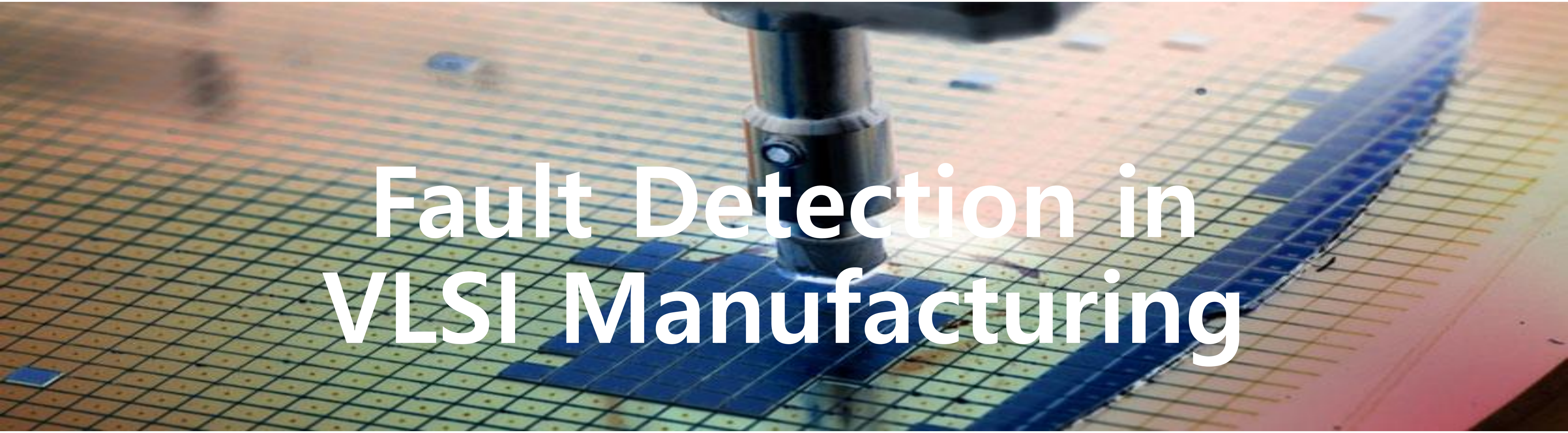

Fault Detection in VLSI Manufacturing

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AI202216001

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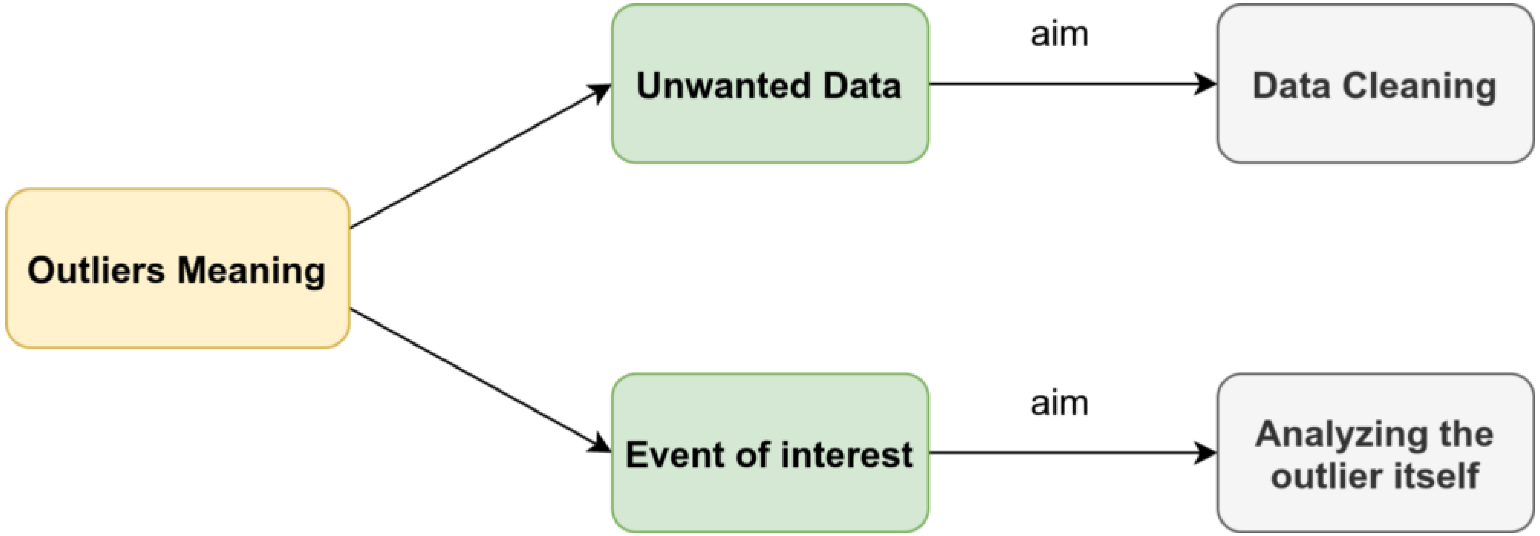
- Paper: Hsu, CY., Liu, WC. **Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing**. *J Intell Manuf* **32,** 823–836 (2021). https://doi.org/10.1007/s10845-020-01591-0

