**SEMI Challenge Overview**

**PHASE 1: UNDERSTANDING THE CHALLENGE**

| **Task No.** | **Task Description** | **Status** | **Notes** |
| --- | --- | --- | --- |
| 1 | Understand the competition topic | ✔ Completed | Focus on "smart sampling", "AI models", and "real-time QC" |
| 2 | Identify the semiconductor process chain | ✔ Completed | 9 stages identified; 3 main inspection points highlighted |
| 3 | Zoom in on the Final Inspection stage | ✔ Completed | Based on AQL; current bottleneck |
| 4 | Analyze weaknesses in AQL sampling | ✔ Completed | Missed defects, no data generated, labor-intensive |
| 5 | Identify pain points for businesses in Singapore | ⚠ In progress | Shortage of inspection labor, missed defects, hard to scale AI |
| 6 | Research how leading companies handle the problem | ⚠ In progress | Need data from TSMC, Intel, GlobalFoundries, etc. |

**PHASE 2: SOLUTION DESIGN**

| **Task No.** | **Task Description** | **Status** | **Notes** |
| --- | --- | --- | --- |
| 7 | Design new process: Vision AI + Smart Sampling | ⚠ In progress | Vision checks all; AI learns & analyzes defects; adaptive sampling |
| 8 | Select hardware modules (IoT devices) | ⚠ To be done | Jetson Nano, Raspberry Pi, camera modules, sensors? |
| 9 | Choose AI models | ✅ Suggested | YOLOv8n, MobileNet, LightGBM for machine data |
| 10 | Develop Smart Sampling Engine (flexible sampling logic) | ⚠ Critical | Replace AQL logic with AI-based decision engine |

**PHASE 3: PRESENTATION & PITCHING**

| **Task No.** | **Task Description** | **Status** | **Notes** |
| --- | --- | --- | --- |
| 11 | Design a non-technical, business-focused presentation strategy | ⚠ Important | Focus on emotional appeal, real-world impact, business benefits |
| 12 | Prepare a 1-slide visual poster (3 zones) | ⚠ To be done | Problem – Solution – Results |
| 13 | Build pitch slide deck (5–7 slides) | ⚠ To be done | Problem → System → Demo → Benefits → Expansion |
| 14 | Write a 3-minute pitch script | ⚠ To be done | Must be concise, inspiring, and focused |
| 15 | Create system pipeline diagram | ⚠ In progress | Use Canva or Lucidchart for visual clarity |

**PHASE 4: DATA & SIMULATION**

| **Task No.** | **Task Description** | **Status** | **Notes** |
| --- | --- | --- | --- |
| 16 | Extract or simulate data from AQL tables | ⚠ In progress | Can write Python script to generate from websites |
| 17 | Prepare simulated defect images (for AI demo) | ⚠ In progress | Use wafer/PCB defect samples |
| 18 | Generate sample AI outputs (CSV/JSON format) | ??? | Needed to explain AI insights and decision logic |

**PHASE 1: CHALLENGE ANALYSIS**

**PART 1: UNDERSTANDING THE BRIEF**

We have carefully analyzed the competition brief and broken down each requirement to clarify what the project must deliver. Below is the detailed analysis:

**A. Breakdown of Challenge Requirements**

| **Component in the Brief** | **Meaning** | **Action Required** |
| --- | --- | --- |
| **“Smart automation and AI”** | You must use actual AI and automation, not manual work disguised as “smart” | Your system must implement real AI models – not just manual inspection routines |
| **“Smart sampling”** | Improve the sampling method – move away from fixed AQL | You need to design a dynamic sampling logic based on risk, defect trends, or alerts |
| **“Monitor production line”** | Must oversee the whole production line, not individual items only | System should report by shift, by machine, or by production zone |
| **“Anticipate failures before it happens”** | Go beyond defect detection – predict failures in advance | Use AI trained on historical data to predict potential defect trends (if available) |
| **“Machine Learning models”** | Specify which algorithms are used and where | Propose lightweight, practical models like YOLOv8n, MobileNet, or LightGBM |
| **“Computer vision… in real time”** | Mandatory use of computer vision for direct inspection | Include camera + image processing model – not just theory or mockups |

**B. HARDWARE: SMART IOT INSPECTION SYSTEM**

**Objective**:  
Develop a practical, low-cost, scalable hardware system to:

* Attach to the semiconductor production line
* Capture images of products/dies/wafers
* Send data to AI models for real-time processing
* Support multiple node expansion per machine/line

