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Computer Vision Defect Detection For an Electronics Manufacturer

How switching from a rule-based machine vision system to an advanced computer vision solution for early-stage defect detection on the production line helped an electronics manufacturer reach **97+%** accuracy in identifying flaws and save **$2.4 million annually** thanks to drop in warranty claims.

Business challenge

Our client is a Saudi-based electronics manufacturer producing laptops for the MEA region in partnership with one of the global tech leaders. Years earlier, we had created digital twins of their factories, so when new challenges surfaced, the client turned to us again.

The company had long moved from fully manual defect detection on the production line to an automated non-contact product quality inspection. However, their **automated optical inspection (AOI)** in the conveyor video surveillance system **was too demanding**, **rigid**, and **costly**, posing numerous limitations.

- **Overdependence on consistent imaging.** The system cannot function efficiently if lighting and camera positioning aren't stable.
- **Inflexibility.** AOI operated on strict "if-else" rules, making the system unable to perform continuous trend analysis and adjust dynamically to enhance both speed and accuracy of defect detection.
- **Slow adaptability.** Every time the component configuration, size, or color changed, the system required recalibration.
- **Low scalability.** One AOI system couldn't simply be replicated across multiple factories. Each production line will require extensive manual parameter tuning.
- **Costly maintenance.** Traditional machine vision systems like AOI require highly specialized experts to take over routine manual inspections, regular calibrations, software updates, and hardware repairs.

The client needed a more flexible, scalable, and budget-wise form of <u>computer vision</u> at the core of their conveyor video surveillance system.

Solution

Our development team ensured the **smooth shift from basic AOI to advanced computer vision**.

01 Shaping up the tech stack

We decided to rely on a **pre-trained object detection and image classification model**. Then, we had to choose between **single- and two-stage detectors** to perform object detection. The scale was clipped in favor of a single-stage algorithm due to its several advantages.

- Faster inference
- Lower computational demand
- Easier maintenance

Having experience with various single-stage detectors, we settled on **YOLO** over EfficientNet, SSD, FaterRnet, and FCOS, as it offers superior inference speed, ensuring truly real-time performance. Despite YOLOv10 being available, we used **YOLOv8**, as it was the most tested and stable version at the moment.

02 Optimizing the training dataset

The client's previous pre-computer vision system relied on a three-tier defect classification framework: "definitely defective," "borderline," and "definitely non-defective". Rather than discarding the existing dataset, we capitalized on it by reconfirming defects' coverage and enforcing consistent, high-quality labeling.

Augmenting data to address the class imbalance issue

The original dataset was limited in size, with a maximum of 200 images per defect category. In addition, **different defect types weren't represented equally**. For example, issues such as misaligned components and incorrect placement appeared frequently, while rarer defects, like cracked housing, solder defects, open circuits, or lifted leads.

To address both the small dataset size and class imbalance, we applied **data augmentation techniques**.

- Random photo cropping and flipping
- Controlled blurring and noise injection
- Tweaking lighting
- Changing the background

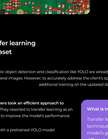
That way, we **multiplied the dataset tenfold** while ensuring balanced representation across all defect categories.

Improving labeling consistency and reliability

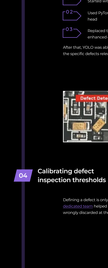
Given the diversity of subtle defects, high-quality labeling was a must. Our AI engineers focused on refining the labeling process to:

- Reduce annotation noise
- Improve consistency across classes
- Enable more statistically reliable quality assessments

In addition, we ensured the dataset included images both with and without the target object, improving the model's ability to distinguish true defects from background artifacts and thus, reducing the false positive rate.



More consistent labeling enhances the reliability of model performance. Here, we've used bounding boxes to annotate defects in the solder joints, rather than to group several objects within a single bounding box.



03 Running model transfer learning on the enhanced dataset

Models for object detection and classification like YOLO are already trained on hundreds of millions of general images. However, to accurately address the client's specific needs, it had to undergo additional training on the updated dataset.

Instinctools' AI engineers took an efficient approach to tackle this challenge. They resorted to transfer learning as an ML training technique to improve the model's performance.

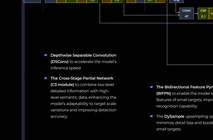
- Started with a pretrained YOLO model
- Used PyTorch to remove the default classifier head
- Replaced the model's classifier head with the enhanced dataset

After that, YOLO was able to instantly detect and classify all the specific defects relevant to the client's production line.

