Computer Vision for Quality Control in Manufacturing

1. Executive Summary

Problem Statement: Your manufacturing line relies on manual, subjective, and slow visual inspections for quality control, leading to inconsistent product quality, production bottlenecks, and high labor costs.

Proposed Solution: We propose a computer vision solution that uses AI to automatically inspect products on the assembly line for defects. Cameras will capture images, and a deep learning model will analyze them in real-time to identify flaws, ensuring consistent quality.

Expected Business Impact: This will increase quality control efficiency by over 50%, reduce product defect rates, and free up manual inspectors for more complex tasks.

2. Introduction and Background

Manual quality inspection is a bottleneck in many manufacturing processes. A computer vision system provides an objective, fast, and scalable solution to ensure every product meets your quality standards, boosting your brand reputation and bottom line.

3. Project Scope and Deliverables

Detailed Scope:

Data Collection: We will work with your team to set up a camera system and collect a dataset of images of both flawless and defective products.

Image Classification Model: We will train a Convolutional Neural Network (CNN) to classify products as either "Pass" or "Fail" based on a set of defined defect types.

Real-time Inference System: The model will be optimized for fast inference, allowing it to provide a pass/fail judgment in milliseconds as products move down the line.

Dashboard & Reporting: A dashboard will be created to track the number of defects found per shift, the types of defects, and the system's overall performance.

Non-Deliverables: We will not be responsible for the physical installation of cameras or the integration with robotic arms or rejection systems. We will provide the software and technical specifications for your hardware team to follow.

4. Technical Approach and Methodology

AI/ML Technique: We will use Computer Vision with Deep Learning, specifically Convolutional Neural Networks (CNNs). We will use transfer learning with a pre-trained model like ResNet to accelerate development and improve accuracy.

Development Lifecycle:

Data Collection & Annotation (8 weeks): Set up cameras, collect images, and manually annotate them to mark defects.

Model Training & Optimization (12 weeks): Train the CNN model on the annotated dataset and optimize it for real-time performance.

Deployment & System Integration (8 weeks): Deploy the model to an edge device or a local server and assist your team with integrating it into your production line.

Technology Stack: Python, TensorFlow/PyTorch, OpenCV, and potentially NVIDIA Jetson for on-premise, real-time inference.

Model Performance Metrics: The model's success will be measured by Precision, Recall, and Inference Speed (milliseconds per image).

5. Project Timeline and Milestones

Timeline: 5-8 months

Key Milestones:

Month 3: Initial Dataset Labeled and Ready.

Month 5: Model Trained and First-Pass Testing Complete.

Month 7: Final System Deployed and Running on the Production Line.

6. Team and Resources

Team Roles: 3-4 Data Scientists with Computer Vision expertise, 1 Hardware/Integration Specialist.

Man-days: Approximately 450-800 man-days.

Client Responsibilities: Provide access to the production line for camera setup, provide samples of both good and bad products, and dedicate a hardware engineer for integration support.

7. Pricing and Payment Schedule

Total Project Cost: $75,000 - $120,000

Cost Breakdown:

ML & Development Time: 60%

Hardware & Infrastructure: 25%

Project Management & Overhead: 15%

Payment Terms: 30% upfront, 30% after model training, 40% upon successful pilot and delivery.

8. Risk Assessment and Mitigation

Risk: The lighting or camera angle on the production line may be inconsistent, affecting the model's accuracy.

Mitigation: We will conduct an on-site visit to determine the optimal camera placement and lighting setup. The model will also be trained on images captured under various lighting conditions to improve its robustness.