**Suggested Hardware Setup:**

| **Component** | **Recommended Options** |
| --- | --- |
| **Camera Module** | Raspberry Pi Cam / ESP32-CAM / HD USB Webcam |
| **Edge Processor** | Raspberry Pi 4 / NVIDIA Jetson Nano (must support lightweight YOLO models) |
| **Data Transfer** | Local Wi-Fi or LAN; optionally send to cloud gateway for central aggregation |
| **Power & Housing** | Customizable based on factory needs (battery or adapter + 3D-printed enclosure) |
| **Scalability** | Modular plug-and-play nodes for parallel deployment |

**To Be Done**:

* Design a hardware system layout diagram (for one node and multi-node)
* Explain the role of each hardware component
* Provide estimated cost breakdown (low cost is a major advantage)

**C. SOFTWARE: AI / MACHINE LEARNING – THE SYSTEM’S BRAIN**

**Objective**:  
Build an efficient, lightweight AI model that works in real time to:

* Detect product defects directly from images
* Classify defects as Critical / Major / Minor
* Learn from previous data (reinforcement, if possible)
* Suggest dynamic sampling thresholds to replace fixed AQL

**Suggested Models:**

| **Application** | **Recommended Model(s)** |
| --- | --- |
| **Real-time image defect detection** | YOLOv8-nano / MobileNetV3 / EfficientNet-lite |
| **Sensor/machine data analysis** | LightGBM / Random Forest (if sensor data is available) |
| **Smart Sampling Logic** | Rule-based + Threshold AI / Reinforcement Learning |

**To Be Done**:

* Justify model selection in your presentation
* Draw a process flowchart: Input → AI → Output → Decision
* If needed: Simulate input using sample images and show classification output

**PART 2: PROCESS UNDERSTANDING**

**I. Overview of the Semiconductor Manufacturing Process**

The semiconductor manufacturing chain involves several complex stages, typically grouped into four main phases:

| **Stage** | **Description** |
| --- | --- |
| **1. Front-End Wafer Fabrication** | - Begins with a silicon wafer base  - Includes oxide growth, photolithography, etching, ion implantation |
| **2. Wafer Inspection & Dicing** | - Optical inspection to detect wafer defects  - Dies (individual chips) are cut from wafers |
| **3. Back-End Packaging** | - Chips are packaged into housing  - Includes wire bonding, encapsulation, and molding |
| **4. Final Testing & Quality Control** | - Electrical testing and visual inspection  - AQL (Acceptable Quality Level) Sampling is primarily used |

**II. Identifying Failure Points in the Process Chain**

Among the stages above, the most critical error-prone areas are:

* **Wafer Inspection**: Small but repetitive 2D/3D defects may be missed
* **Die Inspection**: Bonding misalignment, wire lift issues, surface cracks
* **Final Visual Inspection**: Relies heavily on random sampling (AQL), which misses critical issues

As a result, our **focus is on the Final QC stage**, which is still dependent on outdated **AQL Sampling** methods.

**Why Final Inspection Is the Bottleneck**

| **Current Pain Points of Final QC** |
| --- |
| ❌ High-risk defects may go undetected due to sampling limitations |
| ❌ Labor-intensive visual inspection by humans |
| ❌ No data generated for training or improving AI models |
| ❌ Not compatible with modern real-time Edge AI-based inspection systems |

This process presents a **significant opportunity** for disruption using Vision AI + Smart Sampling, as it directly impacts:

* Product quality consistency
* AI readiness of the production line
* Cost reduction through automation
* Scalability across machines and shifts

**PART 3: ZOOM IN – FINAL VISUAL INSPECTION PROCESS**

The **Final Visual Inspection** is the **last quality control step** before semiconductor chips are packaged and delivered to clients. This step plays a crucial role in ensuring product appearance and basic defect screening.

**Key Characteristics of the Final Visual Inspection**

| **Aspect** | **Details** |
| --- | --- |
| **Objective** | Detect minor visual defects: cracks, scratches, laser engraving errors, wrong logos, ID issues, chipped corners |
| **Tools Used** | Cameras, optical microscopes, and human inspectors |
| **Method** | Inspected based on AQL (Acceptable Quality Limit) sampling or predefined checklists |
| **Main Risks** | - Small defects may be missed due to low-resolution vision or human fatigue  - High subjectivity: inspectors may interpret differently  - High operating costs: manual shift-based inspection  - No recorded data for AI training or traceability |

**Conclusion: Why Automate Final Visual Inspection with AI + Computer Vision?**

This is currently the **main bottleneck** in the AQL-based quality control system and should be **fully automated** using AI + computer vision to:

* Eliminate quality risks
* Reduce labor costs
* Generate training data for continuous AI improvement
* Improve reliability and transparency for clients during chip delivery

**Why Focus on Final Visual Inspection for Automation?**

We based our choice on three strategic reasons:

**a. Based on the Challenge Brief**

The brief clearly states:

“...Smart sampling... to monitor production lines and anticipate failures…”

Therefore, the selected process must:

