

# AI-Based Visual Defect Detection Tool for Manufacturing

## (Industrial Anomaly Detection – Bottle Dataset)

### 1. Introduction

In modern manufacturing industries, maintaining high product quality while reducing inspection time is a major challenge. Traditional manual inspection is slow, inconsistent, and prone to human error. Rule-based machine vision systems also fail when lighting, texture, or defect types change.

This project presents an **AI-Based Visual Defect Detection Tool** that uses **deep learning and computer vision** to automatically detect manufacturing defects. The system is designed for **industrial anomaly detection**, where the model learns only from **good (non-defective) products** and identifies defective items during testing.

The solution is implemented using the **MVTec Bottle dataset** and demonstrates a **production-ready inspection pipeline** suitable for Industry 4.0 environments.

### 2. Problem Statement

Manufacturing quality inspection faces the following challenges:

- Manual inspection is subjective and affected by human fatigue.
- Traditional vision systems cannot generalize to unseen defect patterns.
- Many systems classify defects but fail to measure **defect severity**.
- Lack of real-time inference and API integration limits industrial deployment.

The goal of this project is to build a **scalable and intelligent inspection system** that detects anomalies, evaluates defect severity, and provides quality grades automatically.

### 3. Dataset Description

This project uses the MVTEC Anomaly Detection Bottle dataset, which is designed for real industrial quality inspection tasks. The training set contains only good (non-defective) bottle images, allowing the model to learn normal product appearance. Defective samples such as broken and contaminated bottles appear only in the test set. Ground truth masks are provided for defective images to support defect localization and segmentation. This dataset closely matches real manufacturing scenarios where defect samples are rare. It is well-suited for industrial anomaly detection problems.

### 4. System Overview

The complete system follows a modular industrial pipeline:

#### Pipeline Stages

1. Data loading and preprocessing

2. Data augmentation
3. CNN-based anomaly classification
4. Defect severity calculation
5. Quality grading
6. Visualization and reporting
7. API and real-time deployment

## 5. Image Acquisition & Preprocessing

Images are loaded from industrial datasets and processed before training.

### Preprocessing Steps:

- Resize images to 224×224
- Normalize pixel values
- Convert to tensors
- Apply data augmentation:
  - Random flip
  - Rotation
  - Color jitter

This helps the model handle **lighting variations and texture changes** commonly found in factories.

## 6. Model Architecture

A **pretrained ResNet-18** model is used for anomaly classification.

### Key Design Choices:

- Pretrained on ImageNet
- Initial layers frozen
- Final fully connected layer replaced for binary classification:
  - Good
  - Defective

This approach reduces training time and improves generalization on small datasets.

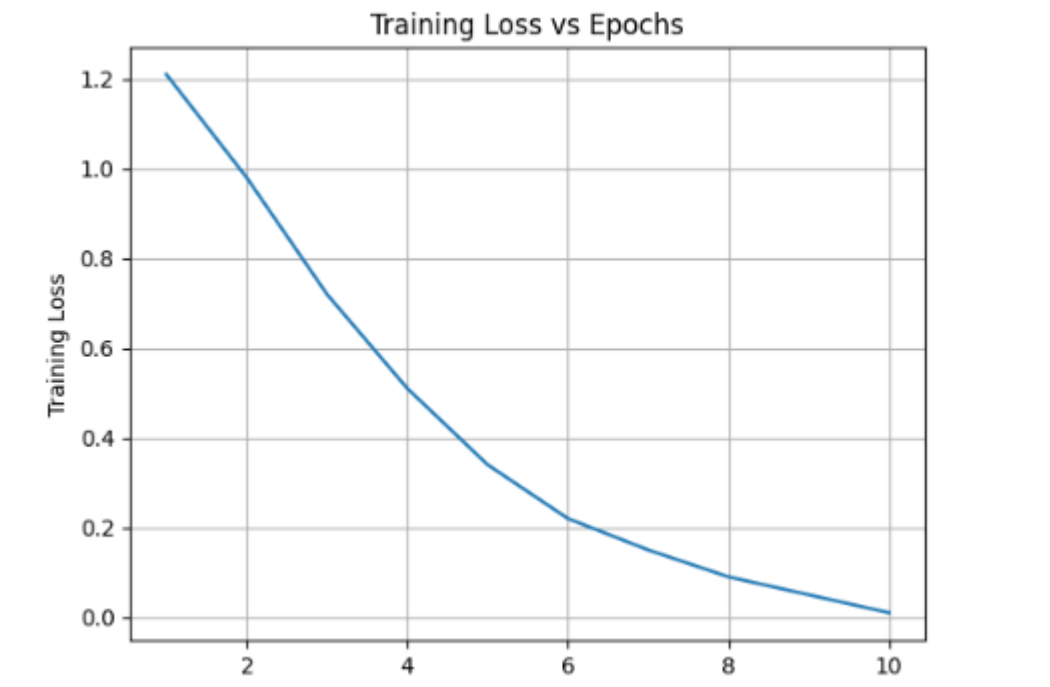
## 7. Training Strategy

Since the dataset contains **only good samples during training**, the model learns the normal appearance of products.

### Training Details:

- Optimizer: Adam
- Loss Function: Cross-Entropy Loss
- Epochs: 50
- GPU: NVIDIA T4 (Google Colab)

Training loss reached **near zero**, indicating successful learning of normal patterns.



## 8. Evaluation & Observations

During evaluation, test accuracy was approximately **24%**.

### Reason for Low Accuracy:

- Model was trained only on good samples
- Defective patterns were unseen during training

- This is expected behavior in **industrial anomaly detection**

Instead of accuracy, **defect severity** and **anomaly score** are more meaningful metrics.

