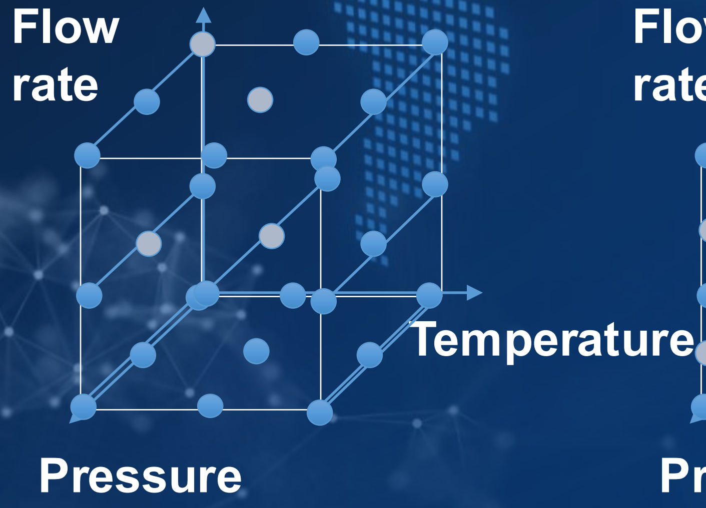


Need Better Data Representation Methodology

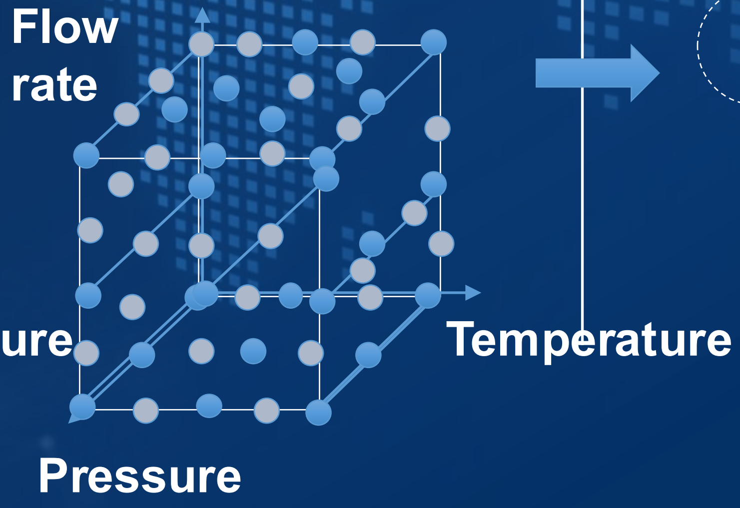
Limited Data Scenario

- Difficult for modeling
- Usually need data augmentation strategy to generate more data
- Whole data space is not fully explored

Traditional DOE methods



Sampling methods

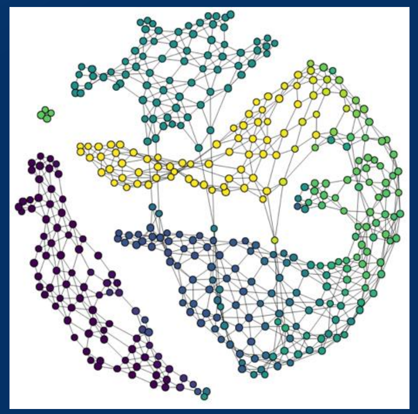


High Volume Data Scenario

- High model complexity
- Labeling would be demanding work for user
- Computation expensive

clustering methods

Topological Data Analysis



Low Complexity/Quantity

High Complexity/Quantity

Challenges of Data-Centric Modeling for Complex Industrial Systems

Data Usability

High

- Uncertain Quality (Drifted or Shifted)
- Comprehensive
- Background Unclear

- Good Quality
- Comprehensive
- Background Recorded
- Baseline Defined

Low

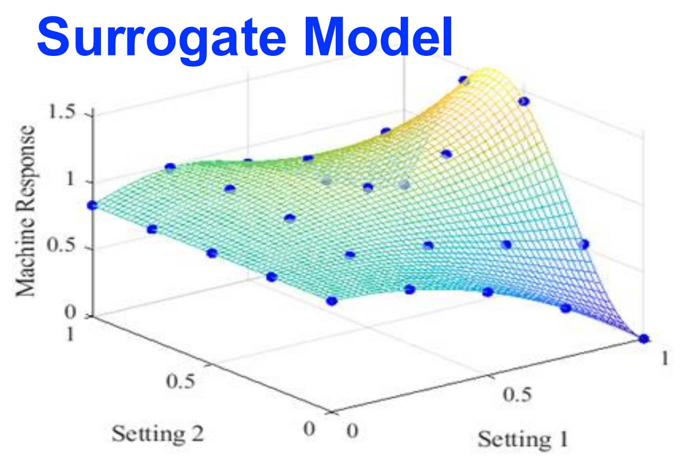
- Bad Quality
- Broken (Not comprehensive)
- Background Missing

- Broken (Not comprehensive)
- Background Missing
- Baseline Not Defined

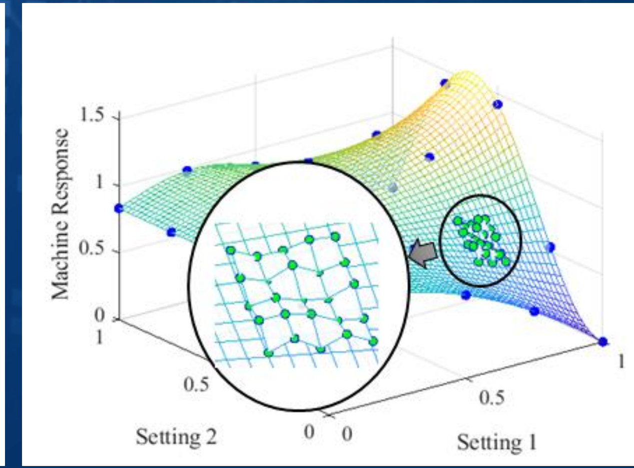
Low | High

Data Usefulness

Reference Source



Target Source

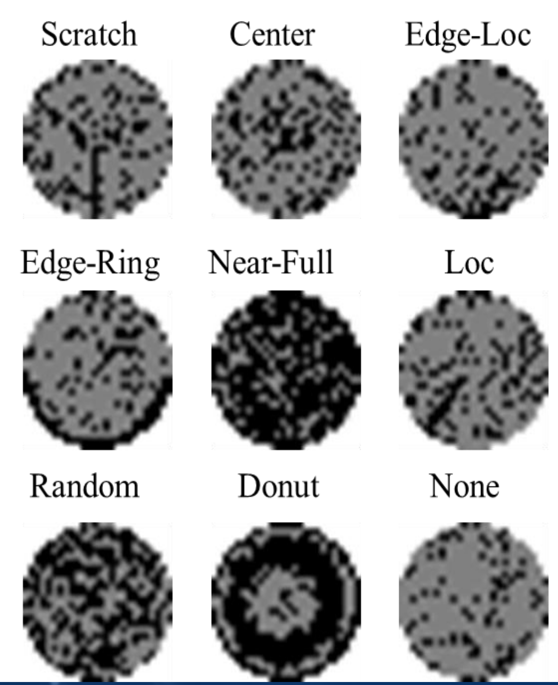


Source	Reference Source
Data Quantity	✓ High Volume
Data Quality	✓ High Quality
Data Representativeness	✓ Comprehensive
Data Availability	✓ High Availability

Target Source
✓ Low Volume
✓ Dynamic ✓ Time-restricted ✓ Drifted / Shifted ✓ Noisy
✓ Local ✓ High Variation
✓ Low Availability

Data Representation using Topological Data Analysis (TDA)

TSMC WM-118K Dataset (810,000)



Data Generation
- Preprocessing
- Feature Extraction

Graph Construction
- Construct graph by graph-based TDA

Initialization
- Selected data from nodes of graph

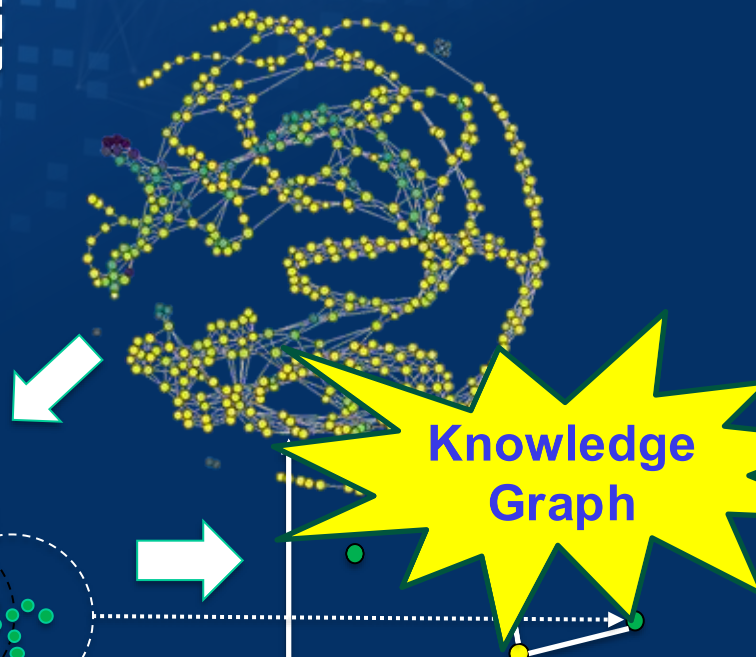
Modeling
- Develop an adaptive model to evaluate the data space

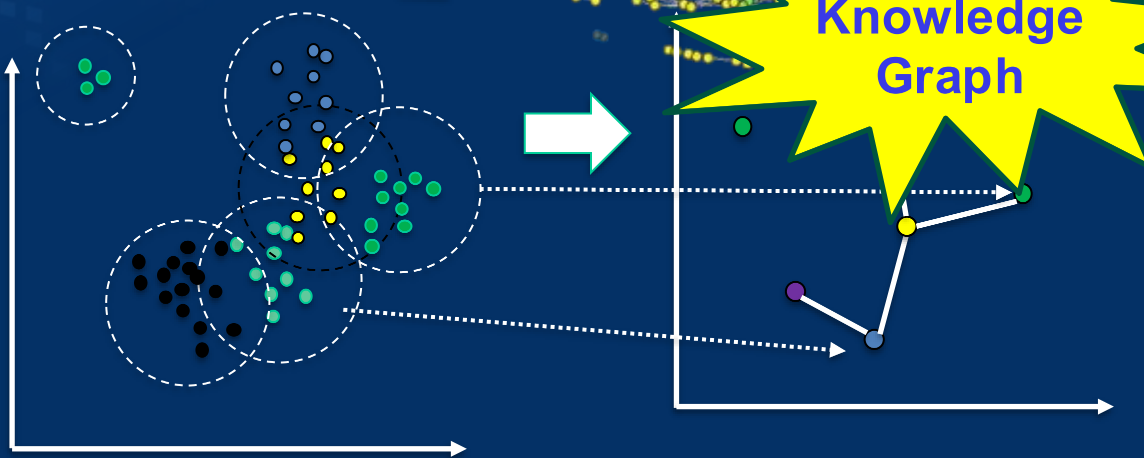
Evaluation
- Design an evaluation strategy to decide next representative data

New Representative Data

Result

Constructed by only labeled data (170,000)
Node color is represented by mixture proportion of each class





Ref:https://en.wikipedia.org/wiki/Wafer_testing#/media/File:Wafer_prober_service_configuration.jpg

Hsu, Jia, Li, Lee, A Novel Quality Clustering Methodology on Fab-Wide Wafer Map Images in Semiconductor Manufacturing
ASME 2022 17th International Manufacturing Science and Engineering Conference.