Anomaly Detection basics (1/2)

- Anomaly detection mean identifies data points, events, and/or observations that deviate from a dataset's normal behavior
- There are 2 aspects of Anomaly detection:

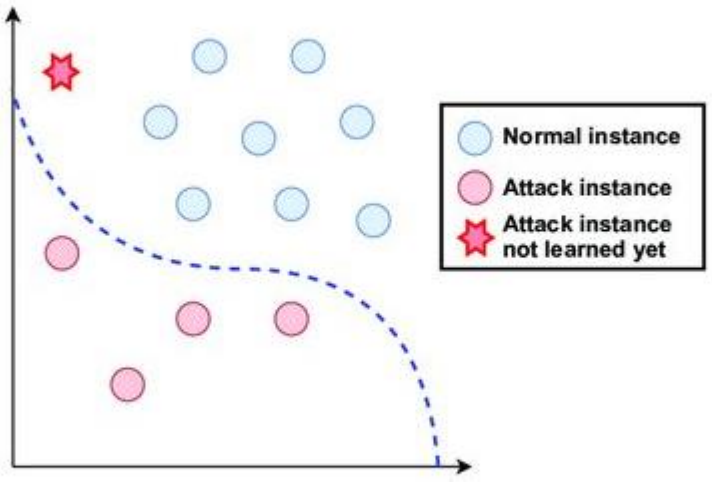


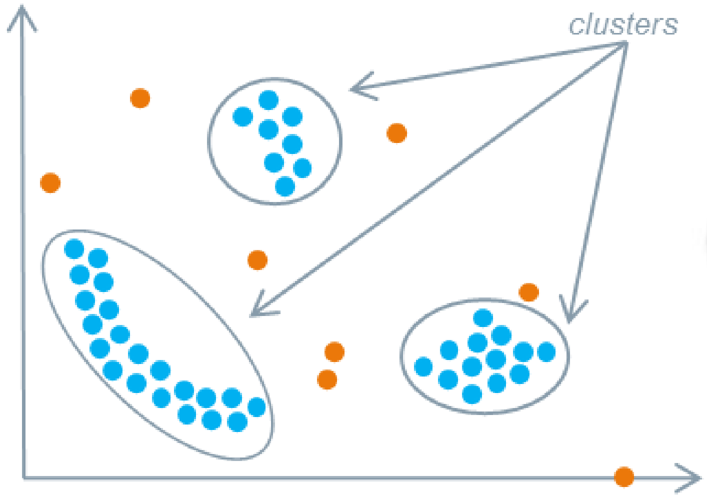
Remove anomalous data from data set to enhance training phase

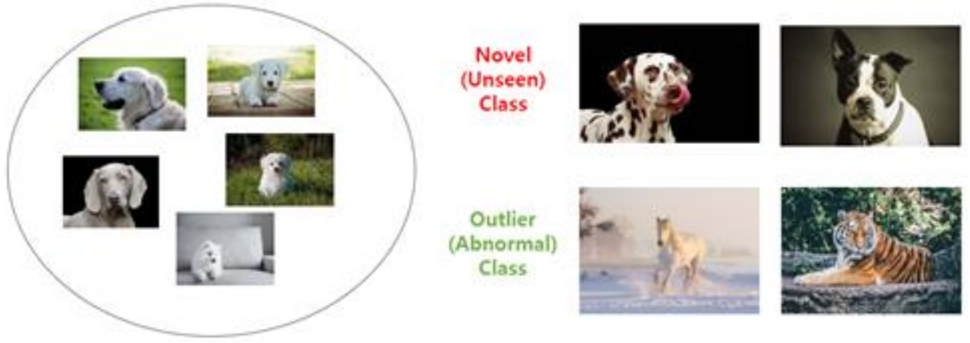
Intrusion detection, fraud detection, fault detection, health monitoring, …

Anomaly Detection basics (2/2)

- There are 3 categories of Anomaly detection:
  - ➢ Supervised anomaly detection techniques require a data set that has been labeled as "normal" and "abnormal" and involves training a classifier
  - ➢ Unsupervised anomaly detection techniques assume the data is unlabelled
  - ➢ Semi-supervised anomaly detection techniques assume that some portion of the data is labelled