What is transfer learning in computer vision?

Transfer learning is a machine learning training technique, which capitalizes on the pre-trained model's general knowledge (the ability to detect different objects in various surfaces) instead of training the model from scratch.

With transfer learning, you only retrain the model on your take-specific dataset (examples of external and internal defects of the client's laptops), enabling the model to adapt its existing knowledge to your reality. This method significantly reduces training time and computational resource consumption.



04 Calibrating defect inspection thresholds

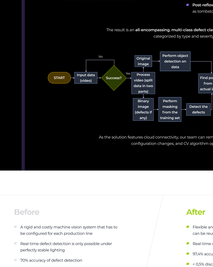
Defining a defect is only part of the process. Next, our dedicated team helped minimize the number of items wrongly discarded at the production stage through:

- Basing a **confidence threshold ratio** from 0.5 to 0.85 to prevent the model from flagging low-certainty cases as sure defects
- Setting up **detailed defect severity scoring** to minimize false positives while not letting critical defects slip further
- Adjusting **NMS (Non-Maximum Suppression) parameters** so that the model always chooses one clean, highest-confidence box per object instead of overlapping bounding boxes

05 Going the extra mile for near-100% defect detection accuracy

After transfer learning and threshold calibration the model's accuracy reached 96.8% which was already more than 11% higher than with the previous AOI system. Still, our team aimed for as close to 100% accuracy as possible.

<u>Instinctools' AI experts</u> **enhanced YOLO-based defect detection capabilities** by applying:



- Depthwise Separable Convolution (DSConv) to accelerate the model's inference speed
- The Cross-Stage Partial Network (CSP models) to minimize too-level detailed information with high-level semantic data, enhancing the model's adaptability to target scale variations and improving detection accuracy
- The Bidirectional Feature Pyramid Network (BiFPN) to enable the model to identify fine features of small targets, improving its recognition capability
- The **DySample** upsampling operator to minimize detail loss and boost accuracy for small targets

With these enhancements, the **new CV defect detection system consistently hits the 97.4% accuracy benchmark.**

06 Integrating the CV mechanism into the client's manufacturing execution systems (MES)

The computer vision solution was installed at one of the client's facilities. There, it underwent further model training based on collected metadata and outputs generated by the system during operation. Those adjustments helped align the system with real-world production conditions and **replaced AOI at each critical juncture**.

- **Post-solder paste application.** The system verifies if paste volumes are adequate and properly aligned.
- **Post-component placement.** The solution validates whether each component is present, oriented correctly, and positioned within acceptable tolerances.
- **Post-reflow.** Software runs a final check for defects such as bridging, misalignment, and cold solder joints.

The result is an **all-encompassing multi-class defect classification**, with all defects categorized by type and severity.

As the solution features cloud centricity, our team can remotely perform model updates, configuration changes, and CV algorithm optimizations.

Before

- A rigid and costly machine vision system that has to be configured for each production line
- Real-time defect detection is only possible under perfectly stable lighting
- 70% accuracy of defect detection
- Items falsely discarded as defective

After

- Flexible and highly scalable computer vision system that can be reused across production lines
- Real-time defect detecting under any lighting conditions
- 97.4% accuracy of defect detection
- ~3.5% discarded items

Business value

Operational impact:

- ~ 272/h accuracy of production line inspections
- ~ 26% in production throughput due to immediate defect detection
- ~ 3% false positive rate
- ~ 0.3% discarded items
- ~ 40% defect-related warranty claims

Financial impact:

- ~ $1.2 million in waste-related costs
- ~ $2.4 million annually due to the drop in warranty claims
- ~ 26% in quality control labor costs

Client's testimonial

*Every collaboration with *instinctools takes our factories to the next level. The new computer vision system for defect detection reimagined our quality control at production lines. The* ***drop in discarded items below 0.3%*** *alone fully justified the investment, but a year into implementation, we also saw that it translated into a* ***millions-worth reduction in warranty claims****, exceeding our boldest expectations.*

Lead Quality Engineer,
Electronics Manufacturer

Multiplier effect

Stronger quality control systems on a production line lead to **fewer defective products reaching customers and ruining their experience**. With the stakes as high as one in three customers* leaving a brand after a single bad experience involving defective products, playing it safe becomes essential for business survival.

Computer vision can be the key to achieving higher quality products and improved customer satisfaction.

*According to Zen...

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