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Industrial AI, Physical AI, and Industrial Physical AI

Area	Focus	Key capability
Industrial AI	Data-driven industrial systems	Prediction and optimization
Physical AI	Embodied AI in real environments	Action + autonomy
Industrial Physical AI	Sense, act, learn, think improve in the real world	Self-Improving Resilience

- Physical AI → AI capability revolution
- Industrial Physical AI → AI economic impact revolution

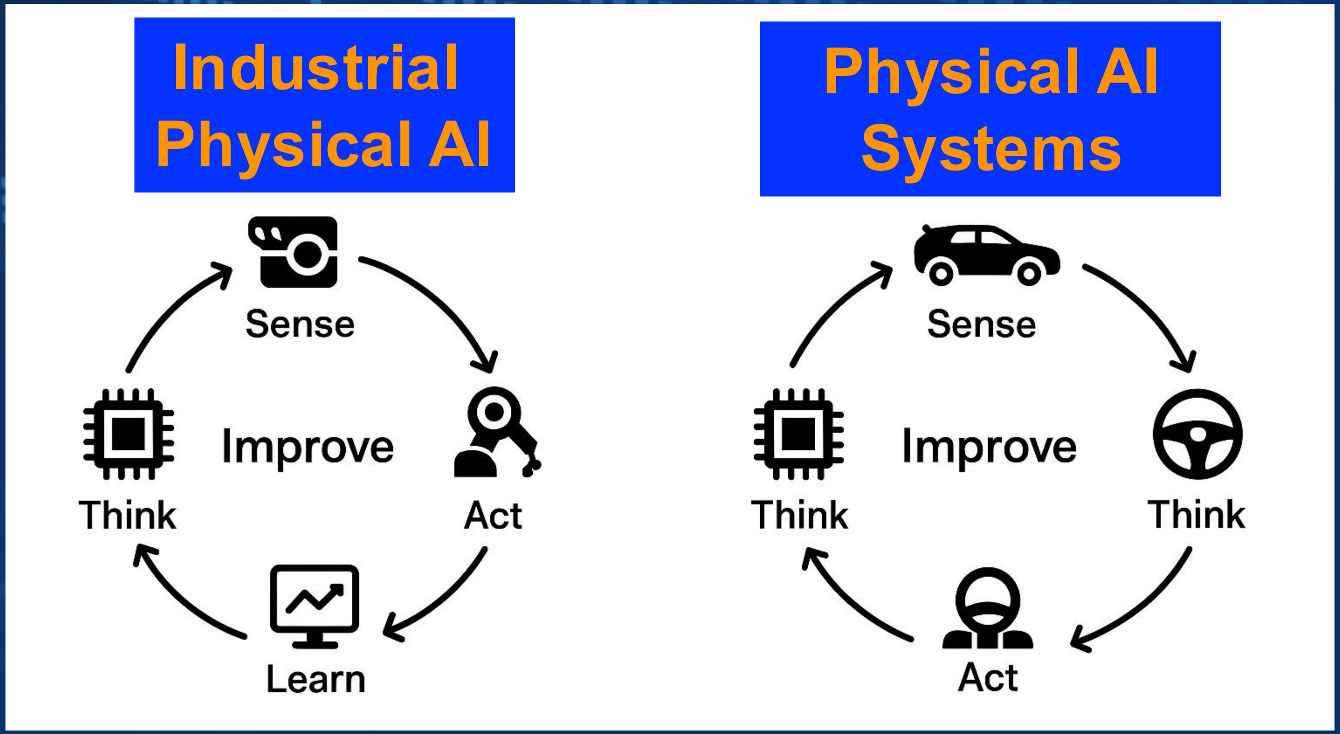
Industrial systems already have:

- massive installed base (plants, grids, machines)
- rich sensor data
- clear KPIs (cost, uptime, energy, safety)

Industrial Physical AI Systems vs. Physical AI

Physical AI Systems= Sense → Think → Act → Think → Improve

Industrial Physical AI Systems= Sense → Act → Learn→ Think → Improve



Context Engineering for Industrial Physical AI

- Context Engineering is the discipline of designing systems, AI, and processes that understand and use context — the *situational information* surrounding an event, user, or machine — to make better, more adaptive decisions to continuously improve the efficiency and performance.

- Context Engineering = Designing intelligence that senses, interprets, and acts based on situational awareness.

In Summary

- Context Engineering = Engineering intelligence that understands "why" — not just "what."

Traditional System	Context-Engineered System
Acts on raw data	Acts on interpreted context
Fixed rules	Adaptive, situation-aware
Reactive	Predictive and proactive
Data-driven	Meaning-driven

Context Engineering in Industrial Physical AI

Element	Description	Example
Perception of Context	Collect environmental, behavioral, and operational data.	Sensors, cameras, or logs detect machine, human, and environment states.
Context Modeling	Represent relationships and conditions that define a situation.	Knowledge graphs, ontologies, or semantic models.
Context Reasoning	Use AI to infer what’s happening and why.	AI predicts anomaly cause based on operating context.
Context-Aware Action	System takes the best action for that situation.	Robot slows down near a human or adjusts speed for humidity.
Continuous Learning	Update contextual models from feedback.	System learns new operating norms automatically.

Robotaxi as Industrial Physical AI

Embodiment in the Physical World

A Tesla Robotaxi is **an autonomous, self-driving vehicle** that perceives, reasons, and acts in the **physical environment** — it *moves, navigates, and interacts* with real-world elements (roads, traffic, humans). That's the core of **Physical AI**: **AI with embodiment**.

Why It's a Strong Example of Physical AI

- **Continuous perception and decision-making in dynamic environments.**
- **Real-world learning — the car's neural network improves from billions of real miles.**
- **Physical actuation — the AI doesn't just compute; it *drives*.**
- **Closed-loop intelligence — sensing → reasoning → acting → learning → improving.**

This makes it one of the largest and most advanced Physical AI systems deployed at scale (alongside industrial robots and autonomous drones).

Challenges and Next Frontier of Industrial Physical AI Factory

Challenges

- Integration of AI with legacy machines.
- Data quality and real-time synchronization between digital twins and shop floor.
- Human trust and safety standards for autonomous physical systems.
- Cybersecurity for physical systems.

Next Frontiers

- Self-Improving production systems — machines that detect and avoid process issues automatically.
- Cognitive robots — learn from human demonstration on the shop floor.
- Physical AI factories as “AI organisms” — continuously sensing, learning, and adapting without manual reprogramming.

Industrial Physical AI Roadmap for Manufacturing Systems

Short-Term (1–3 Years): Foundational Integration and Safe Autonomy

Focus: Build reliable, explainable, and human-compatible AI systems that integrate safely with existing manufacturing infrastructure.

1. Core Capabilities

•Perception & Sensing:
- Robust multimodal perception (vision, lidar, tactile, force sensors).
- AI-based defect detection and quality control with explainable outputs.

•Digital Twins:
- Establish physics-informed digital twins for process monitoring and optimization.

•Edge AI Deployment:
- Low-latency decision-making at the machine or cell level.

•Adaptive Control:
- Hybrid AI + model-based control for precision and repeatability.

2. Human-AI Collaboration

•Collaborative robots (cobots) with real-time safety assurance.
•Learning from demonstration (LfD) to capture human expertise.
•Visual and speech-based human–machine interfaces.

3. Data Infrastructure

•Unified industrial data lakes connecting sensors, PLCs, MES/ERP systems.
•Data quality pipelines and labeling automation.
•Interoperability standards (OPC UA, MTConnect, ISA-95).

4. Governance and Safety

•Establish AI safety frameworks compliant with ISO 10218 / ISO 12100.
•Internal AI ethics and audit boards for industrial AI deployment.
•Initial regulatory engagement for certifiable AI components.

Industrial Physical AI Roadmap for Manufacturing Systems

. Mid-Term (3–7 Years): Cognitive Manufacturing Systems

Focus: Transition from task-specific automation to *adaptive, learning-based systems* capable of context understanding and flexible production.

1. Cognitive Robotics

- Self-adaptive robots for small-batch and mixed-product manufacturing.
- Vision-language-action models (similar to multimodal foundation models) for generalized manipulation and assembly.
- Real-time skill learning and transfer across machines or production lines.

2. Predictive and Prescriptive Intelligence

- Multi-agent AI for system-level optimization (e.g., scheduling, logistics, energy use).
- Prescriptive maintenance based on causal reasoning, not just prediction.
- Cross-factory learning for global optimization and continuous improvement.

3. Human–AI Synergy

- Context-aware AI assistants supporting operators in troubleshooting and quality assurance.
- Dynamic task allocation between humans and AI systems based on workload and risk.
- Adaptive interfaces personalized to operator experience and cognitive load.

4. Infrastructure and Standards

- AI-ready manufacturing cells with standardized APIs.
- Federated learning to share insights securely across sites.
- Integration with Industry 5.0 principles — human-centric, sustainable, and resilient production.

Industrial Physical AI Roadmap for Manufacturing Systems

Long-Term (7–10 Years): Autonomous and Evolutionary Manufacturing Ecosystems

Focus: Achieve fully adaptive, self-organizing manufacturing systems where Physical AI acts as an intelligent, collaborative agent network.

1. Autonomous Factory Systems

- Holistic optimization across design, production, and logistics.
- Swarm intelligence among machines for self-organization and task distribution.
- Continuous learning loops between simulation (digital twin) and reality.

2. Physical Intelligence and Self-Maintenance

- Robots with self-calibration, self-heal, and reconfiguration abilities.
- Materials and actuators with embedded intelligence (“smart matter”).
- Integration of neuromorphic and energy-efficient edge computing.

