



DT4CHIPS-Secure: Digital Twin Framework for Chip Manufacturing Processes Security



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Abstract and Introduction

- The semiconductor manufacturing process, with its interconnected devices, poses information security risks alongside increased production efficiency.
- DT4CHIPS-Secure utilizes Digital Twin to model physical characteristics, effectively managing and deploying digital twin models. Anomaly detection safeguards devices against security threats, improving semiconductor yield.
- The framework's associated reports optimize device behavior, further enhancing semiconductor yield.

DT4CHIPS-Secure Framework

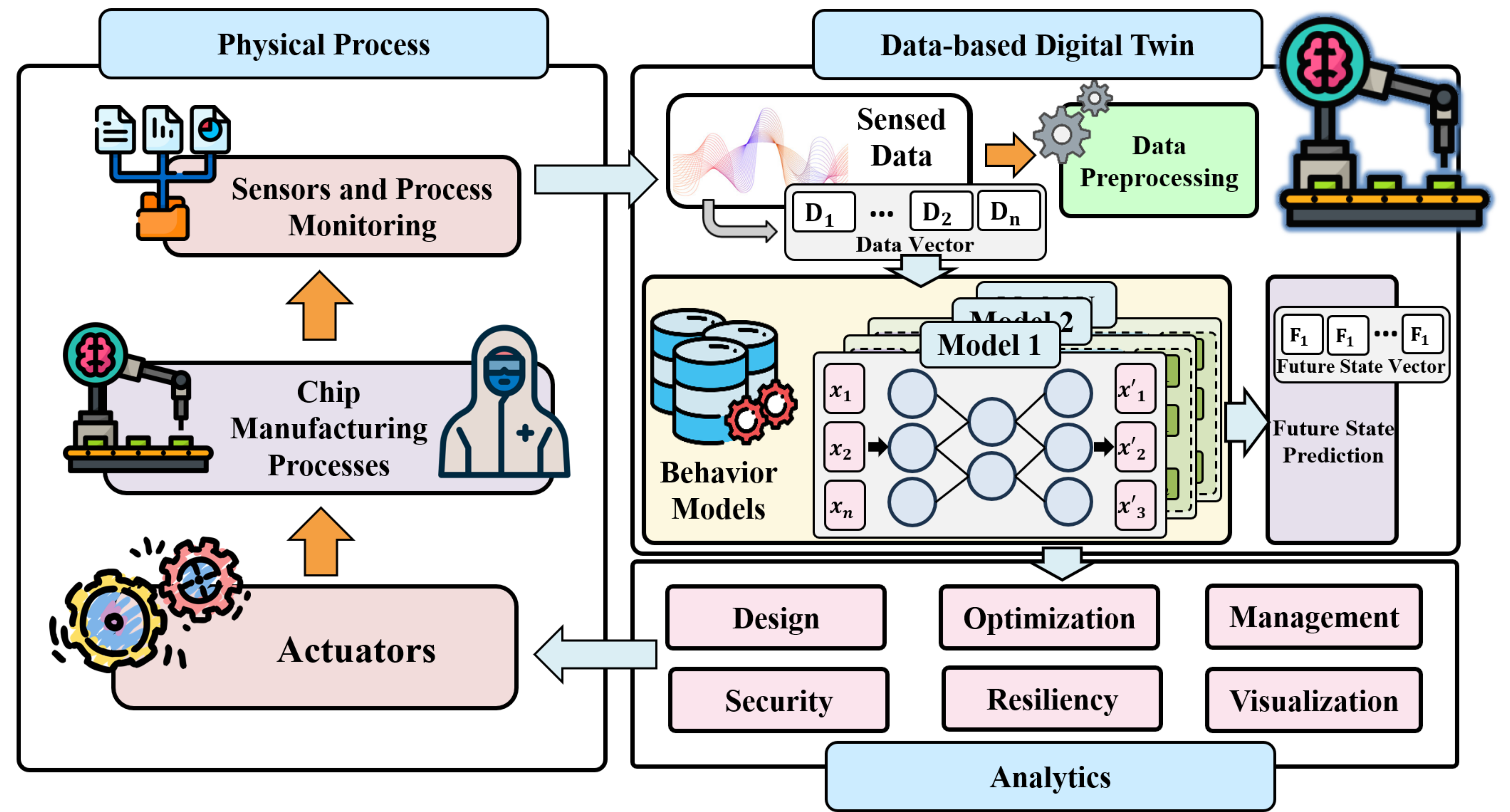


Fig1. Digital Twin Framework for Chip Manufacturing Processes Security (DT4CHIPS-Secure Architecture).