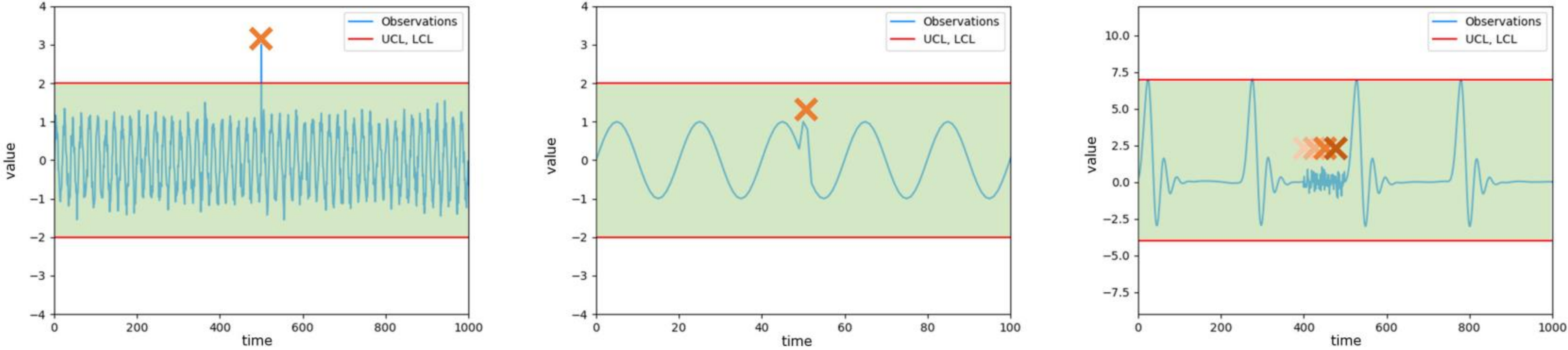






Anomaly Detection in time-series (1/3)

- Anomaly types in time-series data



(a) point anomaly (b) contextual anomaly (c) collective anomaly

Anomaly Detection in time-series (2/3)

- Classical approaches:
  - ➢ Time/frequency domain analysis by Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT)
  - ➢ Statistical model
  - ➢ Distance-based model by Euclidean distance, Dynamic time warping (DTW), Hamming distance
  - ➢ Predictive model by autoregressive integrated moving average (ARIMA)
  - ➢ Clustering model by k-means, one-class support vector machine (OCSVM), Gaussian mixture model (GMM)
  - ➢ Density-based spatial clustering of applications with noise (DBSCAN)

Anomaly Detection in time-series (3/3)

- Modern approaches:

Autoencoder

- SPREAD (Gugulothu et al., 2018) [104]
- S-RNNs (Kieu et al., 2019) [114]
- LSTM-AE (Hsieh et al., 2019) [29]
- MU-Net (Wen et al., 2019) [62]
- MSCRED (Zhang et al., 2019) [51]
- USAD (Audibert et al., 2020) [72]

GAN

- BeatGAN (Zhou et al., 2019) [115]
- MAD-GAN (Li et al., 2019) [59]
- WGAN-based (Choi et al., 2020) [53]
- RSM-GAN (Khoshnevisan et al., 2020) [74]

VAE

- LSTM-VAE (Park et al., 2018) [112]
- GGM-VAE (Guo et al., 2018) [113]
- OmniAnomaly (Su et al., 2019) [68]

Transformer

- SAnD (Song et al., 2018) [119]
- MTSM (Meng et al., 2019) [120]
- GTA* (Chen et al., 2021) [109]

GNN

- MTAD-GAT (Zhao et al., 2020) [73]
- GTA* (Chen et al., 2021) [109]
- GDN (Deng et al., 2021) [108]

RNN

- LSTM-NDT (Hundman et al., 2018) [110]
- LGMAD (Ding et al., 2019) [111]
- THOC (Shen et al., 2020) [60]

TCN

- HS-TCN (Cheng et al., 2019) [116]
- TCN-GMM (Liu et al., 2019) [117]
- TCN-ms (He et al., 2019) [118]