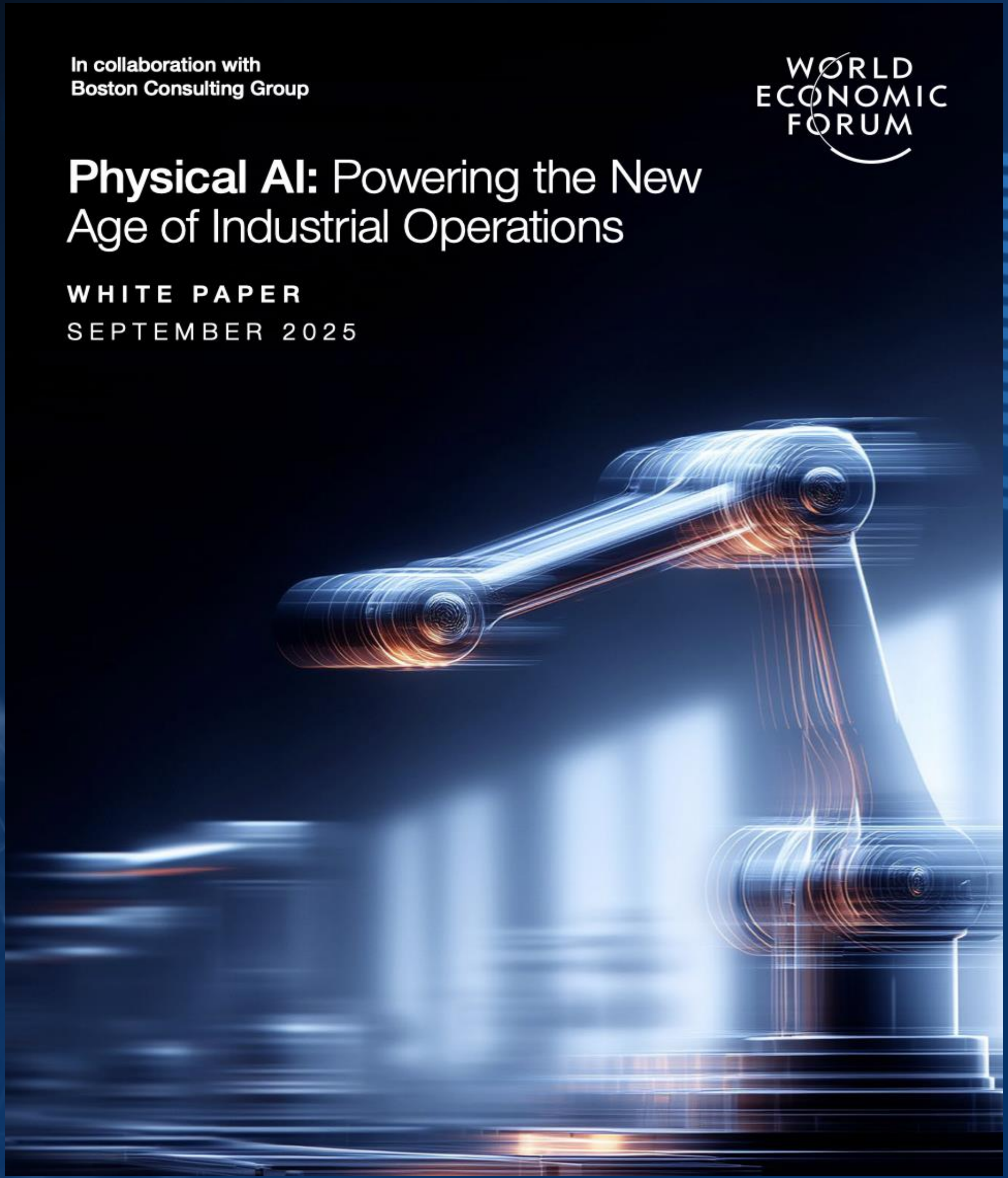
3. Human-in-the-Loop Governance

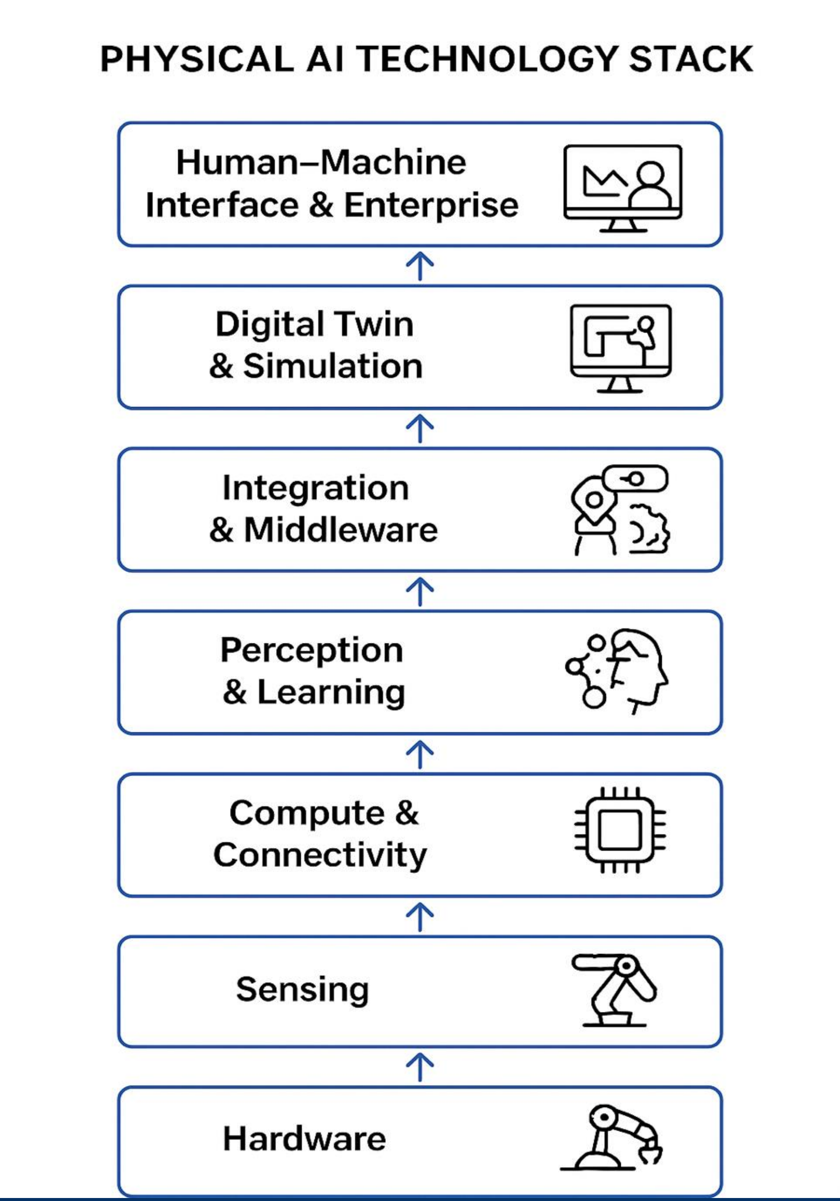
- Humans as supervisors, trainers, and ethical arbiters of AI systems.
- Transparent, auditable AI decision pipelines.
- AI safety certification standards for autonomous industrial systems.

4. Sustainability and Circularity

- Closed-loop AI optimization for material reuse, recycling, and emissions reduction.
- Lifecycle-aware production planning (AI optimizing environmental impact).
- Sustainable compute for AI workloads (edge inference, green data centers).

WEF Physical AI Report Sept. 2025





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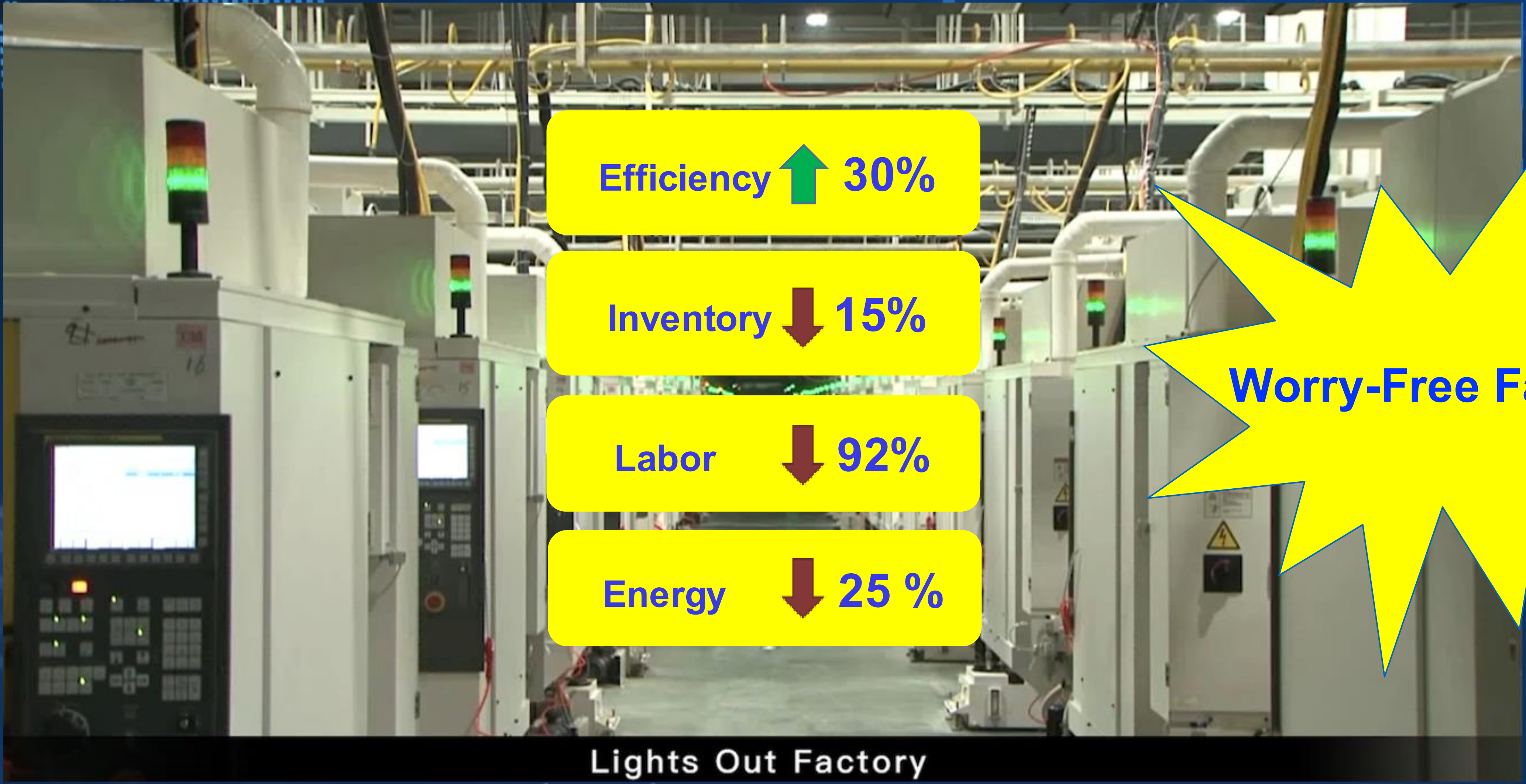
Best Practice Example:

Foxconn World Economic Forum (WEF) Lighthouse Factory Award 2019



https://english.cw.com.tw/article/article.action?id=3775

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Needs and Challenges

- Useable Data for ML→ Automated Segmentation
- Real-time Data for ML→ Continual Machine Learning

The Challenge of Advanced Fab: Raw Fab Data Is Continuous and Complex

A fab's sensors generate billions of data points per day — pressure, temperature, power, vibration, flow, etc.
However:

- These signals run continuously across hundreds of wafers and thousands of process steps.
- There are no clear boundaries between:
  - "Recipe start" and "recipe end"
  - "Idle," "processing," and "transition" states
- Each sensor behaves differently depending on *tool, chamber, and material type*.

So before any machine learning model can learn, the system must first segment the data into *coherent slices* — one *wafer run*, one *step*, one *recipe stage*, etc.

Automated Segmentation Turns Chaos into Structure

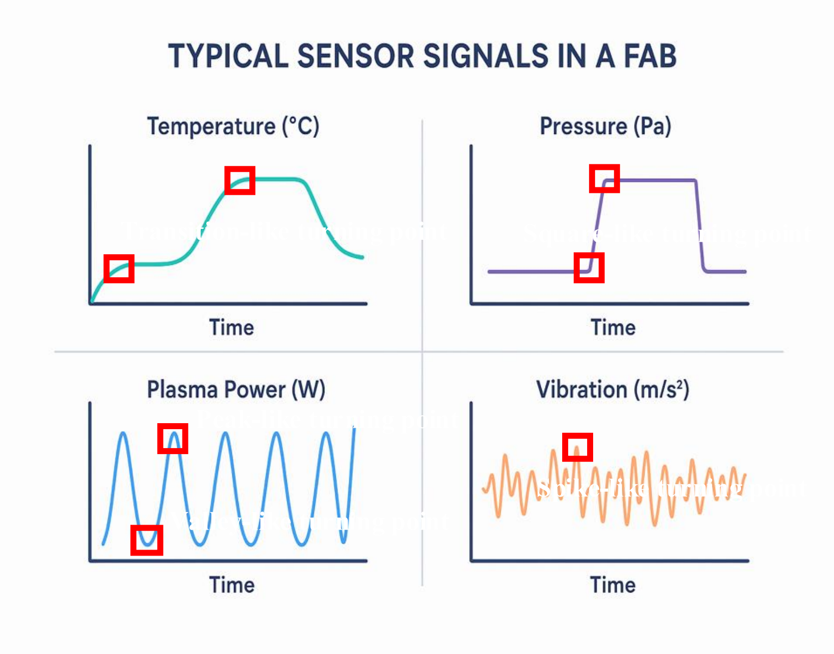
Without Segmentation	With Automated Segmentation
Continuous noisy data streams	Clean, labeled process segments
Hard to align signals with recipes	Data precisely matched to each wafer/step
ML models confused by mixed patterns	ML learns true behavior per process context
Manual labeling needed	AI automatically detects step boundaries

Sensors in Semiconductor Processing (an example)

Typical Types of Sensor Signals

Type	Example Sensor	What It Measures	Typical Frequency	Unit	Data Pattern
Thermal	Thermocouple	Chamber temperature	1–10 Hz	°C	Slowly varying waveform
Pressure/Vacuum	Pirani or Capacitance Manometer	Chamber or pump pressure	10–100 Hz	Torr or Pa	Exponential ramp during pump-down
Flow	Mass Flow Controller (MFC)	Gas or liquid flow	1–10 Hz	sccm	Step or pulse pattern
Optical	Photodiode	Light intensity / endpoint detection	kHz–MHz	a.u.	Sharp spikes, decays
Acoustic/Vibration	Accelerometer	Vibration of motors or stages	kHz range	m/s^2	Sine wave or noise spectrum
Voltage/Current	Power monitor	Plasma power, wafer bias	kHz–MHz	V, A	Periodic or pulse waveform
Position	Encoder / Laser interferometer	Stage or robot arm position	kHz	µm or nm	Smooth ramp or oscillation
Chemical	OES, QMS, RGA	Gas species concentration	1–10 Hz	a.u.	Patterned spectral data
Image / Metrology	Camera / Scatterometer	Pattern dimensions	Frame rate	nm	Pixel array or line scan data