Main Features

- This framework uses the MLOps concept to build Digital-Twin with cloud computing for continuous integration (CI), continuous delivery (CD), and continuous training (CT).
- In the signal reconstruction stage, aimed at detecting anomalies in power consumption signals for various attack scenarios, this study utilizes a 1D CNN-based autoencoder to create a DT model based on normal consumption signal.
- In the anomaly detection stage, this work highlights using dynamic (instead of static) thresholds to improve attack detection performance compared to the DT predictions.

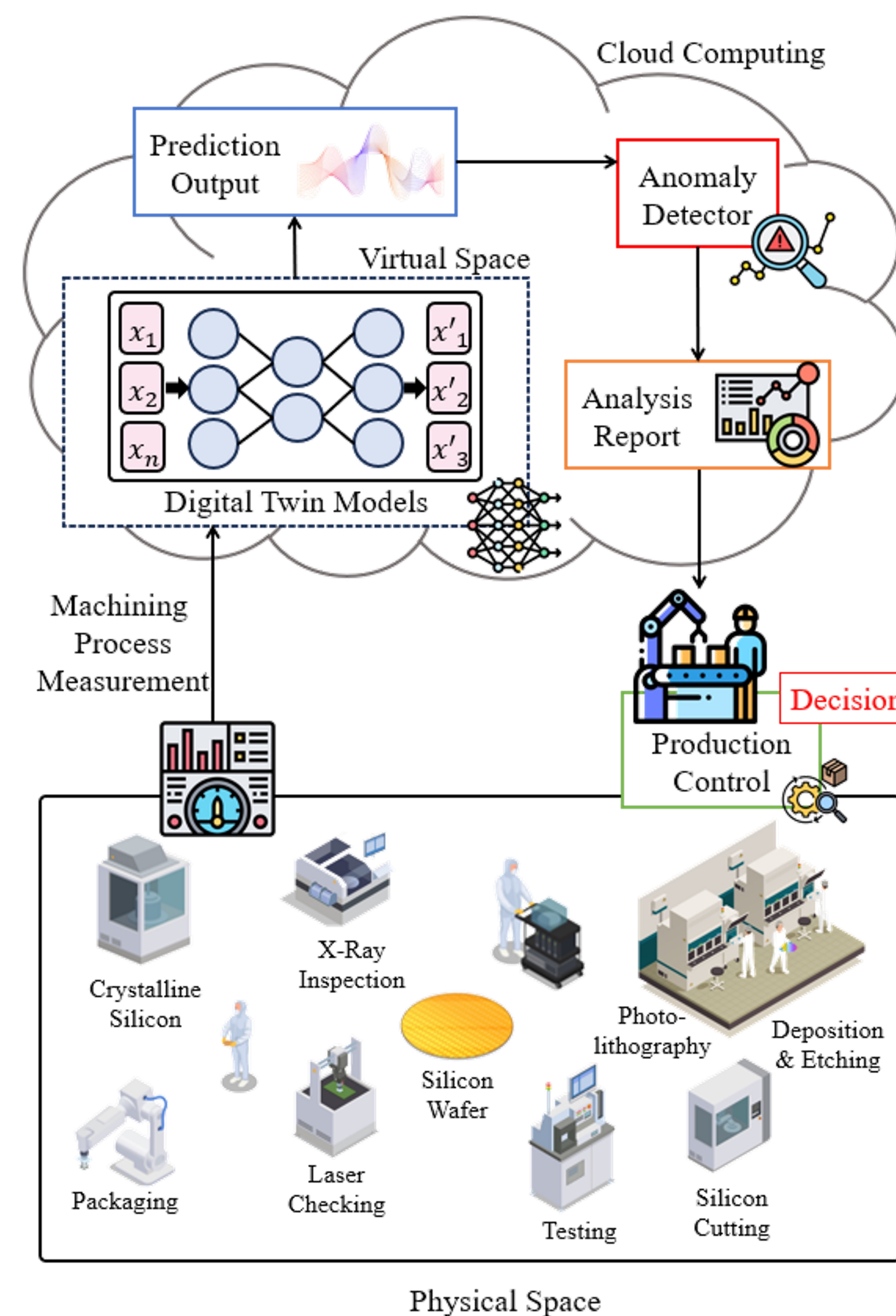


Fig 2. The Architecture of DT4CHIPS-Secure for security service.