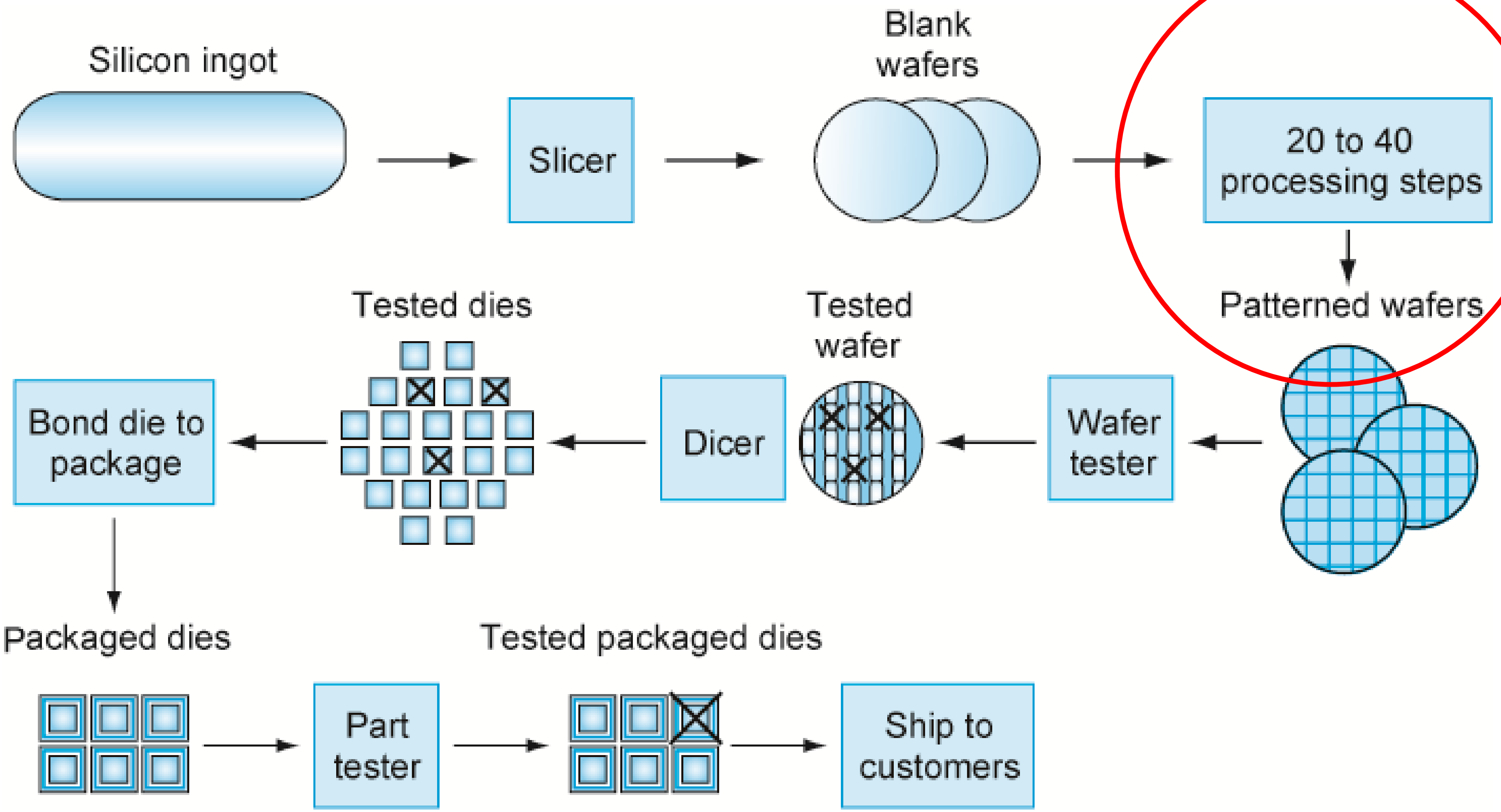
HTM

- HTM-based (Wu et al., 2018) [121]
- RADM (Ding et al., 2018) [69]

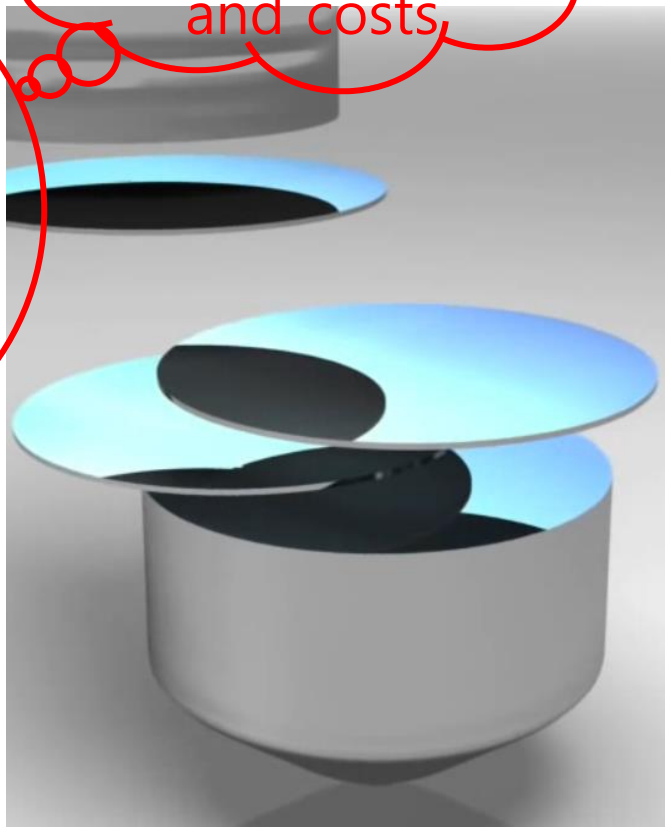
VLSI Manufacturing basics (1/3)