Hitachi Hi-Tech
Etch System 9000 Series



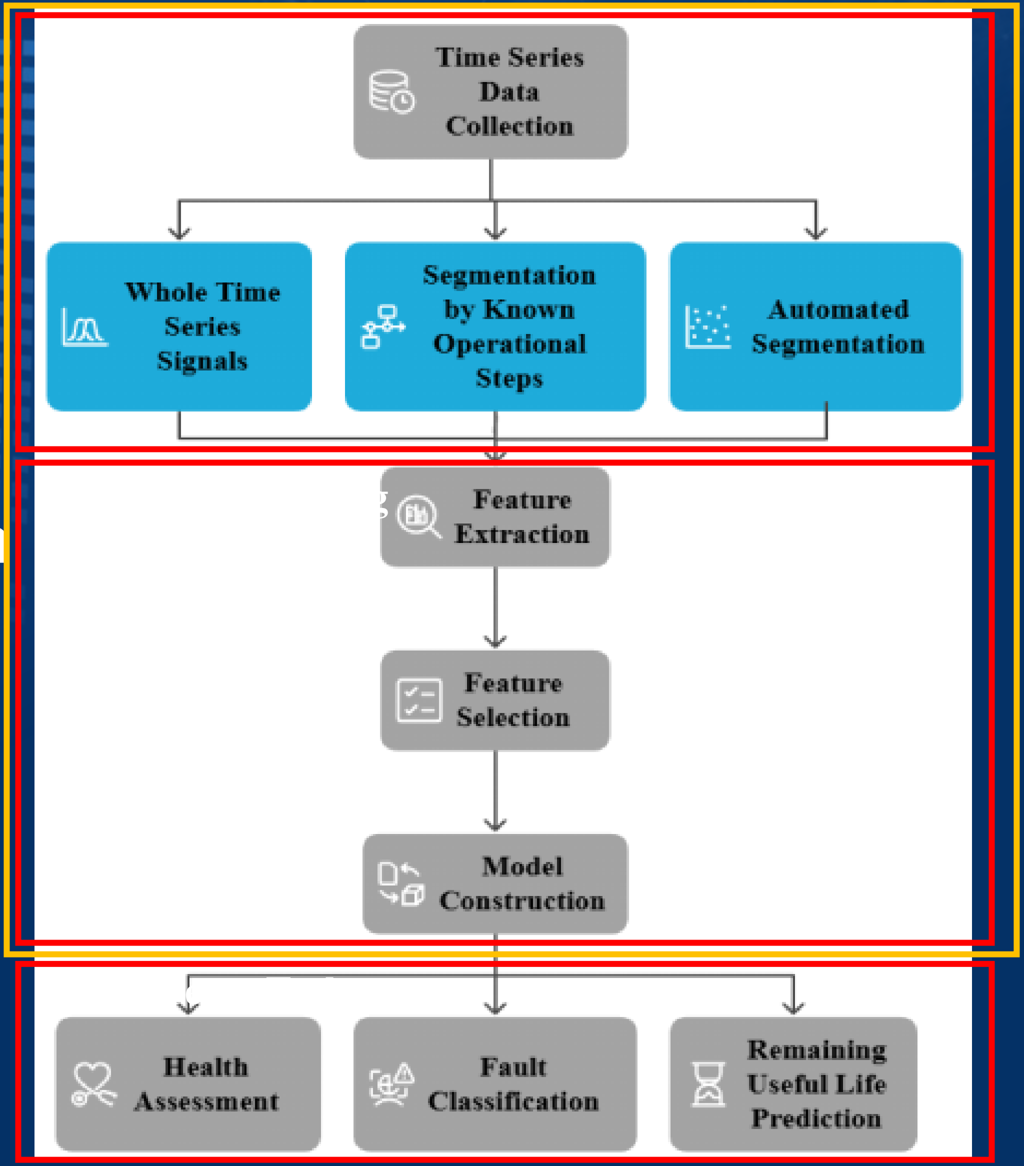
Challenges in Segmentation of Times Series Data

- Time series data is crucial to affect the performance, but:
  - Traditional feature extraction methods (summary statistics: mean, standard deviation, maximum, minimum, skewness, kurtosis)
  - Existing segmentation methods rely on domain-specific rules

Challenge:

- Poor segmentation directly weakens the relevance and separability of extracted features
- Current approaches are sensitive to noise or computationally intensive

80 % Effort



Time-Series Segmentation and Automated Segmentation

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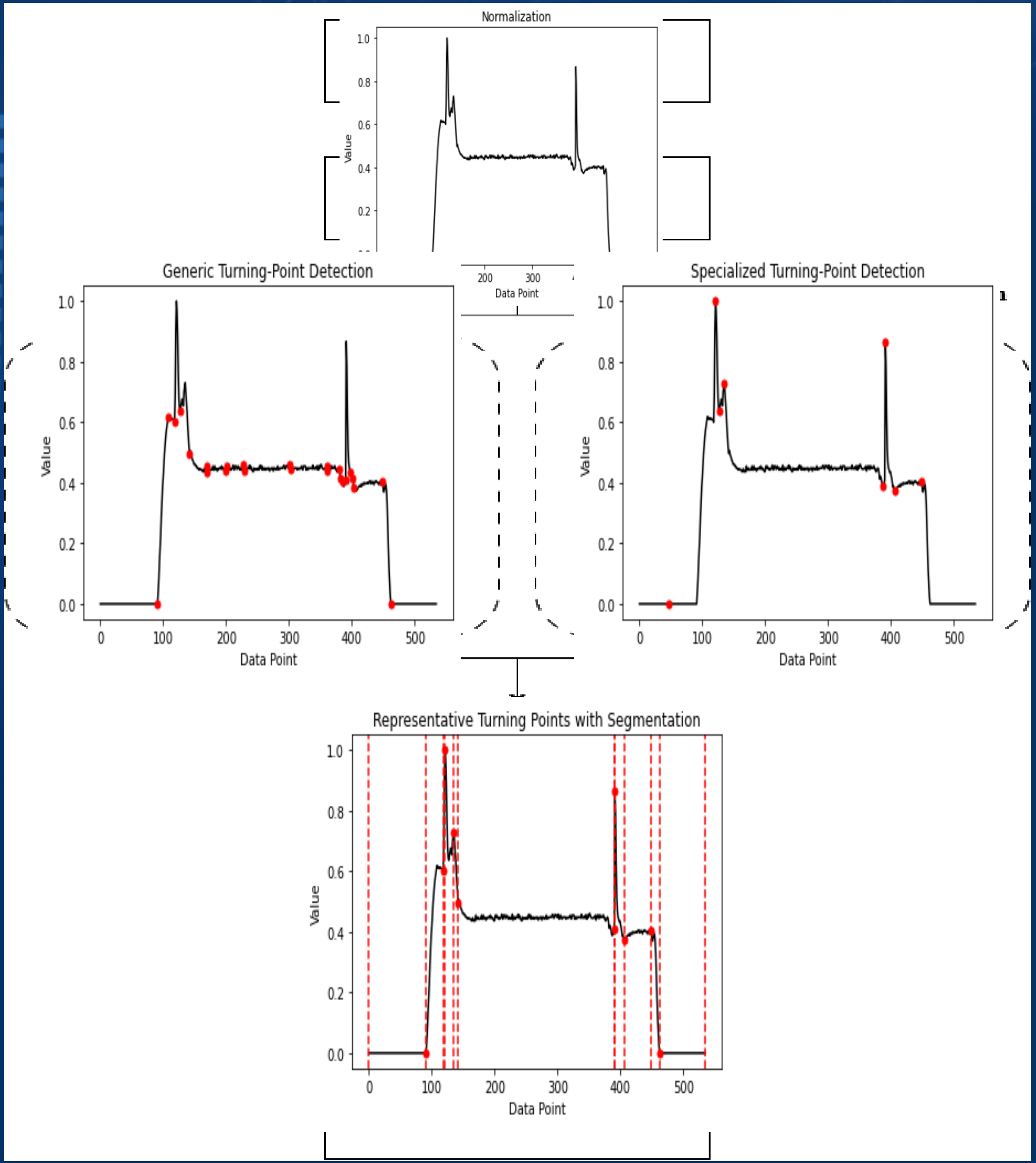
Methods	Strengths	Limitations
Piecewise Approximation (PAA, PLA, PCA, SAX)	• Very fast; scalable to long/streaming signals • Simple implementation • Good for coarse compression & indexing	• Ignores dynamics within segments • Fixed structure can span multiple states • Lower interpretability; weaker features
Event-/Threshold-based	• Aligns with domain events (setpoints, valve states) • Clear semantics for downstream diagnostics • Easy to validate with SMEs	• Heavy reliance on domain rules • Poor cross-system generalization • Brittle under drift or sensor noise
Statistical Changepoint (Binary Seg., PELT)	• Detects distribution shifts (mean/variance) • Can find unknown number of changes • Solid theory; efficient (PELT) with right cost	• Sensitive to noise; needs tuning of penalty/cost • Struggles with gradual transitions • Assumes piecewise-stationarity
Pattern-/Structure-aware (Wavelet spikes, ramps, oscillations, shapelets)	• Captures functional primitives • High semantic value for PHM features • Better alignment with physics/process	• Heavier computation; many hyperparameters • May require template/library design • Risk of overfitting to patterns



Digital-Twin Metrology for Semiconductor Manufacturing

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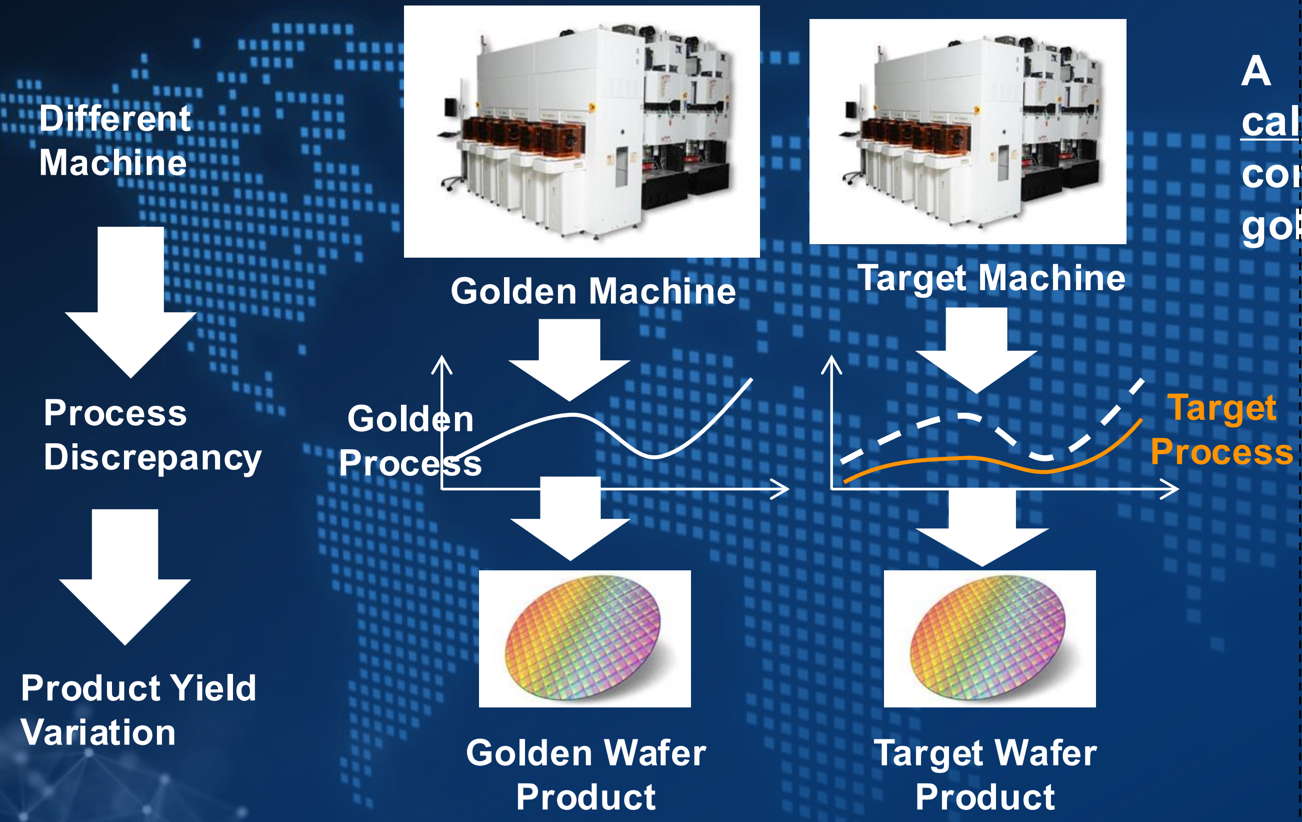
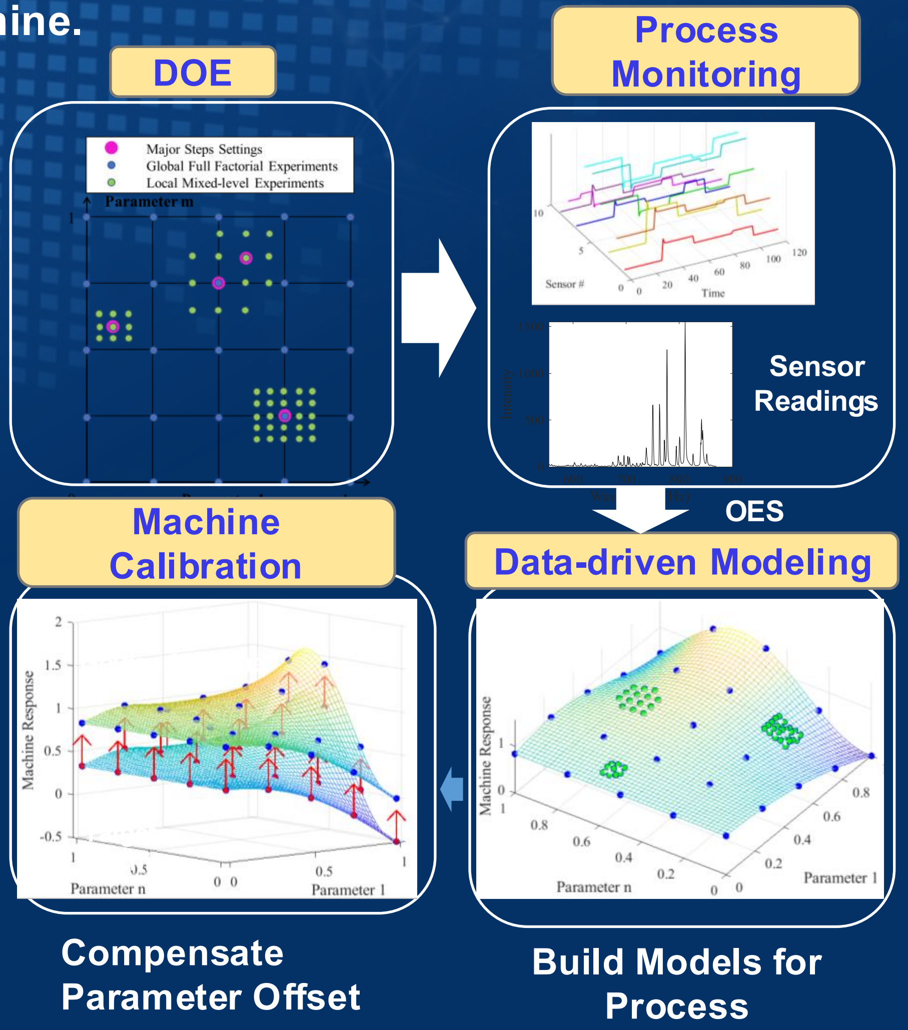
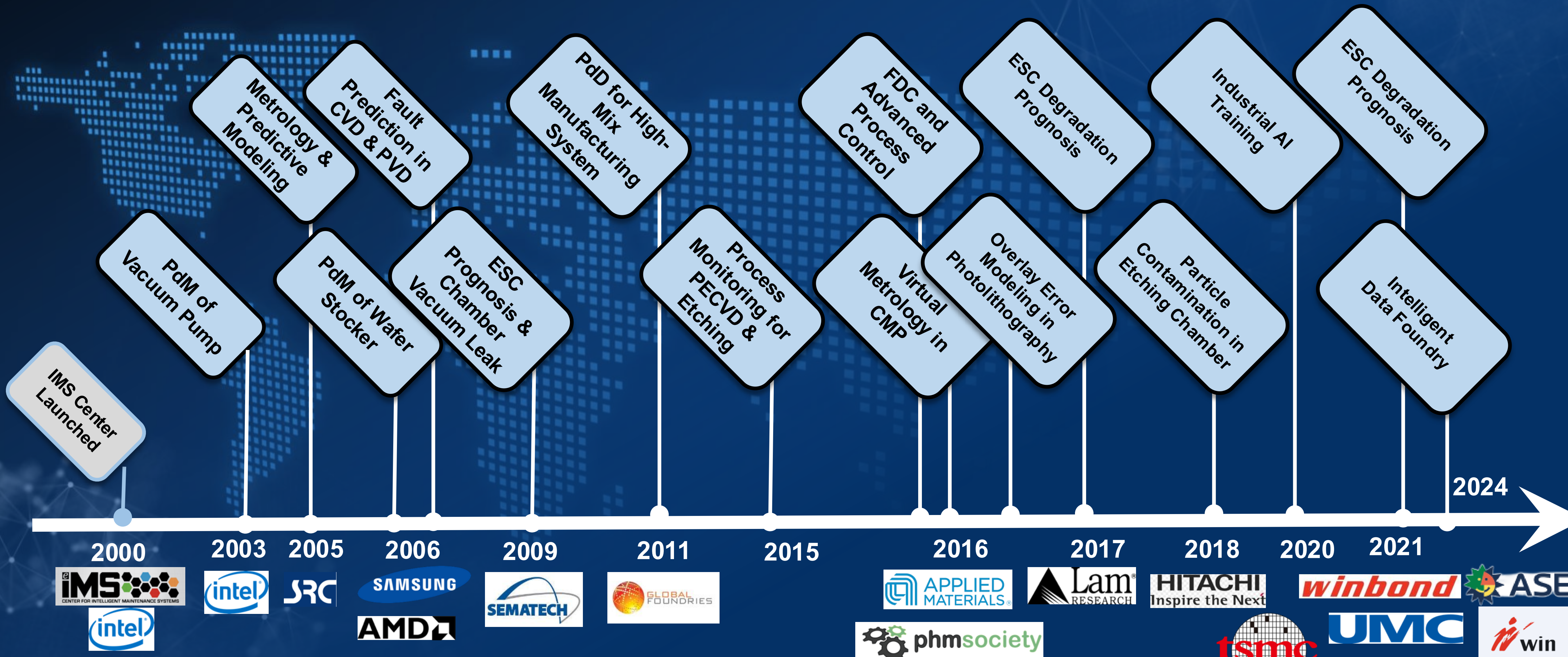