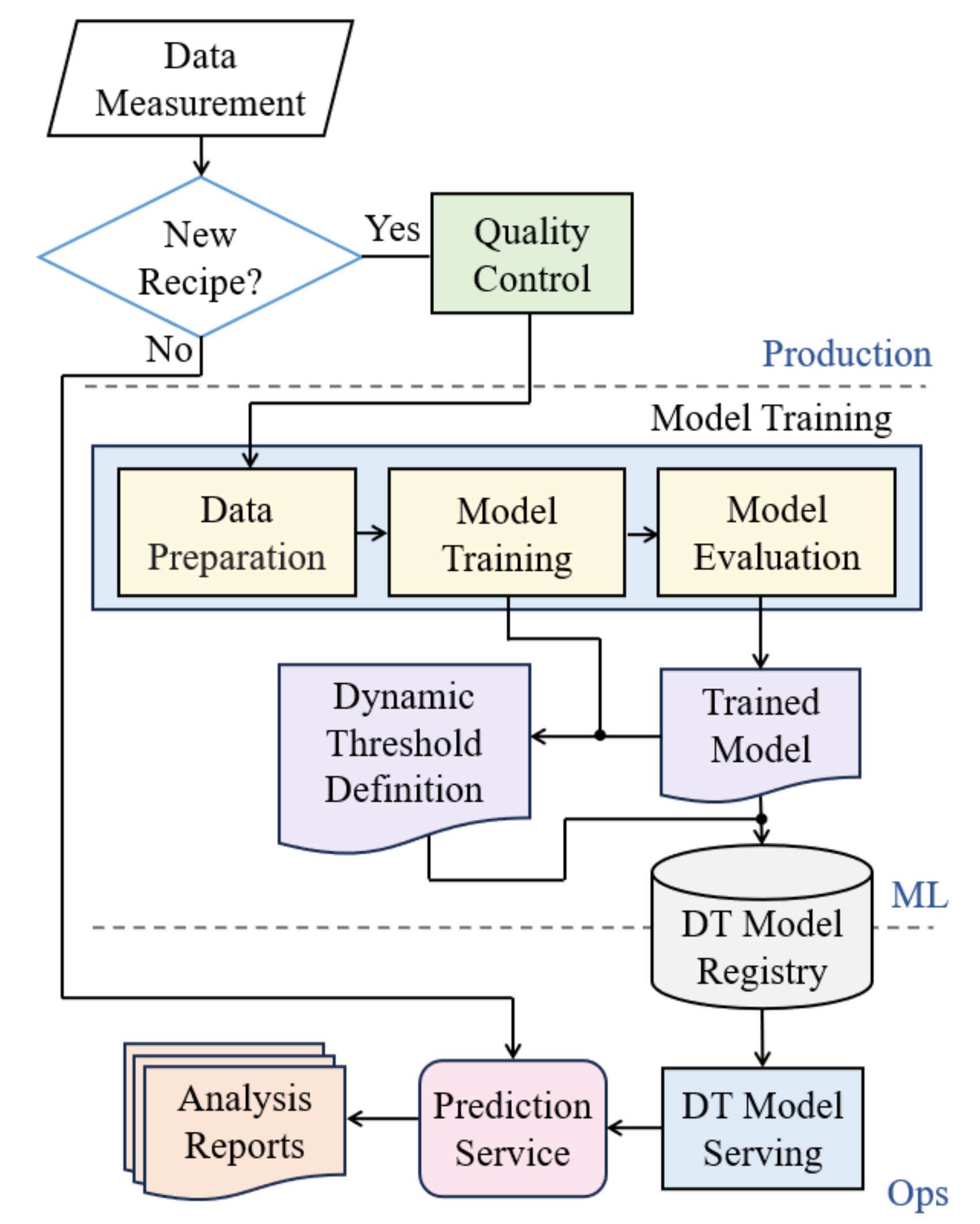


Fig 3. MLOps Pipeline of DT4I4-Secure.