- https://www.youtube.com/watch?v=aCOyq4YzBtY

VLSI Manufacturing basics (2/3)



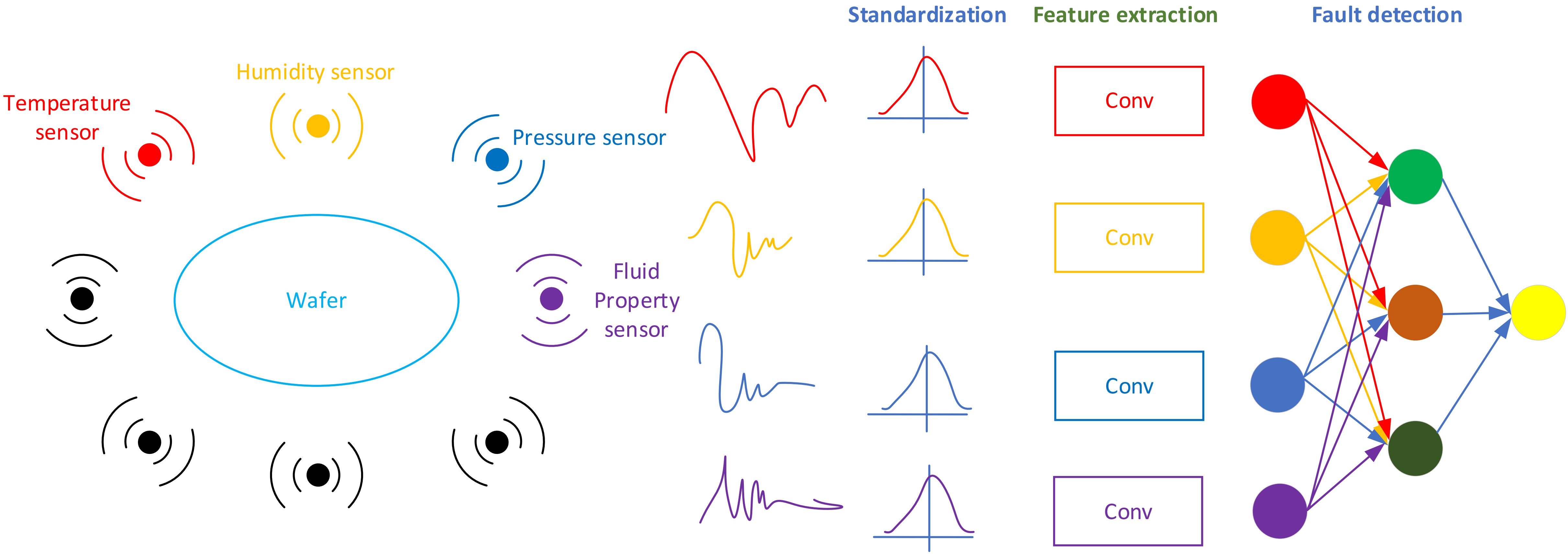
Detecting errors early will save time and costs



VLSI Manufacturing basics (3/3)

	16/12nm	10nm	7nm	5nm
Mass production year and quarter	2015 Q3	2017 Q2	2018 Q3	2020 Q
Capital investment per wafer processed per year	$11,220	$13,169	$14,267	$16,746
Capital consumed per wafer processed in 2020	$993	$1,494	$2,330	$4,235
Other costs and markup per wafer	$2,990	$4,498	$7,016	$12,753
Foundry sale price per wafer	$3,984	$5,992	$9,346	$16,988
Foundry sale price per chip	$331	$274	$233	$238

