Use of Smart Sampling in Wafer Defect Detection

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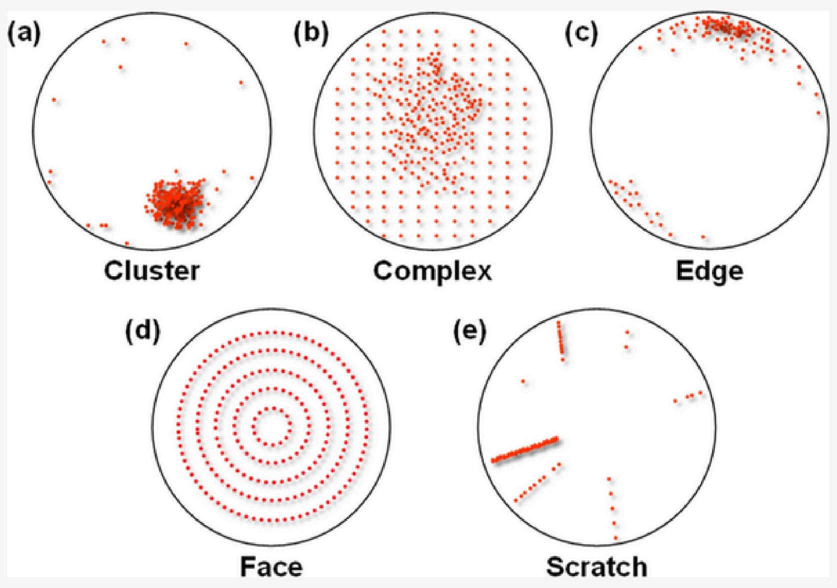
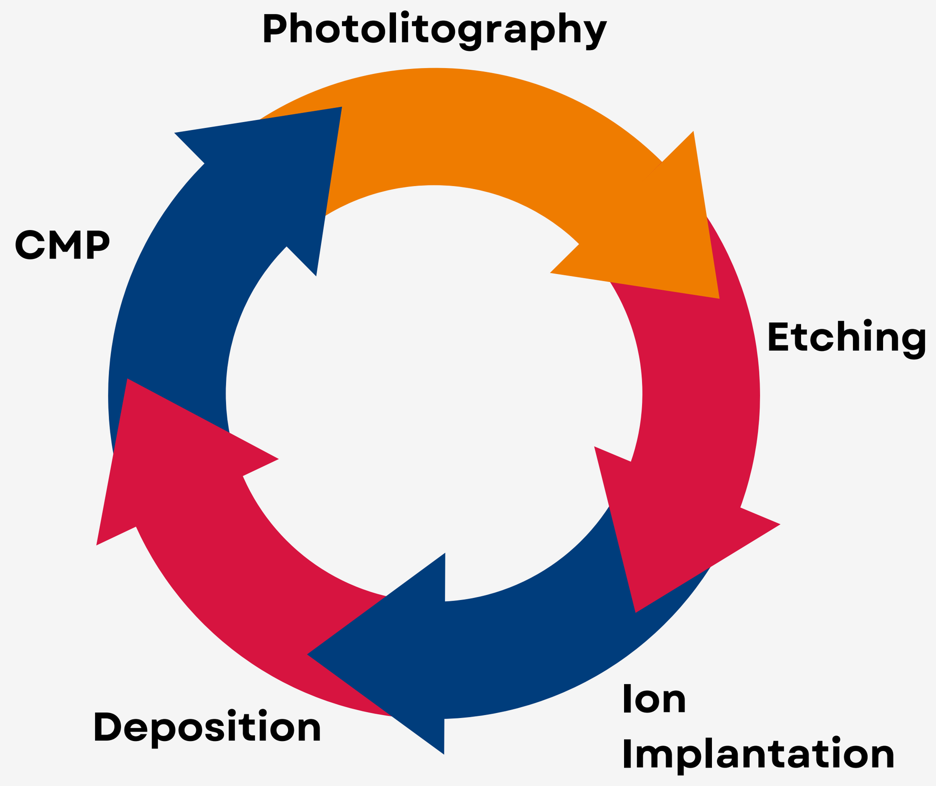
Background

Wafer surface defect



Wafer Fabrication Process



Current measures and Limitations in Detecting Defects

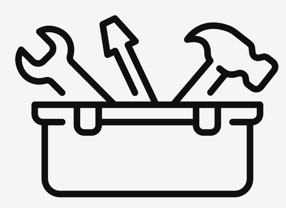
Key Issue	Explanation
Random Sampling	High-risk defects are missed (blind spots not adaptive)
No Link to Production Parameters	Does not consider machine stage, conditions, time-of-day, etc.
No Adaptive Learning	Same sampling rules are used on every batch regardless of risk. Resources wasted on over-inspecting good batches

Methodology

Optimised AI Powered Smart Sampling

- **Sampling**: 100% of wafers undergo initial sampling.
- **Inspection Focus**: Wafers are 20% thoroughly inspected at each production stage or machine station.
- **AI-Driven Monitoring:** AI predicts high likelihood of defects in batches or stages.
- **Focused Attention**: Increased focus and resources on flagged areas, increase thorough inspection.
- **Additional Sampling:** More samples are taken from flagged batches for defect verification.

REAL-TIME PROCESS MONITORING WITH AI SENSORS



Predictive Maintenance for Equipment Monitoring

Preventive Measures Through Early Detection

- **Multi-Modal Sensor Fusion:** AI integrates data from visual, environmental, and vibration sensors to detect subtle defects that individual sensors might miss.
- **Statistical Process Control (SPC):** AI monitors key process variables, detecting statistical anomalies and alerting operators to make adjustments before defects form.
- **Root Cause Analysis (RCA):** Identify the factors behind defects and guides preventive actions.
- **Automated Adjustments:** AI can automatically adjust production parameters to prevent recurrence.