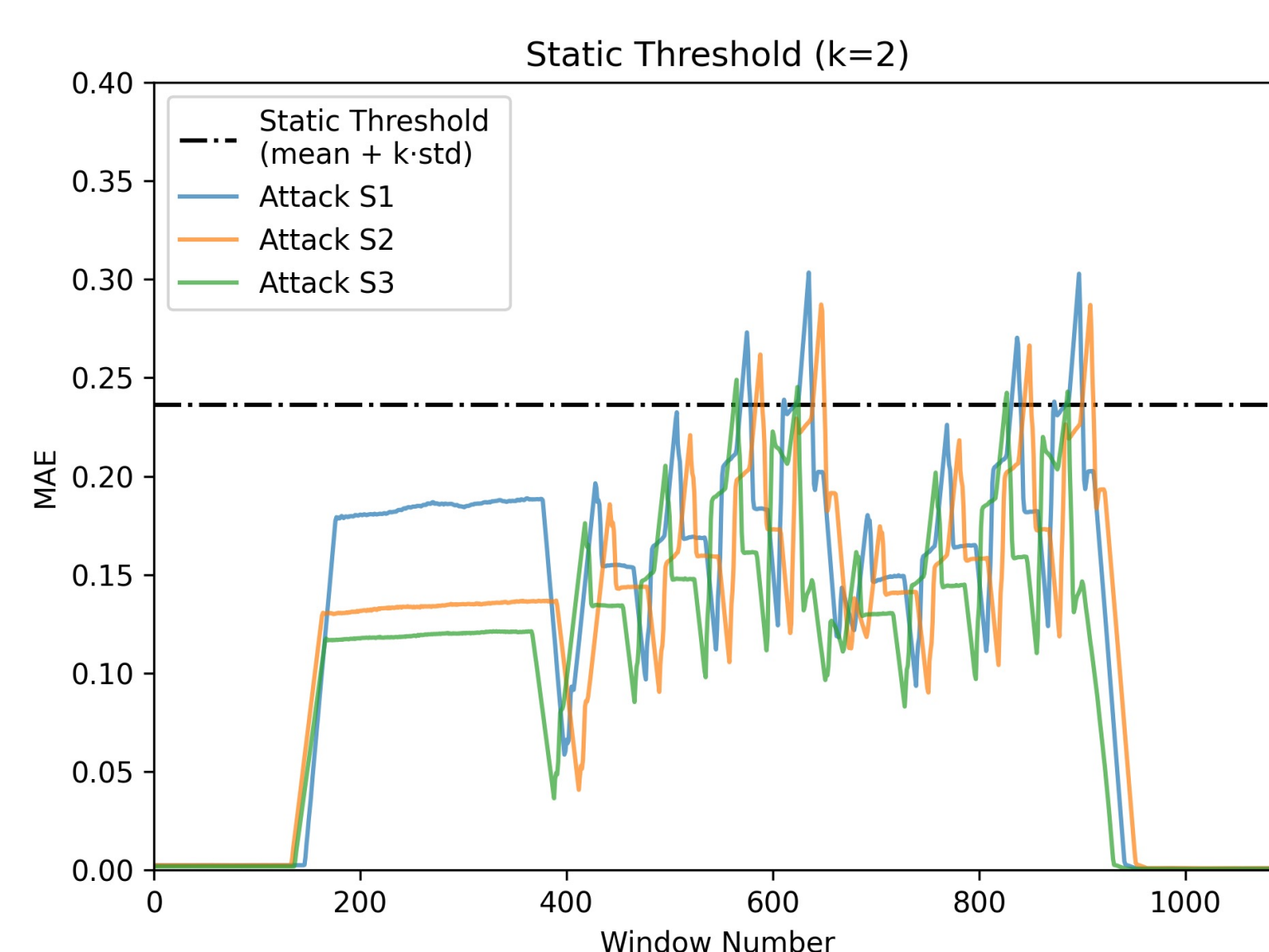
Original Concept: DT4I4-Security

Scan for DT4I4-Security Paper



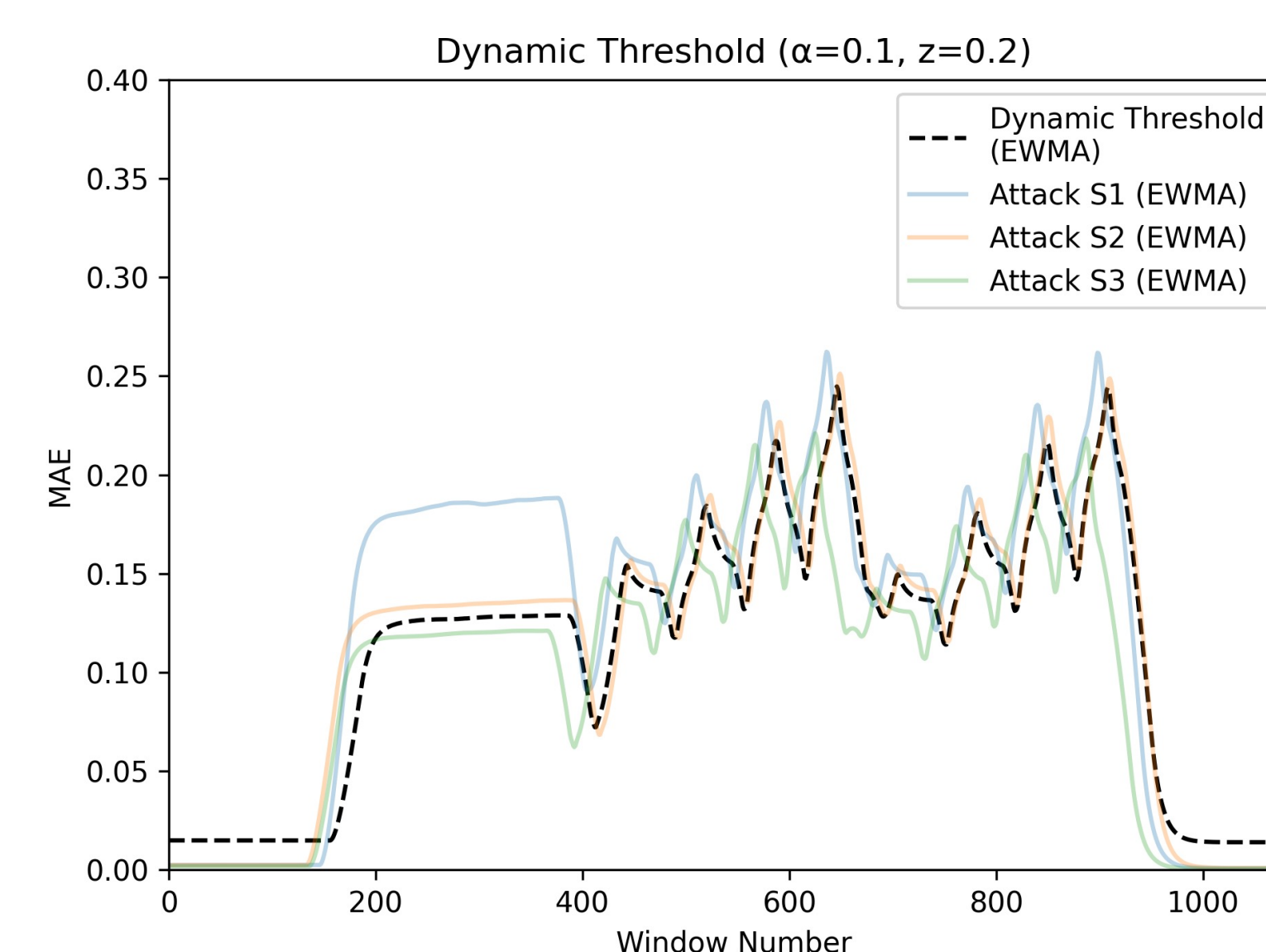
Proposed Methodology

Static Threshold



Input: T_{static} - static threshold, $\{e_{test}^i\}_{i=1}^n$ - error series of test set, n - number of time steps
Output: θ_i - anomaly status
 1: for $i = 1$ to n do
 2: if $e_{test}^i > T_{static}$ then
 3: Set $\theta_i = 1$ // Data is an anomaly.
 4: else
 5: Set $\theta_i = 0$ // Data is normal.
 6: end if
 7: end for
 8: return θ_i

Dynamic Threshold

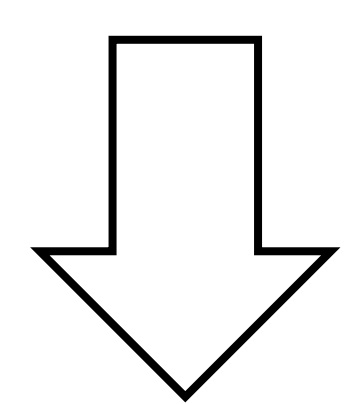


Input: $T_{dynamic}$ - dynamic threshold, $\{e_{test}^i\}_{i=1}^n$ - error series of test set, n - number of time steps, α - smoothing constant
Output: θ_i - anomaly status
 1: for $i = 1$ to n do
 2: Let $e_{test-s}^i = \alpha \cdot e_{test}^i + (1 - \alpha)e_{test-s}^{i-1}$;
 3: if $e_{test-s}^i > T_i$ then
 4: Set $\theta_i = 1$; // Data is an anomaly.
 5: else
 6: Set $\theta_i = 0$; // Data is normal.
 7: end if
 8: end for
 9: return θ_i

Results

Static Threshold

	Attack 1	Attack 2	Attack 3
Accuracy	47.34%	45.78%	87.83%
Precision	86.25%	90.08%	-
Recall	18.81%	17.82%	0%
F1 Score	30.89%	29.75%	-



Dynamic Threshold

	Attack 1	Attack 2	Attack 3
Accuracy	90.56%	88.73%	58.24%
Precision	86.88%	85.21%	14.63%
Recall	100%	99.83%	56.87%
F1 Score	92.98%	91.94%	24.29%

3.45X Improvement