A systematic process-data-driven approach which calibrates the target machine input parameters to compensate machine responses discrepancy from the golden machine.



- Chamber matching is the common practice to increase production consistency and yield by controlling the machine process based on feedback from product metrology.
- Machine calibration is the common practice to adjust machines to have identical performance by assigning global offsets on machine settings.
- Chamber matching and machine calibration could significantly improve production yield of the etching process.

Our Semiconductor Research Journey



PdM: Predictive Maintenance
ESC: Electrostatic Chuck
PECVD: Plasma Enhanced Chemical Vapor Deposition
CMP: Chemical Mechanical Polishing
FDC: Fault Detection & Classification
PVD: Physical Vapor Deposition

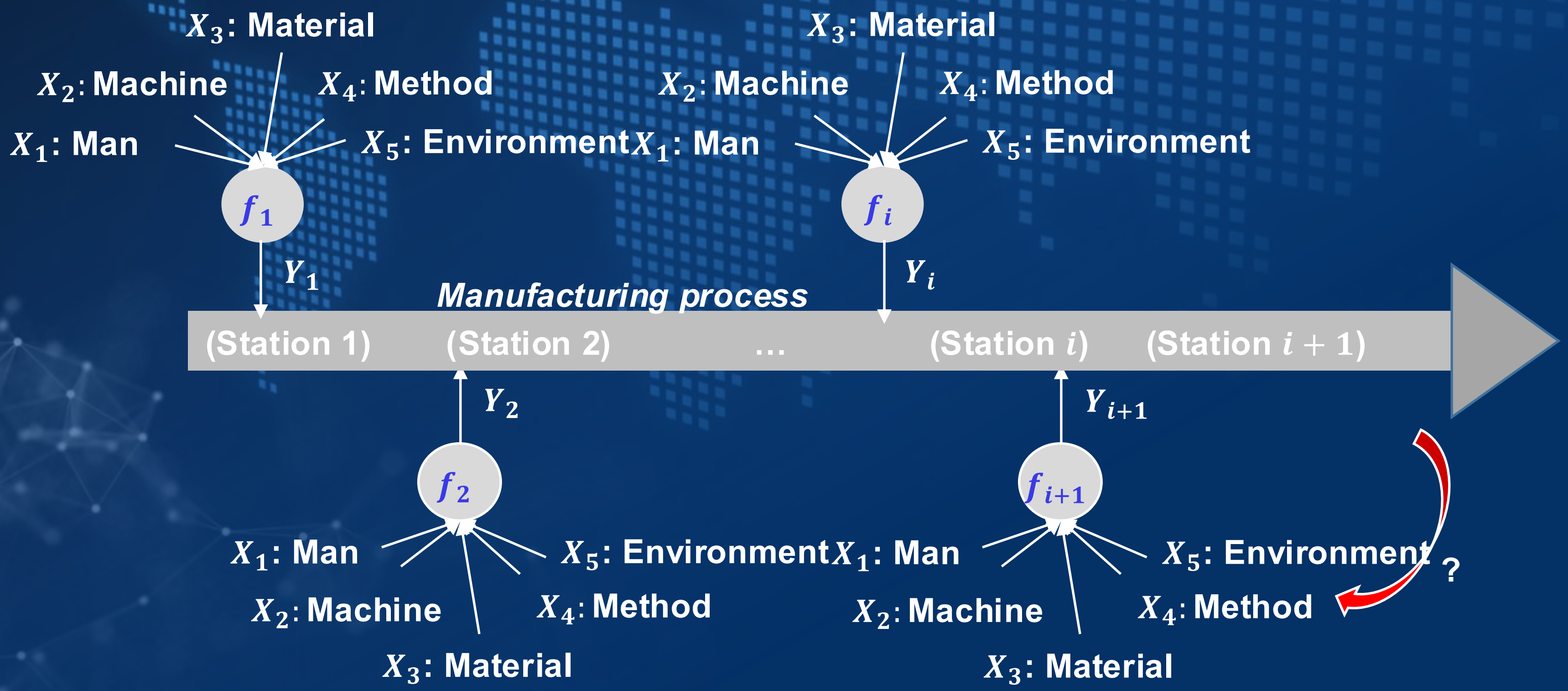
Stream-of-X Based Continual Machine Learning for Self-Improving Manufacturing Systems

Stream-of-Quality (SoQ)

Continual Machine Learning Methodology

Stream of Quality™ (SoQ™) is a traceable systematic methodology for connected quality.

- It can collect the manufacturing information of a product during its production processes.
- The data of each station can be labeled with a time stamp and saved in an immutable block. Then the product quality data forms an information stream and can be stored in structured block chain.
- It can be used to describe the product, trace the entire production process and analyze the root cause of quality issues.



Y_j: Quality

X_i: Process factor

$Y_i = f_i(X_1, X_2, X_3, X_4, X_5, Y_{i-1})$

$Y = g(Y_1, Y_2, \ldots, Y_n)$

Lee, J., Stream-of-Quality (SoQ) methodology for industrial Internet-based manufacturing system, https://www.sciencedirect.com/science/article/abs/pii/S2213846322001912

Continual Machine Learning Methodology

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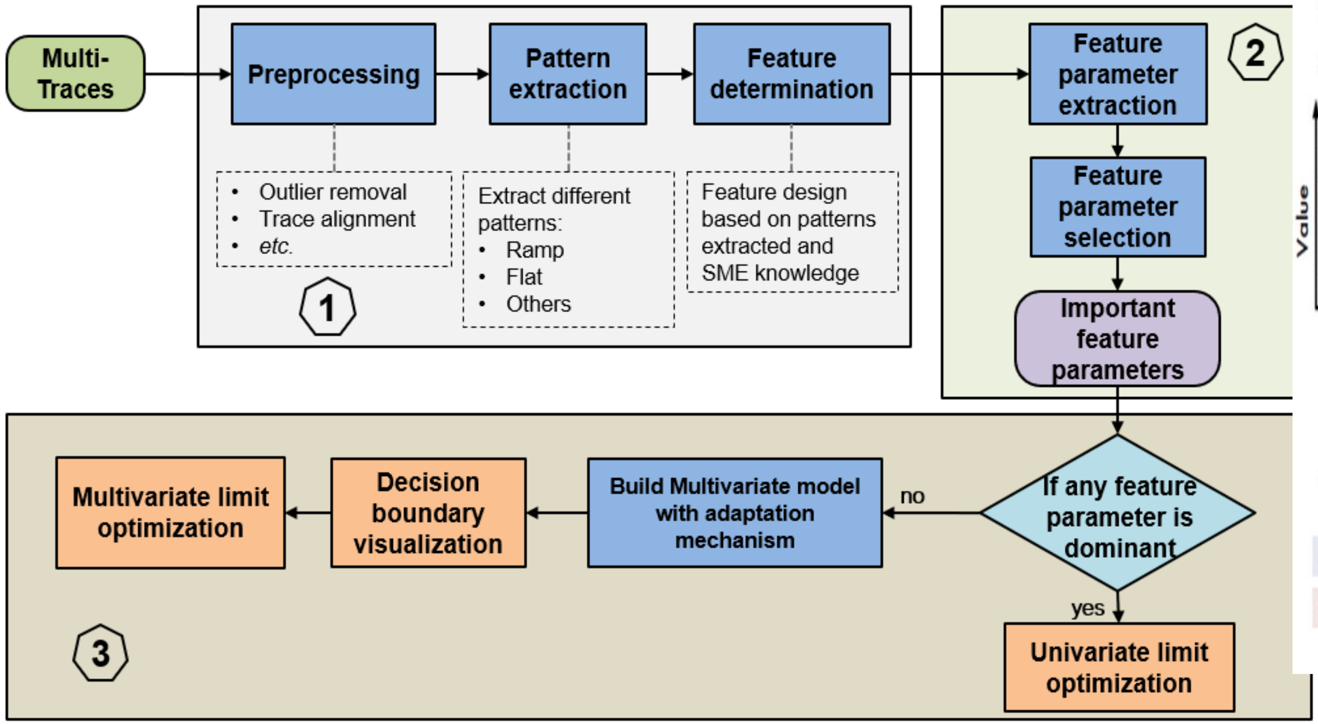
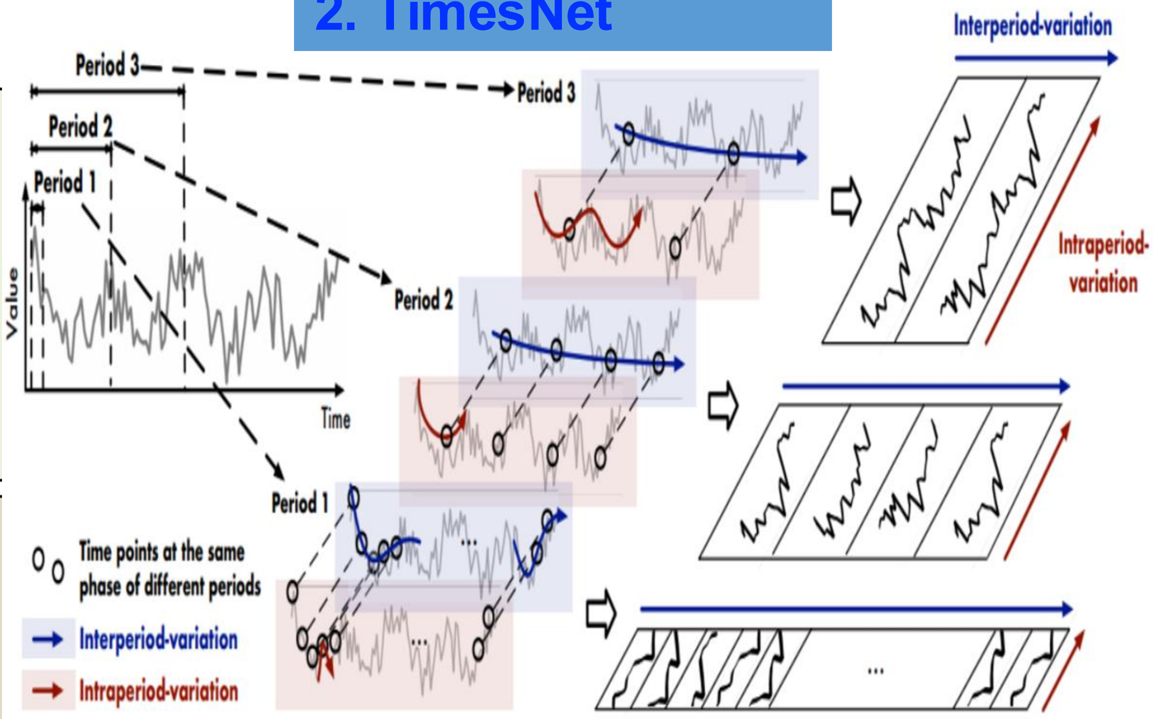
Data Dynamics and Segmentation