Dynamic Resource Allocation — Defect Source Prediction/Diagnosis — Non-Defect Sampling — AI Model Validation and Drift Detection — Data Comparison with Historical Records

AI Prediction and Self-Learning

Data Collection & Real-Time Monitoring

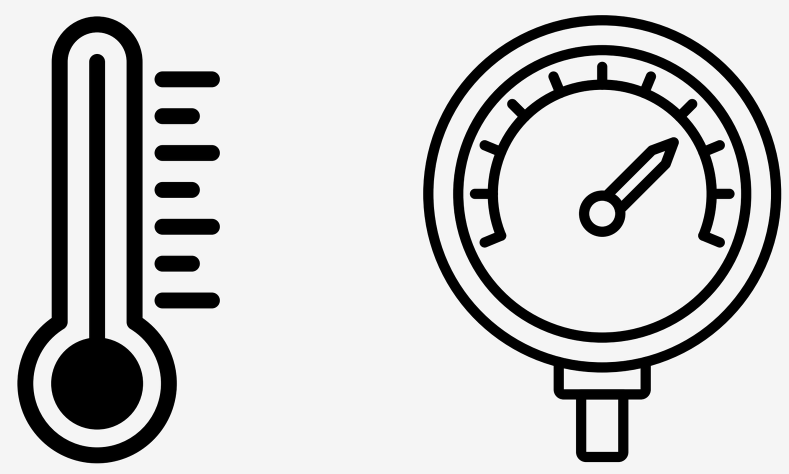
- **Sensors & IoT Devices:** Integrate sensors throughout the production line to collect data
- **Process Control Data:** Data from equipment are used to track conditions where defects are most likely to occur.

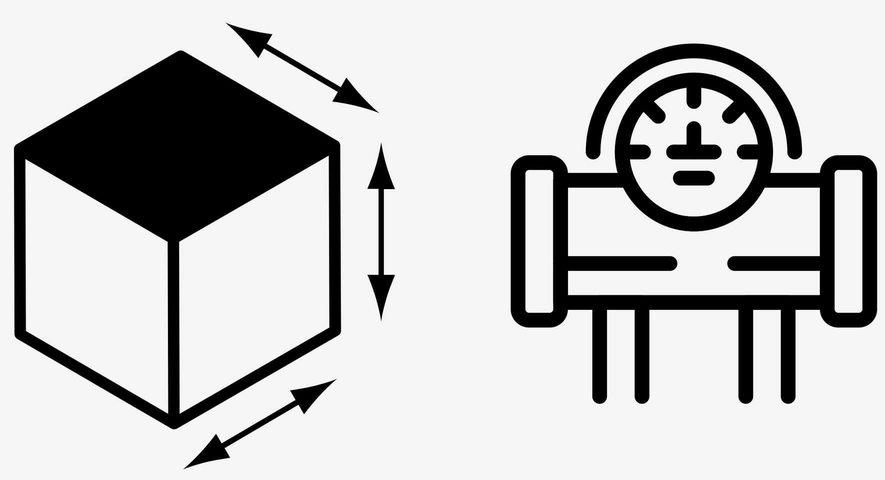
AI Model Validation and Drift Detection:

- Compares defect-free and defective samples to evaluate AI performance and detect drift.

Real-Time Model Monitoring:

- Implements a performance monitoring dashboard that tracks AI prediction accuracy in real-time.
- Retrain when Detects drift in performance.





Non-Defect Sampling:

- Some defect-free wafers are still sampled to ensure that the model isn't overlooking potential issues.
- These samples are compared to defective ones to refine the AI's accuracy and model learning

Forced feedback learning, where every new sample (defective or not) contributes to refining the AI

AI Model Enhancement

- Compares current data with 20 years record
- validate and refine AI predictions.

Ensemble Learning:

- Combines multiple models trained on diverse datasets
- Uses synthetic defect generation to expand the dataset and enhance resilience to rare defect types.

Results

Decision Logic and Confidence

Confidence	Severity	Decision	Justification
> 0.90	Critical	Reject	High-risk defect with high AI certainty
0.80 – 0.90	Major	Resample	Medium risk, borderline confidence
< 0.80	Minor	Accept	Low risk, system confident enough to pass

Severity Classification Logic

Defect_Type	Confidence Range	Explanation (from NEU dataset & YOLO performance)
Crazing	0.90 – 0.98	Easy to detect, distinctive shape
Inclusion	0.85 – 0.95	Moderate edge clarity
Patches	0.80 – 0.90	Broad spots, clearly segmented

Data Column Definitions

Column	Source / Formula	Explanation
Image_ID	File name from NEU-DET folders (e.g., crazing_001.jpg)	Unique filename extracted from NEU dataset folders
Defect_Type	Folder name (e.g., crazing, scratches)	Represents real surface defect class
Confidence	/=RANDBETWEEN(x,y)/100 per class: See table below	Simulates detection confidence of the AI model
Severity	Assigned based on impact (see rule table below)	Categorized into Minor / Major / Critical based on risk & literature
Batch_ID	B00# manually or by grouping every 5 images	Simulates real production batches
Stage	Fixed: "FVI" (Final Visual Inspection)	Our system is applied at final QC stage
Machine_ID	Random from M01 to M04: ="M0"&RANDBETWEEN(1,4)	Simulates deployment across multiple inspection units
Decision	Based on Confidence + Severity using lookup logic	Models system action: Accept / Resample / Reject