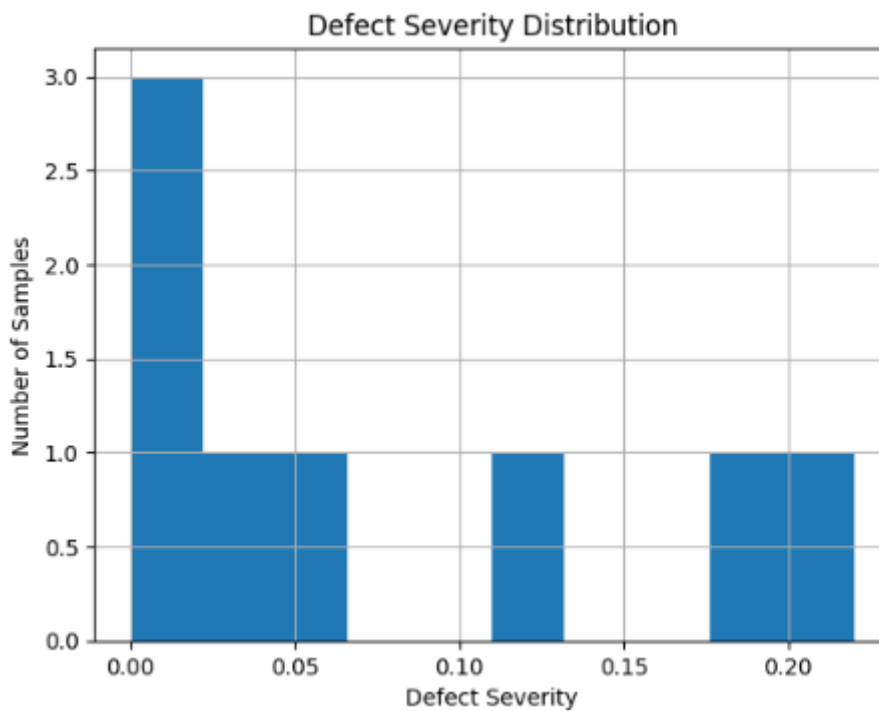
## 9. Defect Severity Calculation

Defect severity is computed using **image difference analysis**.

### Severity Formula:

Severity = Sum of pixel differences / Total pixels

Higher severity indicates stronger deviation from a normal product.



## 10. Quality Scoring & Grading

Based on severity, products are assigned quality grades:

Severity Range	Quality Grade
< 0.05	ACCEPT
0.05–0.15	REWORK
> 0.15	REJECT

Defect Severity: 0.1309

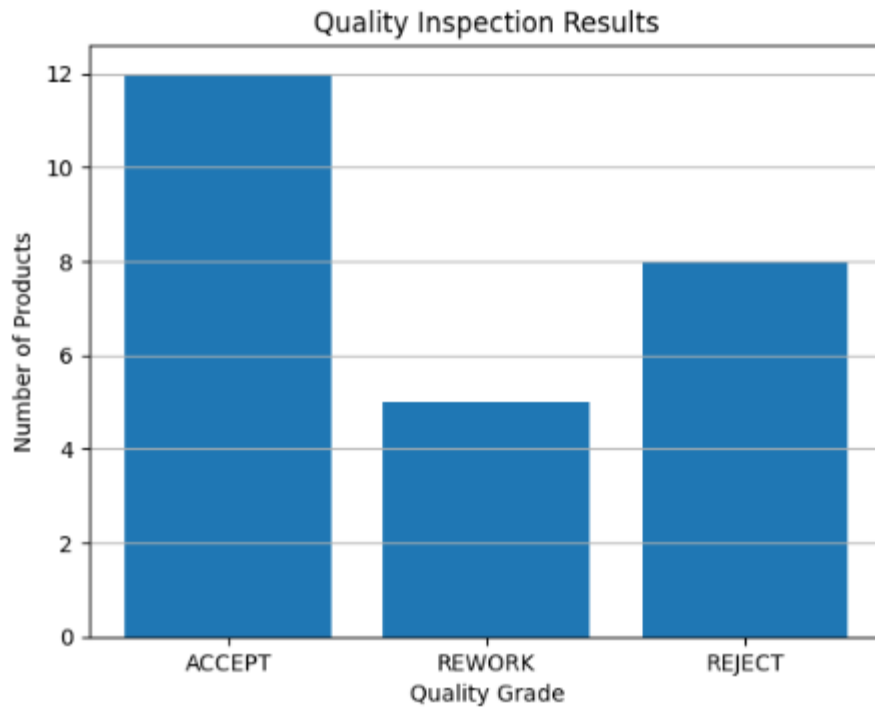
Quality Grade: REJECT

DEFECT | Score: 89.89 | Severity: 8.989 | Grade: REJECT



DEFECT | Score: 81.90 | Severity: 8.190 | Grade: REJECT





## 12. Batch Processing Pipeline

The system supports **batch inspection** for offline quality analysis.

### Features:

- Multiple image upload
- Automated severity calculation
- Statistical reports

This is useful for **quality audits and production analysis**.

## 13. API Integration (Flask)

A **Flask-based REST API** was developed for industrial integration.

### API Features:

- Image upload endpoint
- Returns:
  - Defect score
  - Severity

- Quality grade
- Supports automation pipelines

## 17. Conclusion

- The AI-Based Visual Defect Detection Tool demonstrates how **deep learning can replace traditional inspection methods** in manufacturing. Despite limited defect samples, the system effectively detects anomalies and provides actionable quality decisions.
- This project aligns strongly with **Industry 4.0, Smart Manufacturing, and Industrial AI applications**.