Problem Statement Worksheet (Hypothesis Formation)

Defective Jar Lid Image Detection using Convolutional Neural Networks (CNNs) with a target accuracy of 95%

1 Context

With the rapid rise of industrialization and the increasing scale of manufacturing operations, the demand for automated quality control systems has become more critical than ever. Industries today are under pressure to deliver high volumes of products at consistent quality, while minimizing human labor, downtime, and inspection costs.

In such high-speed production environments, manual defect inspection—especially for repetitive and detailed tasks like identifying imperfections in jar lids—is time-consuming, prone to human error, and not scalable.

That's where Computer Vision steps in—and more specifically, Convolutional Neural Networks (CNNs). CNNs have emerged as the go-to solution for image-based classification and object detection tasks, thanks to their ability to automatically learn spatial hierarchies of features through back propagation.

This project aims to leverage the power of CNNs to develop an automated defect detection system for jar lid images.

2 Criteria for success

Identify intact and defective jar-lids using computer vision techniques with a target accuracy of 95%.

3 Scope of solution space

i. Process images containing multiple jar lids (typically 4–11 per frame).
ii. Standardize image size, enhance contrast if needed, and normalize for better model performance.
iii. Use basic data augmentation (rotation, flipping, slight zoom) to generalize the model.
iv. Use a CNN model to classify each cropped lid as either "Defective" or "Intact".
v. Train, validate, and test the model using labeled images of jar lids.

4 Constraints within solution space

1. With only ~1800 images, the model is at risk of :
- Overfitting to training data
- Poor performance on edge cases
- Sensitivity to noise or minor image shifts

2. Some original images contain multiple jar lids that are overlapping or partially occluded, making accurate cropping and classification harder.

3. Depending on the hardware setup (e.g., just a laptop with no GPU), training a deep CNN could be time-consuming or infeasible.

5 Stakeholders to provide key insight

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6 Key data sources

Source: https://www.kaggle.com/datasets/rrighart/jarlids