Time Series and Invisible Relationship

1. Trace Segmentation



2. TimesNet



Stream-of-Quality (SoQ) Edge AI

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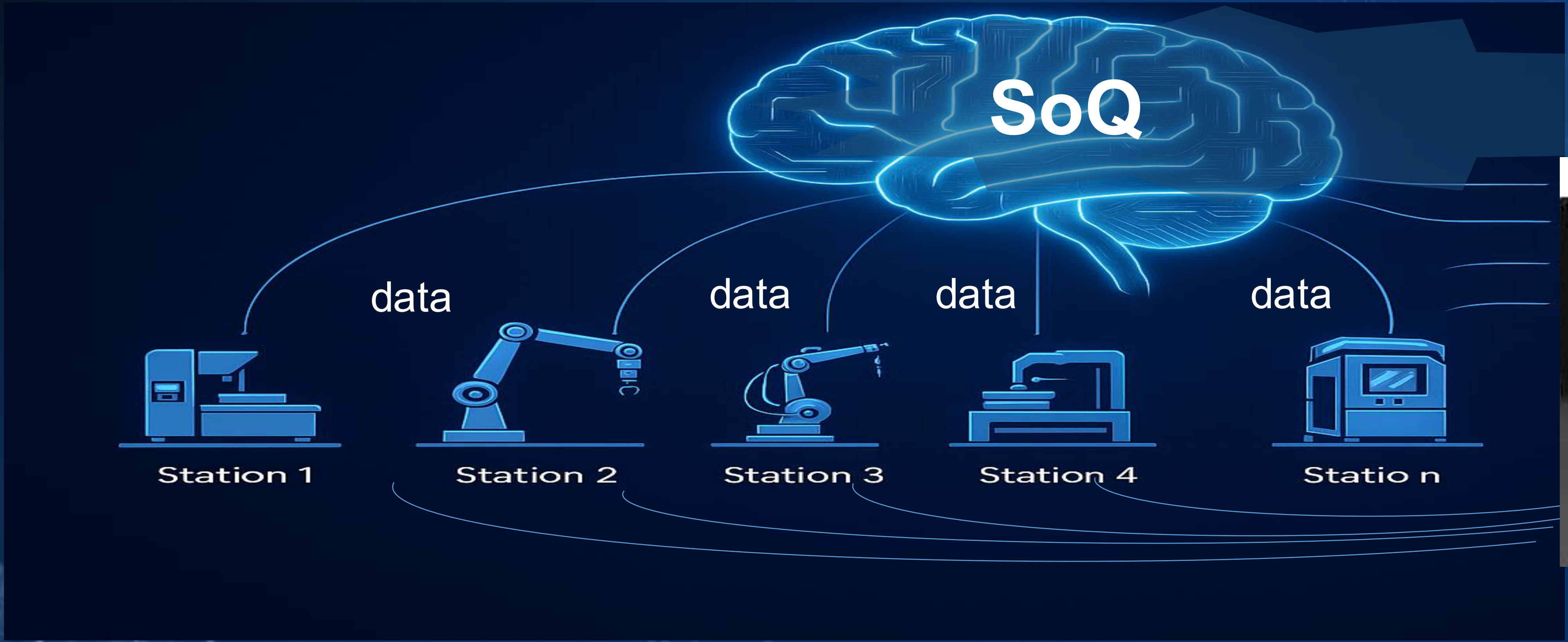
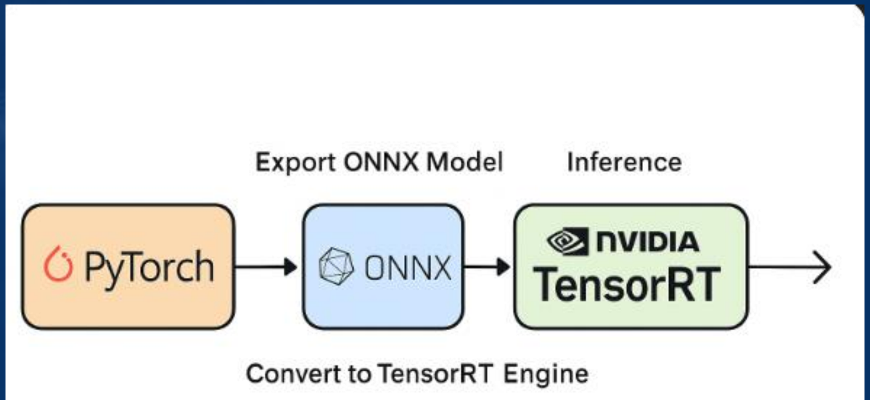
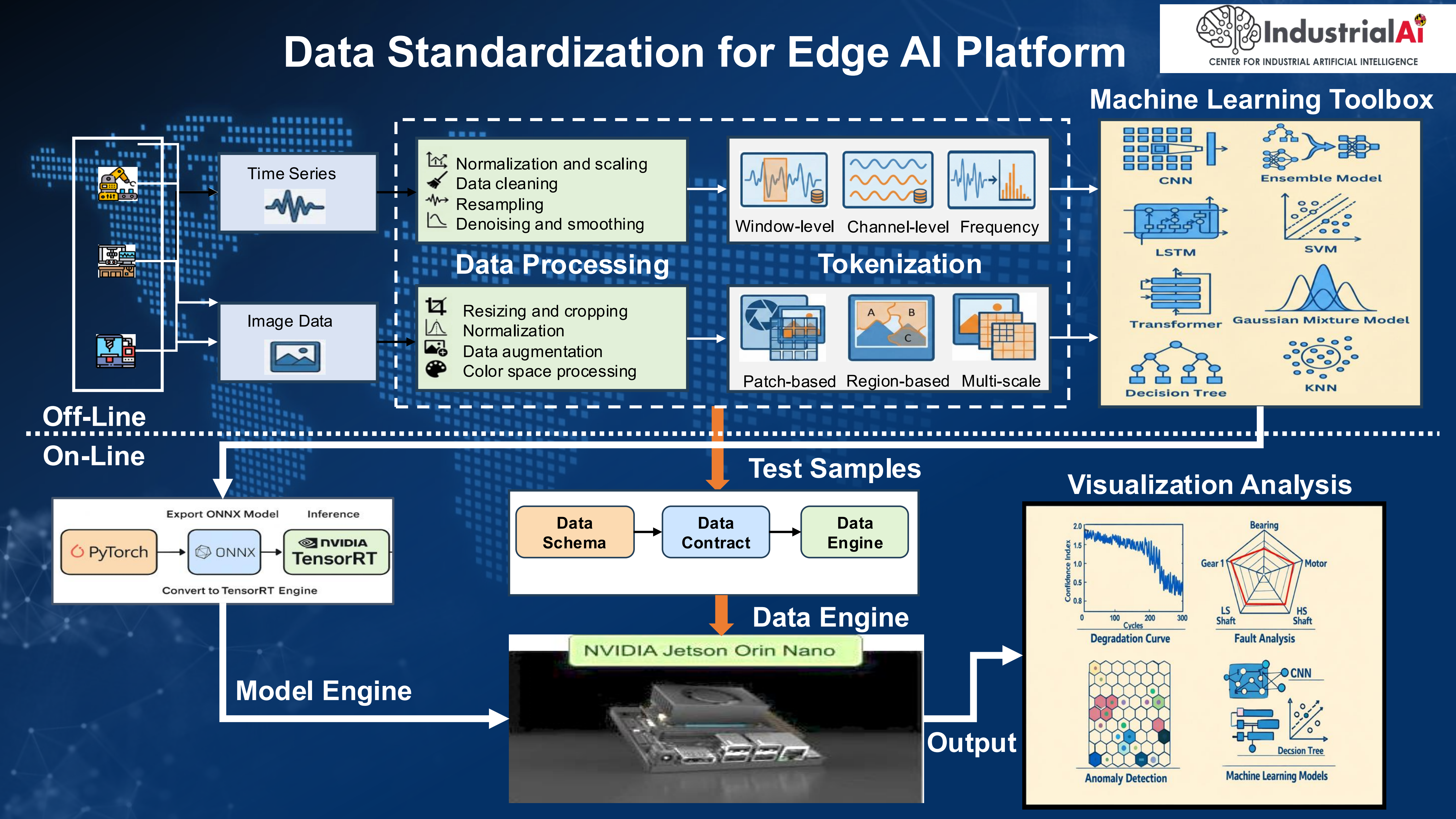


Edge AI



Edge AI



Data Standardization for Edge AI Platform
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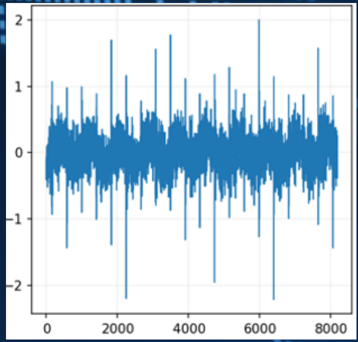
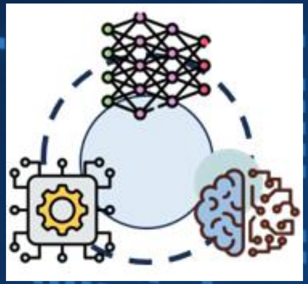
Machine Learning Toolbox
Time Series
Image Data
Normalization and scaling
Data cleaning
Resampling
Denoising and smoothing
Window-level
Channel-level
Frequency
Data Processing
Tokenization
Resizing and cropping
Normalization
Data augmentation
Color space processing
Patch-based
Region-based
Multi-scale
CNN
Ensemble Model
LSTM
SVM
Transformer
Gaussian Mixture Model
Decision Tree
KNN
Off-Line
On-Line
Test Samples
Visualization Analysis
Export ONNX Model
Inference
PyTorch
ONNX
NVIDIA TensorRT
Convert to TensorRT Engine
Data Schema
Data Contract
Data Engine
Data Engine
NVIDIA Jetson Orin Nano
Model Engine
Output
Confidence Index
Cycles
Degradation Curve
Bearing
Gear 1
Motor
LS Shaft
HS Shaft
Fault Analysis
CNN
Decsion Tree
Anomaly Detection
Machine Learning Models