* Involve sampling
* Include defect detection
* Offer potential for AI-based monitoring and predictive analytics

**→ Only Final Visual Inspection** meets all three criteria within the 9-step semiconductor production chain.

**b. Based on Industry Reality**

* Final inspection still relies on manual labor and AQL sampling
* AQL is typically applied at the end of the production chain
* Manufacturers are spending more, missing defects, and **not generating any AI-compatible data**

Thus, Final Visual Inspection is the **ideal point** to:

* Apply real-time AI vision for direct inspection
* Replace static AQL with adaptive Smart Sampling
* Generate valuable datasets for training and improving AI models

**c. Based on Strategic Thinking**

In innovation competitions, it's crucial to:

* Avoid broad, unfocused solutions
* Target one **critical pain point** where real impact and feasibility align

**→ Final Visual Inspection + AQL** is the most strategic choice for focused, high-impact innovation.

**PART 4: DETAILED ANALYSIS OF THE AQL SAMPLING METHOD**

**A. What is AQL Sampling?**

**AQL (Acceptable Quality Limit)** is an international standard (ISO 2859-1) that defines the number of samples to inspect in a production lot, and the maximum number of allowable defects to determine whether to accept or reject the entire batch.

**B. How Does AQL Work?**

* Randomly select a specific number of items from a production batch (based on the AQL table)
* Inspect according to severity levels: **Critical / Major / Minor**
* Compare detected defects against the allowed limits
* Based on the result, **Accept or Reject** the entire batch

**C. Critical Disadvantages of AQL Sampling**

| **Issue** | **Explanation** |
| --- | --- |
| **1. High randomness** | Cannot guarantee that serious defects will be caught due to random selection |
| **2. Defects are only representative** | Risk of “false pass” – the batch may be faulty even if the sample passes |
| **3. No sufficient data for AI** | Sampling only 5–10% of products generates too little data for AI model training |
| **4. Labor-intensive** | Manual inspection requires trained staff and consumes operational resources |
| **5. Inflexibility** | New products or updated processes require manual reconfiguration of AQL |
| **6. No integration with Edge AI** | AQL is a static rule-based method, with no feedback loop or intelligence |

**D. Relevance to the Competition Brief**

The competition requires:

**"Smart Sampling + AI + Vision"**

→ AQL Sampling is **outdated** and **incompatible** with the needs of:

* Real-time defect detection
* Feedback-driven AI
* Intelligent, adaptive inspection workflows

**E. Conclusion: Why AQL Should Be Replaced**

* Enables full automation and compatibility with Edge AI
* Allows continuous **data generation** and real-time **AI learning**
* Reduces the risk of **missing critical defects**
* Enables **defect classification** in ways human inspectors cannot achieve

**PART 5: ANALYSIS OF SEMICONDUCTOR INDUSTRY PAIN POINTS**

***(Singapore and the ASEAN Region)***

While ASEAN’s semiconductor sector is gradually moving toward standardized automation, **Singapore – the regional leader – still faces serious pain points in its final inspection process**, especially as it transitions toward AI-driven quality control.

**1. Shortage of Skilled Manual Inspectors**

| **Challenges** |
| --- |
| - High labor costs (hourly wage in USD) |
| - Limited pool of qualified technical staff; persistent labor shortages |
| - Heavy reliance on experience and subjective judgment in defect detection |

**2. High Missed Defect Rate Under AQL Sampling**

| **Challenges** |
| --- |
| - AQL-based sampling is not representative of the full batch |
| - High risk of overlooking small but critical defects in high-end logic chips |

**3. Lack of Data for AI and Analytics**

| **Challenges** |
| --- |
| - Factories do not systematically collect images and annotated labels |
| - No structured datasets for AI/ML model training |
| - Difficulty integrating legacy processes with digital transformation goals |

**4. Inability to Scale Inspection with Growing Demand**

| **Challenges** |
| --- |
| - A 20% increase in production requires a 30% increase in manual inspection cost |
| - Manual inspection lacks flexibility and scalability |
| - AI-based systems are needed to scale efficiently across shifts and batches |

**5. No Feedback Loop to Improve Quality Control**

| **Challenges** |
| --- |
| - AQL ends at a binary pass/fail result |
| - No system to learn from detected defects and improve upstream processes |

**Summary of Business Pain Points**

The current **Final Inspection process remains outdated, manual, and disconnected**. In contrast, global manufacturing is moving toward:

* **Smart Factories**
* **Zero-Defect Goals**
* **AI-Driven Smart Sampling**

These gaps reveal a **real and urgent need** for innovation—offering a valuable opportunity for our proposed solution to create meaningful impact for semiconductor manufacturers in Singapore and across ASEAN.