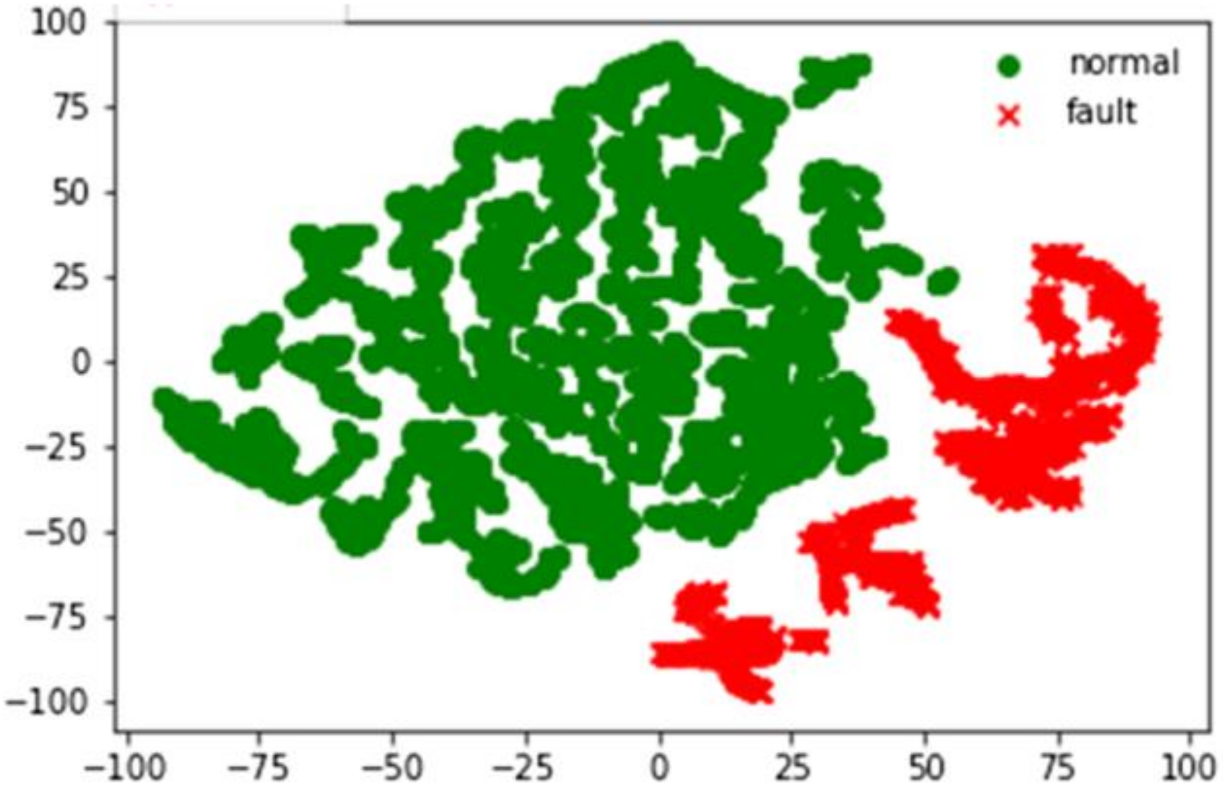
"Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing" (1/6)



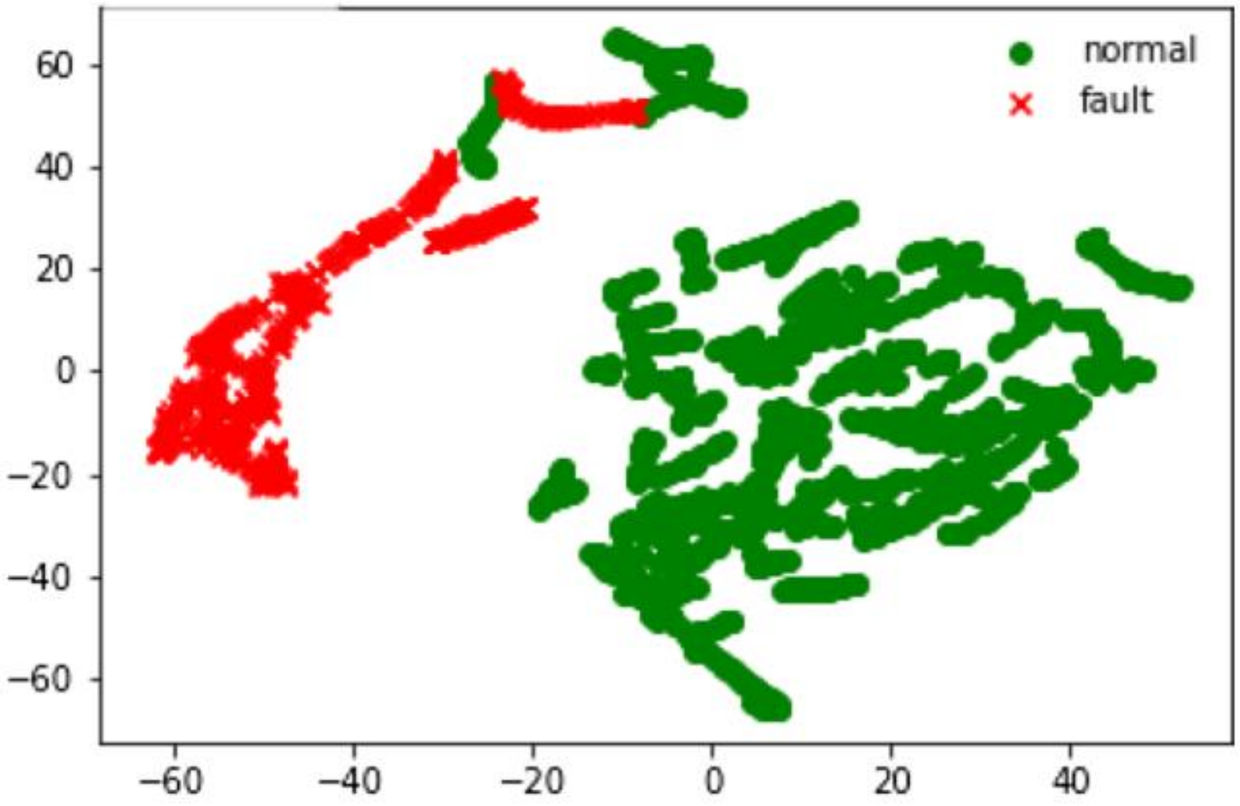
"Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing" (2/6)