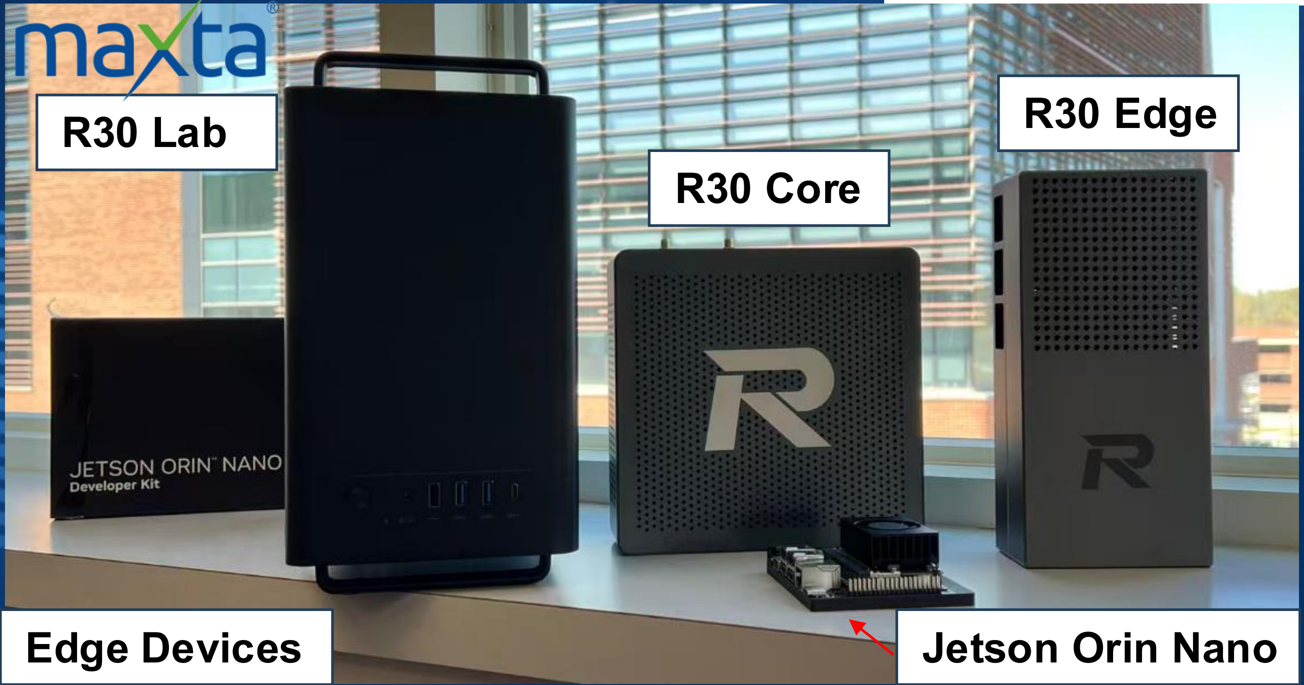
Machine Learning Models Deployed on Different Edge Devices



Time Series Data



Machine Learning Model

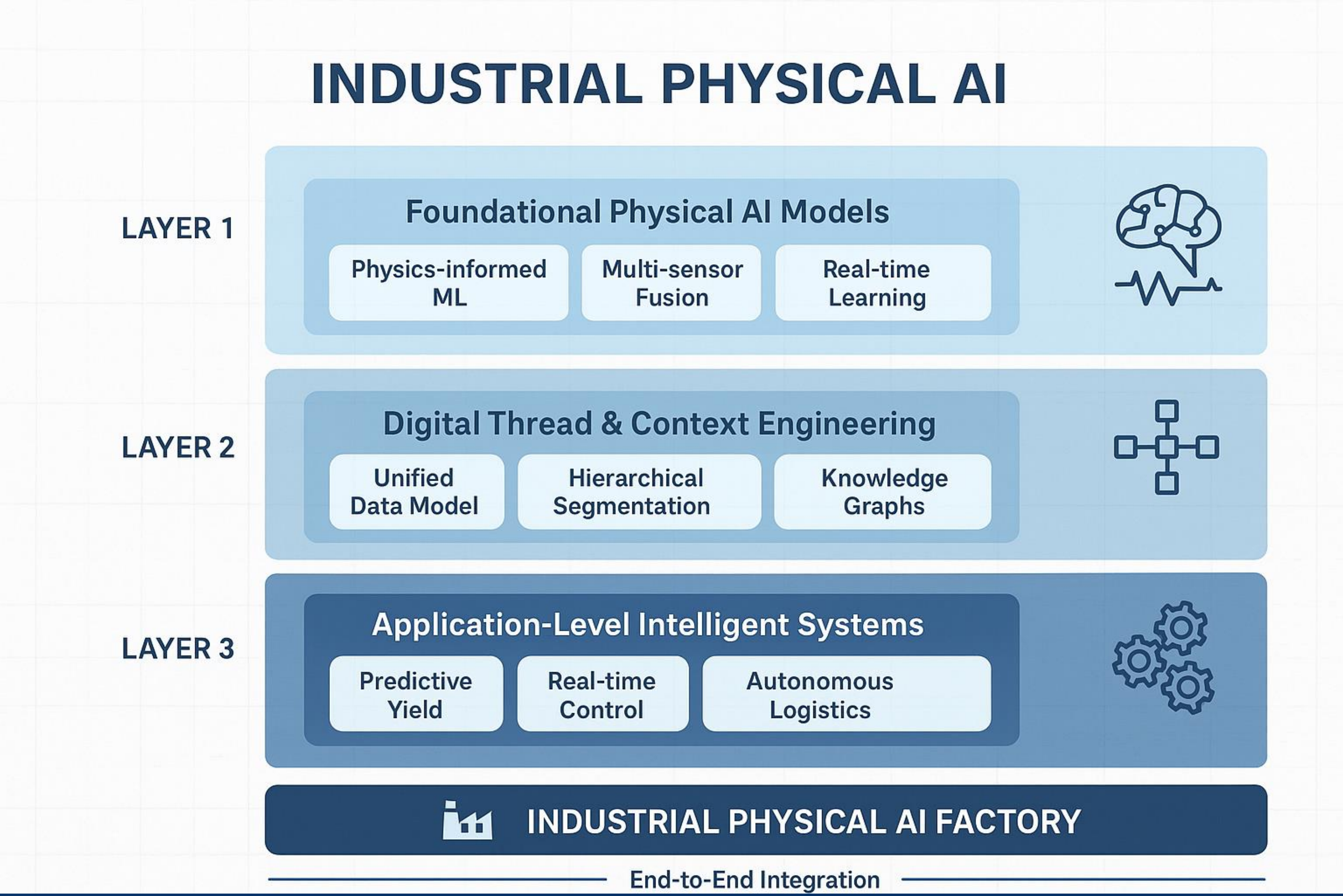


Edge Devices

Edge Device Comparison

Device	CPU	GPU	Memory	Storage	Relative AI Compute
Jetson Orin Nano	6-core Arm Cortex-A78AE	1024 CUDA + 32 Tensor cores (Ampere)	8 GB LPDDR5	microSD / external NVMe	Baseline (1×)
R30 Edge	14-core Arm Neoverse-V3AE	2560-core Blackwell GPU + 5th Gen Tensor cores	128 GB LPDDR5X	1 TB NVMe SSD	**~4–6×** higher than Jetson Orin Nano
R30 Core	Intel Core Ultra 9 285 (24 cores)	NVIDIA RTX PRO 5000 Blackwell	96 GB DDR5	4 TB SSD	**~10–20×** higher than Jetson Orin Nano
R30 Lab	Intel Core i5-14600K	NVIDIA RTX Pro 6000 Max-Q 96GB	192 GB DDR5	4 TB SSD	**~20–40×** higher than Jetson Orin Nano

Summary of Industrial Physical AI Architecture



Outline

- Trends of AI and AI Industry Transformation
- Industrial AI, Physical AI, and Industrial Physical AI
- Recent Advances and Challenges
- New Breed of AI Manufacturing Talents

4P Approach for AI Learning Enterprise

Level 4 Professional-based Learning

Level 3 Project-Based Learning

Level 2 Practice-based Learning

Level 1 Principle-Based Learning

Ref: Jay Lee, Industrial AI Book, Springer, 2020

PHM Society Data Challenges (2008- 2023)

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Competition	Industrial Systems	Research Task
2008 PHM	Prognosis	Aircraft engine
2009 PHM	Unsupervised fault detection &diagnosis	Gearbox
2010 PHM	Prognosis	Milling machine
2011 PHM	Unsupervised fault detection	Anemometer
2012 PHM	Prognosis	Bearing
2013 PHM	Supervised fault detection &diagnosis	Unknown Asset
2014 IEEE	Prognosis and health assessment	Fuel cell
2014 PHM	Supervised risk assessment &fault detection	Unknown Asset
2015 PHM	Supervised fault detection &diagnosis	Power plant
2016 PHM	Virtual metrology	Semiconductor CMP
2017 PHM	Supervised fault detection &diagnosis	Bogie
2018 PHM NA	Detection & Diagnosis & Assessment & Prognosis	Ion Mill Etching System
2019 PHM NA	Assessment & Prognosis	Fatigue Crack
2020 PHM EU	Prognosis	Filtration System
2021 PHM EU	Detection & Diagnosis	Manufacturing Production Line
2021 PHM NA	Prognosis	Turbofan Engine
2022 PHM EU	Detection & Diagnosis	Printed Circuit Board
2022 PHM NA	Detection & Diagnosis	Rock Drill
2023 PHM AP	Detection & Diagnosis	Spacecraft Propulsion System
2023 IEEE	Detection & Diagnosis	Gearbox

Data Issues in Selected PHM Competitions 2008 to 2023

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Competition	Unique Challenges
2008 PHM	Data Noise Contamination & Diverse Operating Conditions
2009 PHM	Insufficient Data Labeling & Limited Data Diversity
2010 PHM	Data Imbalance & Data Labeling Issues
2011 PHM	Limited Data Diversity
2012 PHM	Multiple Operating Conditions
2013 PHM	Data Labeling Quality & Data Scale
2014 IEEE	Data Imbalance & Time Constraint
2014 PHM	Data Imbalance
2015 PHM	Data Imbalance & Label Sparsity
2016 PHM	High Feature Dimensionality & Data Distribution Discrepancy
2017 PHM	Small Sample Size & Feature Diversity
2018 PHM NA	Data Discrepancy, Data Imbalance, Different Operating Conditions & Multiple Fault Modes
2019 PHM NA	Variable Loading Conditions, Limited Physical Information & Limited Data
2020 PHM EU	Different Operation Conditions & Unknown Fault
2021 PHM EU	Missing Data, Noise, Data Imbalance & Limited Data
2021 PHM NA	Multiple Fault Modes & High Variability in Flight Envelopes
2022 PHM EU	Missing Data, Data Imbalance & Component-level Prediction
2022 PHM NA	Domain Shift
2023 PHM AP	Unknown Fault & Limited Data
2023 IEEE	NA

PHM AP Data Challenge 2023
9/11-14, 2023

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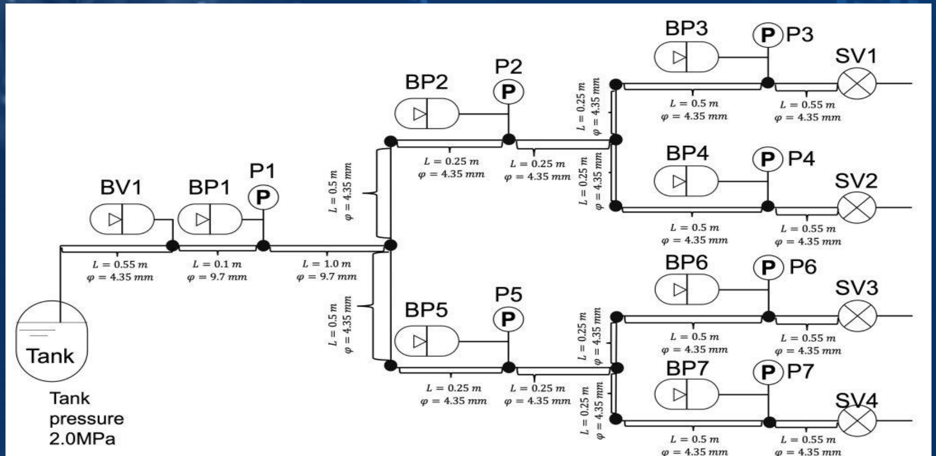
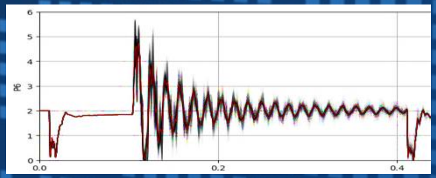
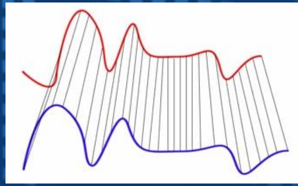
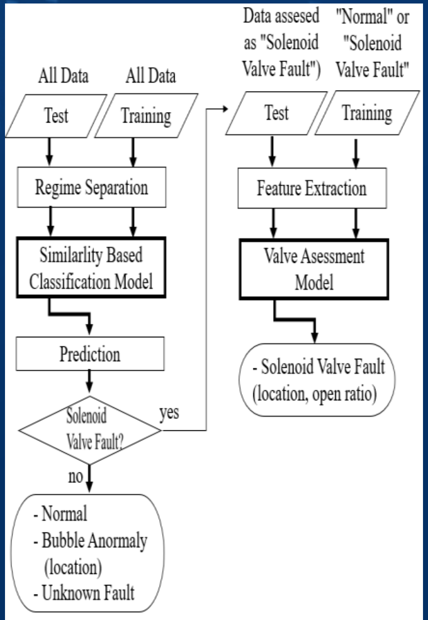