**PART 6: CURRENT LANDSCAPE – AI-BASED QUALITY INSPECTION IN THE SEMICONDUCTOR INDUSTRY**

As global semiconductor companies race toward smarter, automated quality control, several leading players have implemented AI-driven systems across various stages of their manufacturing processes. These strategies offer valuable benchmarks and highlight opportunities for further innovation.

**1. TSMC – Automated Defect Classification (ADC) with Human-in-the-Loop (HITL)**

TSMC integrates machine learning into its **Automated Defect Classification (ADC)** system to enhance defect recognition accuracy. Notably, they apply a **Human-in-the-Loop (HITL)** methodology, where human expertise is used to train and refine machine learning models. This combination ensures high reliability while still maintaining human oversight in critical judgments.  
(Source: [tsmc.com](https://tsmc.com))

**2. Intel – Smart Wafer Inspection with AI and Computer Vision**

Intel has incorporated **AI and computer vision (CV)** into its quality control systems for over a decade. Their approach involves capturing images across multiple manufacturing channels and analyzing thousands of features to automatically detect defects. This system operates with **minimal human intervention** and serves as a cornerstone of Intel's smart factory initiative.  
(Source: Intel)

**3. GlobalFoundries – Automated Visual Inspection Using AutoML**

GlobalFoundries has deployed **hundreds of AI models** in their fabs to detect and control process deviations. Using **Google Cloud AutoML Vision**, their system continuously retrains models with fresh data, ensuring accuracy and adaptability. This allows for full-scale monitoring and management of deployed AI systems across all manufacturing nodes.  
(Source: Google Cloud)

**4. Samsung – AI-Based PCB and Soldering Inspection**

Samsung employs **computer vision** to inspect printed circuit boards (PCBs) and soldering joints, significantly enhancing production quality. This targeted approach reflects Samsung’s broader efforts to integrate AI into electronics assembly lines.  
(Source: Musashi AI)

**5. Foxconn – AI-Powered Automated Optical Inspection (AOI)**

Foxconn leverages **AI-enabled AOI** systems to perform high-speed defect detection in electronics assemblies. These systems are optimized for speed and scalability, allowing Foxconn to maintain high output with consistent quality.  
(Source: Musashi AI)

**6. Texas Instruments – Predictive Maintenance and Process Optimization**

Texas Instruments utilizes AI not only for inspection but also for **predictive maintenance** and **process optimization**. By identifying patterns in machine performance, they proactively address issues before they affect quality or throughput.  
(Source: Musashi AI)

**Strategic Analysis: Commonalities and Differences**

**Common Strategies Across Companies:**

| **Aspect** | **Description** |
| --- | --- |
| **Automation of Quality Inspection** | All companies are shifting towards AI-powered inspection to minimize errors and improve throughput. |
| **Use of Machine Learning + Computer Vision** | ML and CV are the foundational technologies used for image-based defect detection and classification. |
| **Data Integration and Feedback** | There is a shared emphasis on collecting, labeling, and feeding data back into the system to retrain and improve AI models continuously. |

**Key Differences Between Approaches:**

| **Factor** | **Variation Among Companies** |
| --- | --- |
| **Level of Automation** | TSMC maintains human involvement via HITL, while Intel and GlobalFoundries favor full automation. |
| **Stage of Implementation** | Companies focus on different production stages: wafer inspection (Intel), PCB/soldering (Samsung), final assembly (Foxconn), etc. |

**🚀 Breakthrough Opportunity: A New Strategic Proposal**

Given the landscape above, we identify a **critical innovation gap**:  
While most companies apply AI in earlier or mid-process inspection (wafer, PCB, solder), the **Final Visual Inspection stage** remains largely dependent on AQL sampling and manual labor, especially in Southeast Asia.

**Our proposal**:  
Implement a fully automated, AI-powered **Final Visual Inspection system**, combining:

* Real-time computer vision
* Smart, adaptive sampling (replacing AQL)
* Data generation for continuous AI learning
* Integrated feedback loop to enhance upstream processes

**Strategic Impact of the Proposed System:**

| **Benefit** | **Impact** |
| --- | --- |
| **Higher defect detection accuracy** | More defects (especially minor and hidden ones) will be caught in real time |
| **Reduced inspection costs** | Automation reduces reliance on human labor and lowers operational overhead |
| **AI-ready factory** | Continuous data generation feeds back into the AI loop for future improvements |
| **Customer trust and product quality** | Higher quality output improves brand reliability and client satisfaction |

**Conclusion:**

The global trend is moving decisively toward **AI-driven, intelligent, and integrated inspection systems**. Our proposal aligns with this direction, offering a **high-impact innovation** that directly solves current pain points in Singapore’s and ASEAN's semiconductor factories.  
By focusing on the **Final Inspection stage**, we position ourselves to lead a meaningful transformation in quality control.