- Scenario: Fault detection in the Chemical vapor deposition (CVD) process
- Number of sensors: 17
- Type: Supervised anomaly detection
- Time-series anomaly type: Collective anomaly
- Network architecture: CNN-based (MTS-CNN)
  - Kernel size: 5
  - Feature maps: 16 in 1^{st} conv, 64 in 2^{nd} conv
  - Number of CNN (channels): 17
  - Active function: ReLU
  - Pooling method: Average-pooling
  - Learning rate: 0.01; Batch size: 128
  - 0.5 dropout rate to reduce the effect of overfitting
- Dataset: 189 wafers (148 normal wafers, 41 abnormal wafers)
- Time-series: set-3 (Wafer, Data of 17 sensors, record time)

“Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing” (3/6)

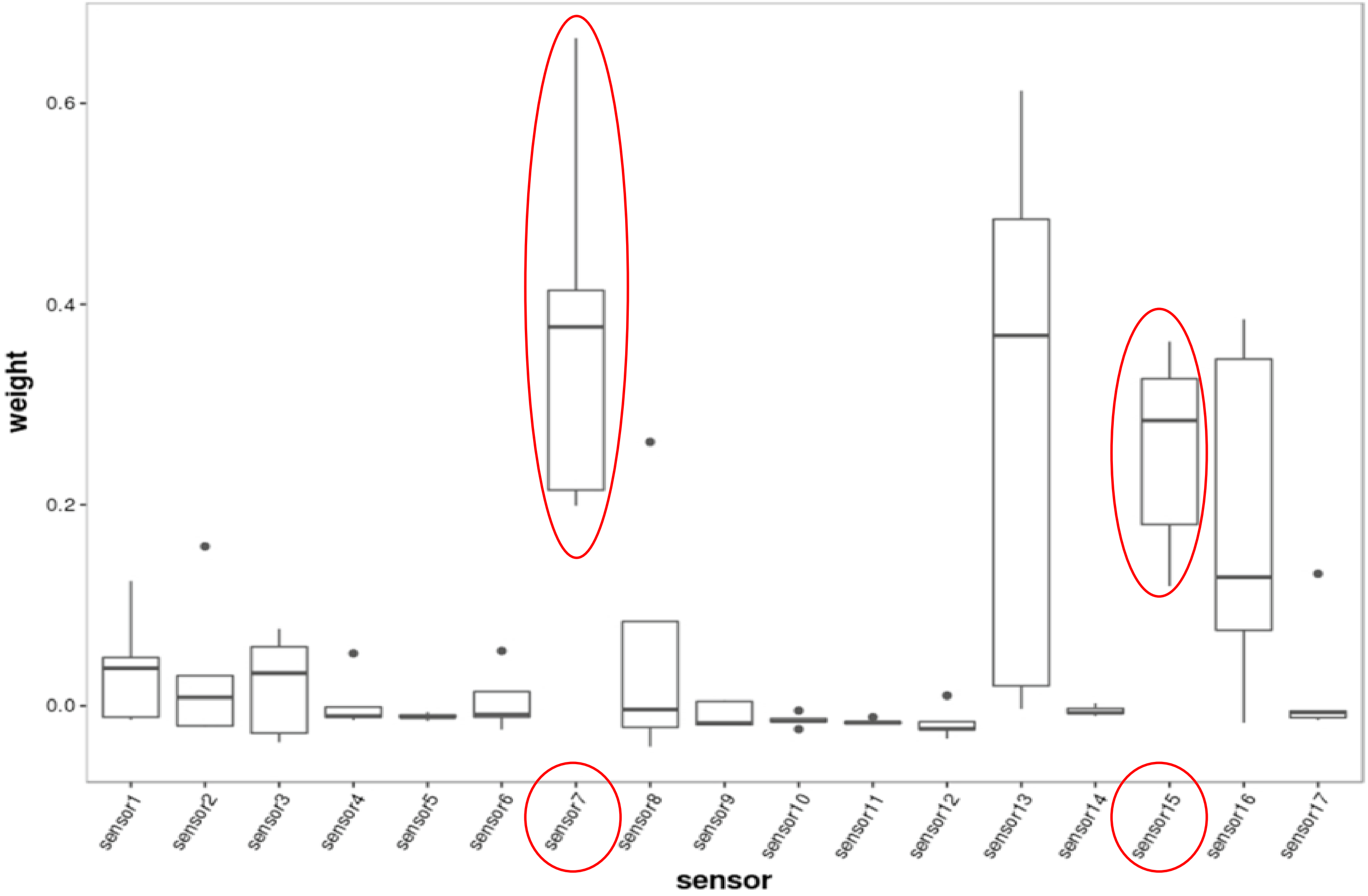


(a) in the training dataset

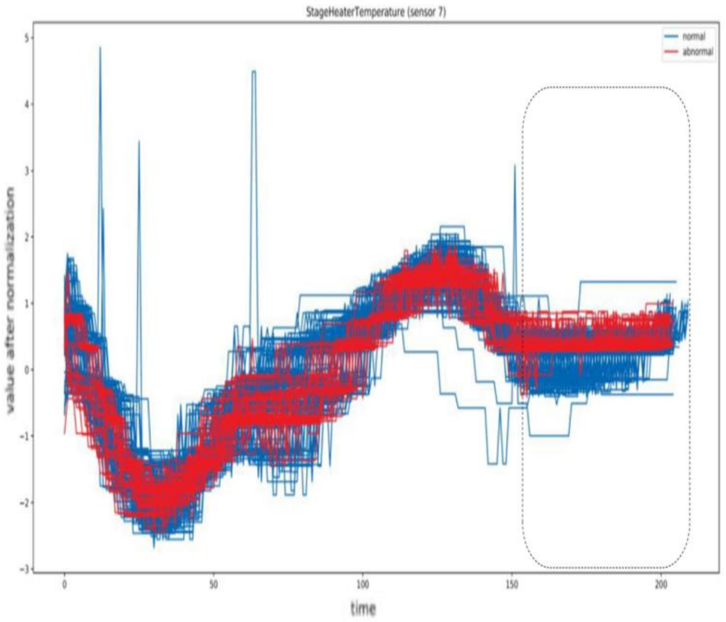


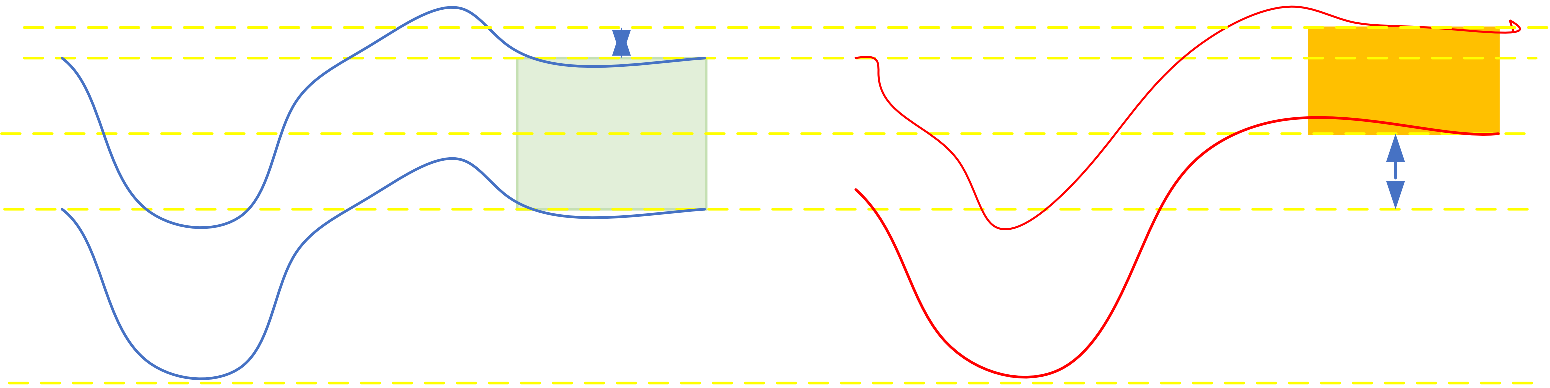
(b) in the testing dataset

“Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing” (4/6)



“Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing” (5/6)





“Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing” (6/6)

- Evaluation

Fivefolds cross-validation	Accuracy (%)
1NN-DTW (Xi et al. 2006)	70.88
SAX–VSM (Senin and Malinchik 2013)	85.66
Shapelet forests (Patri et al. 2014)	94.76
MC-DCNN (Zheng et al. 2014)	96.86
FDC-CNN (Lee et al. 2017b)	98.36
MTS-CNN	99.48

References

- K. Choi, J. Yi, C. Park and S. Yoon, "Deep Learning for Anomaly Detection in Time-Series Data: Review, Analysis, and Guidelines," in IEEE Access, vol. 9, pp. 120043-120065, 2021, doi: 10.1109/ACCESS.2021.3107975.
- Hsu, CY., Liu, WC. Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing. *J Intell Manuf* **32,** 823–836 (2021). https://doi.org/10.1007/s10845-020-01591-0