Approach





Dynamic Time Warping



Final Evaluation Result

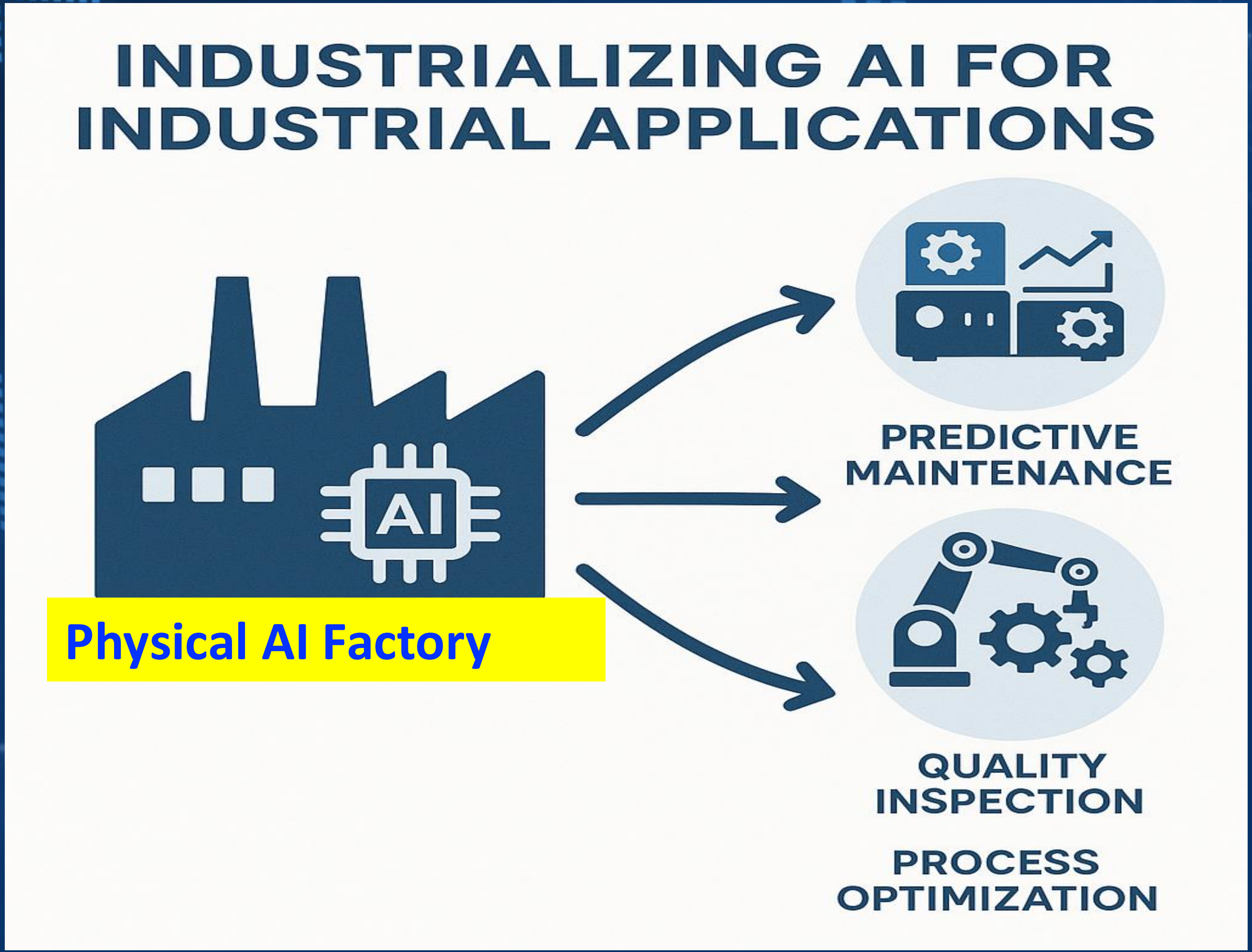
Team	Score
LB	100.00%
vibrationsensor	99.94%
SK	99.86%
Team Tsubasa	99.05%
KYU	97.26%
Kalle Anka PHM	93.77%
LDM	93.08%
MIDAS Wolverines	92.98%
Team HSNR	82.48%
propulsion	82.22%
JANUS	82.02%
CUMT	80.48%
DataCrunchers	79.33%
HEU-Zheng	76.87%
Bubu	76.44%
Jiaxiang	[illegible]
maedatakafumi	[illegible]
P-DX AI	[illegible]
Young	[illegible]
tcs research	[illegible]
MORI	[illegible]
e-kagaku	[illegible]1.49%
YUFC	60.48%
Escape	60.12%
Industrial AI	56.13%

3 Days

Takanobu MINAMI

KOMATSU

Industrial Physical AI Factory: Data, Tokens, and Agentic AI Platform



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Industrial Physical Token Generation Process for ML

1 Data Collection

- Machine sensors (vibration, temperature)
- Operational parameters
- Historical maintenance logs
- Production quality data

2 Preprocessing

- Data cleaning & normalization
- Segmentation
- Feature extraction
- Noise filtering

3 Tokenization

- Segmenting by time windows
- Pattern encoding
- Converting signals to token sequences
- Embedding generation

Key Considerations for Token Generation in PHM

- Time window selection is crucial for capturing relevant patterns
- Multi-dimensional data requires synchronization before tokenization
- Balance between token granularity and computational efficiency
- Context retention across token boundaries prevents information loss

Case Study: Machine Tool AI Example

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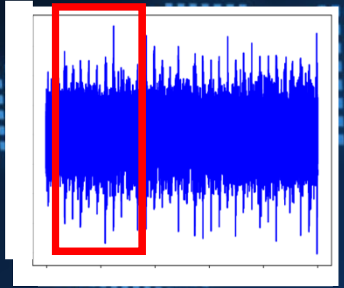
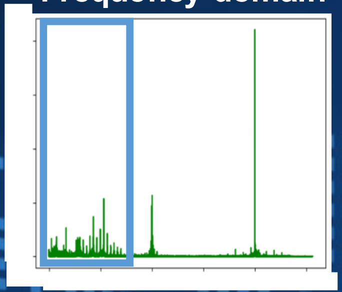
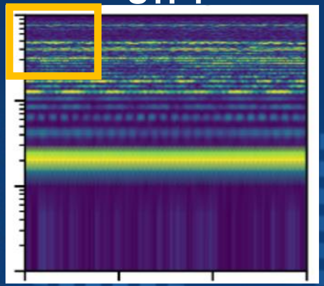
Time-series

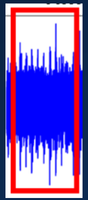


Frequency-domain



STFT



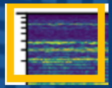


Fixed vector length with time domain information

sig_m1_k: [0.5, 0.9, 1.5, …]

Fixed vector length with freq domain information

sig_m2_k: [0.2, 0.7, 2.5, …]



Fixed-size patches time-freq domain information

img_m3_k: [[xx], [xx], [xx]…]

Time Domain + Position Embedding

Token_m1_k: [0.9, 0.2, 0.7, …]

Label y: class a1

Freq Domain + Position Embedding

Token_m2_k: [0.1, 0.7, 0.3, …]

Label y: class a1

Patch + Position Embedding

Token_m3_k: [0.6, 0.3, 0.8, …]

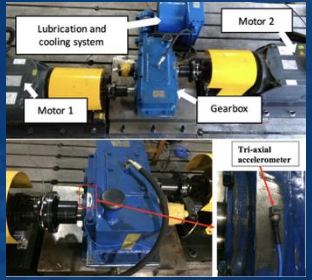
Label y: class a1

Use single/multi domain tokens to train the model

Vector database

Agentic AI Tools

Gearbox System



Database

PHM DFM

Use frequency domain tokens to train the model

Model	Test accuracy
CNN-based	96.54%
LSTM-based	97.99%
Transformer-based	99.26%

Source: Prognostics and Health Management (PHM) North America 2023 Conference Data Challenge

Key Takeaway

- Physical AI → AI capability revolution
- Industrial Physical AI → AI economic impact revolution

Call to Action 1

"AI for Manufacturing" is not simply the application of AI to manufacturing;
it is the transformation of manufacturing into a high-tech, high-paying career path.

Call to Action 2

**“AI is not just about making AI companies rich—
it must make our industry more prosperous and resilient.”**

“Industrial AI” Book by Springer in 2020

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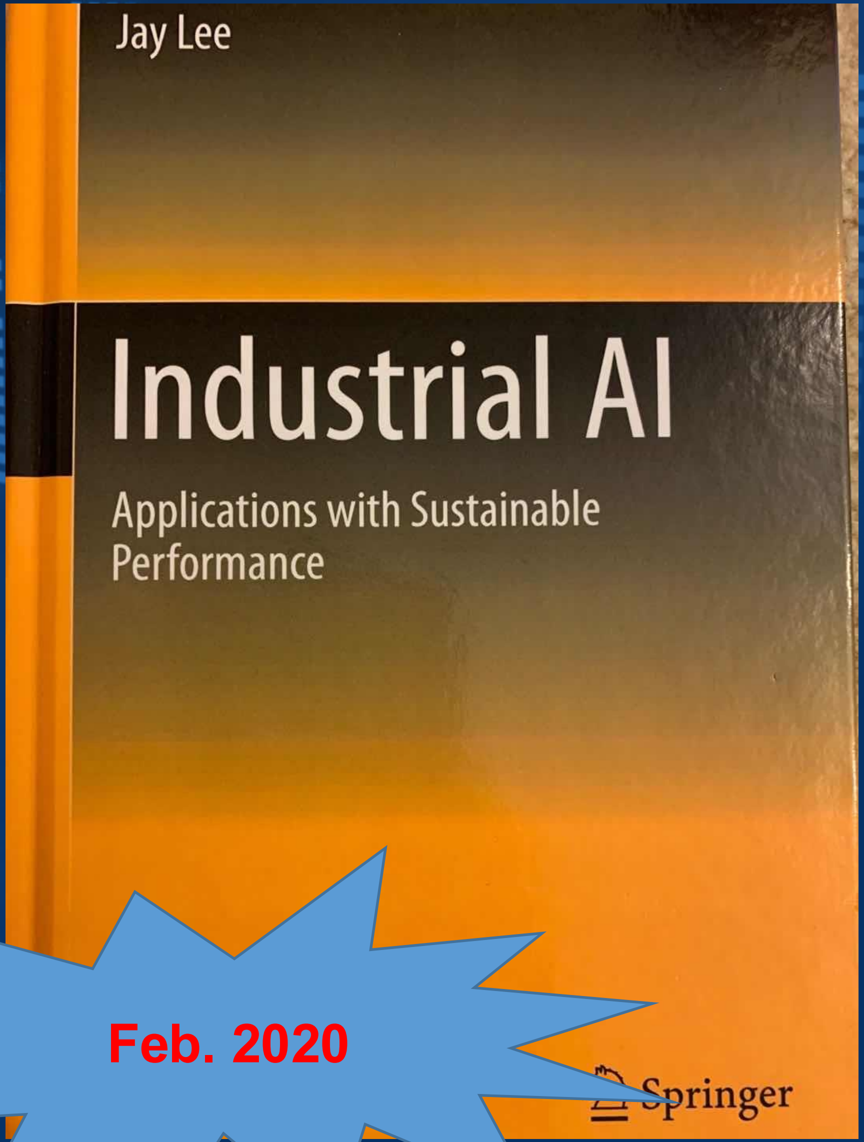

Feb. 2020

Thank You

More Information See

www.iaicenter.com

Contact: leejay@umd.edu