Project Review: AI for Defect Detection

The Problem

Obtaining real broken TV screen data is expensive, rare, and difficult.

The Solution

Generative AI (Inpainting) creates synthetic, high-quality datasets for QA models.

Novelty

Using synthetic data to ensure the final product is without any flaw.

Changes from Proposal: Due to inconsistent generation quality with small masks, we shifted to using Full-Screen Masks.
Since the generated defects now characterize the entire screen rather than a specific isolated point, the task logically shifted from Object Detection, classification to only Image Classification

Related Work & Project Context

Title / Year	Task	Methods	Data	Results	Relation to Project
Latent Diffusion for Defect Segmentation (2024)	Surface Defect Segmentation	**Stable Diffusion** for Data Augmentation (Synthetic Generation)	NEU-DET (Steel Surfaces)	Improved Mean IoU (mIoU) by **6.85%** compared to baseline models	Provides empirical evidence that **Stable Diffusion** specifically improves defect detection accuracy in industrial tasks.
DefectFill (2025)	Realistic Defect Generation	**Inpainting Diffusion Model** to inject defects into healthy samples	MVTec AD (anomaly detection dataset)	Validated that inpainted synthetic defects significantly improve detection model performance	**Direct validation:** Uses the exact same logic as our project—taking a clean product and "inpainting" a defect to solve data scarcity.
YOLOv11 Benchmark (2025)	Real-time Object Detection	Comparative study of **YOLOv5, v8, and v11**	Solar Panel Defect Dataset	**YOLOv11** achieved **93.4% mAP**	Justifies our choice of classification model.

Dataset & Generation Pipeline

Base Generation

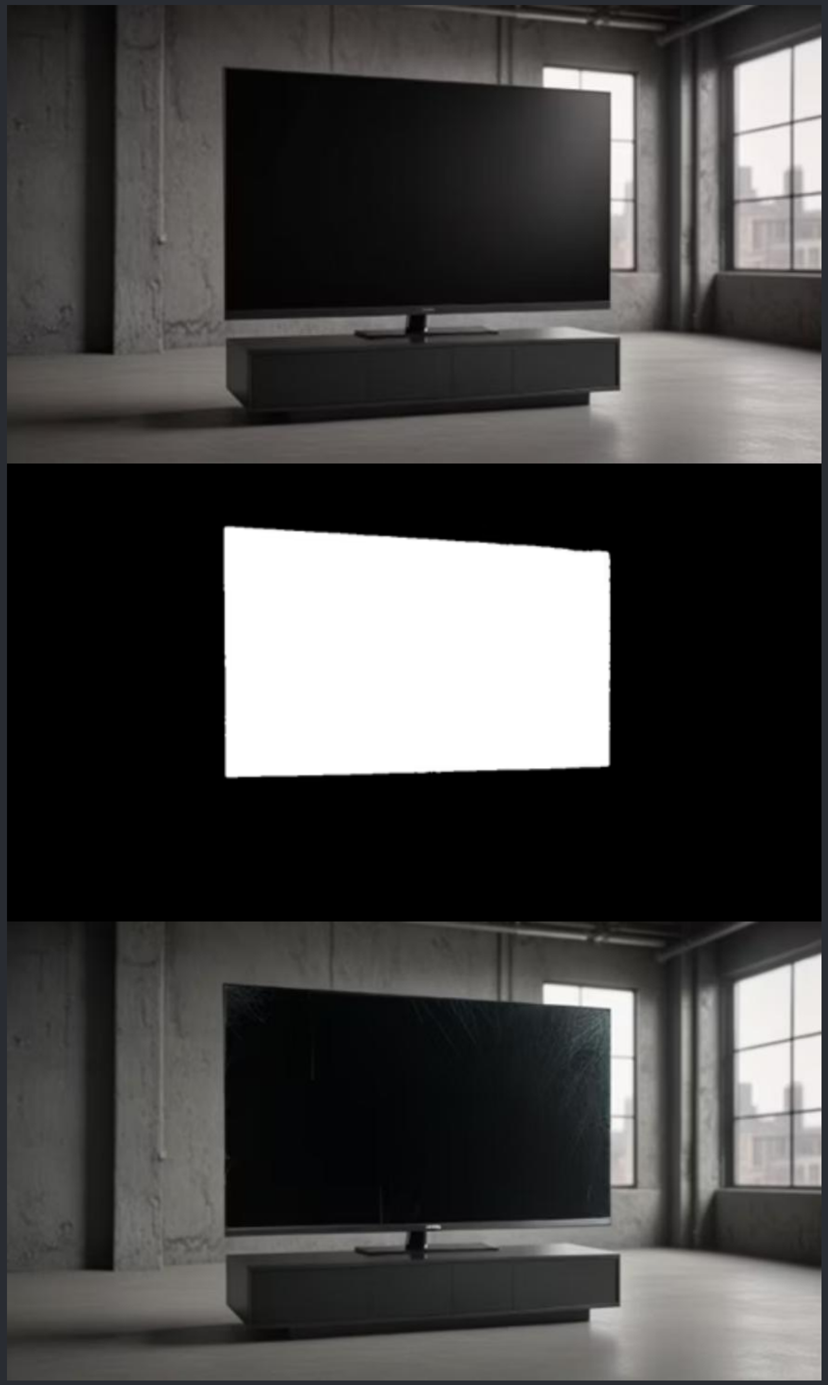
SDXL Lightning (RealVisXL V4.0) for realistic TV pictures.

Smart Labeling & Masking

OWLv2, SAM for binary masks of the screen.

Defect Injection

SDXL Inpainting to inject specific defects into masked areas.



Class Distribution

4 distinct classes generated cyclically for balance:

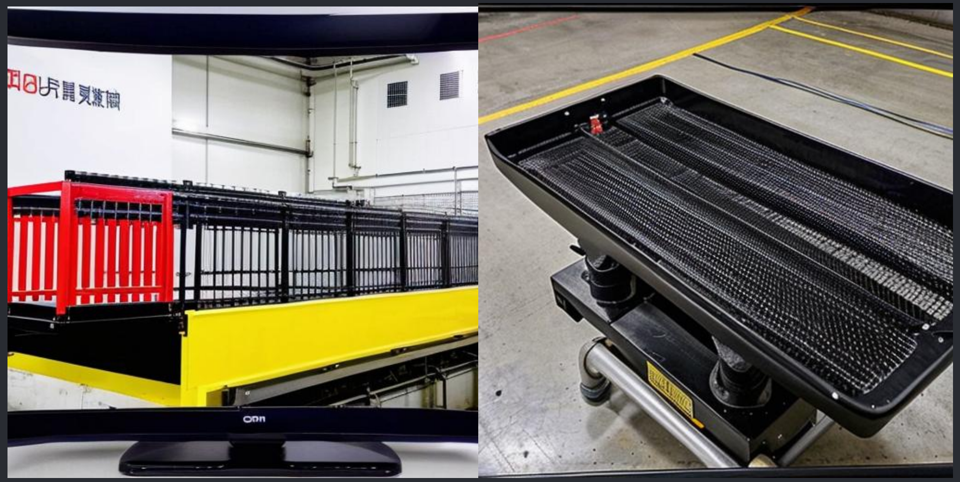
Spiderweb (cracks)

Scratch (surface damage)

Shattered_corner (structural damage)

Puncture (impact holes)

We iterated through four model versions and plenty of trial and error to transform these early attempts into the final, high-quality results.

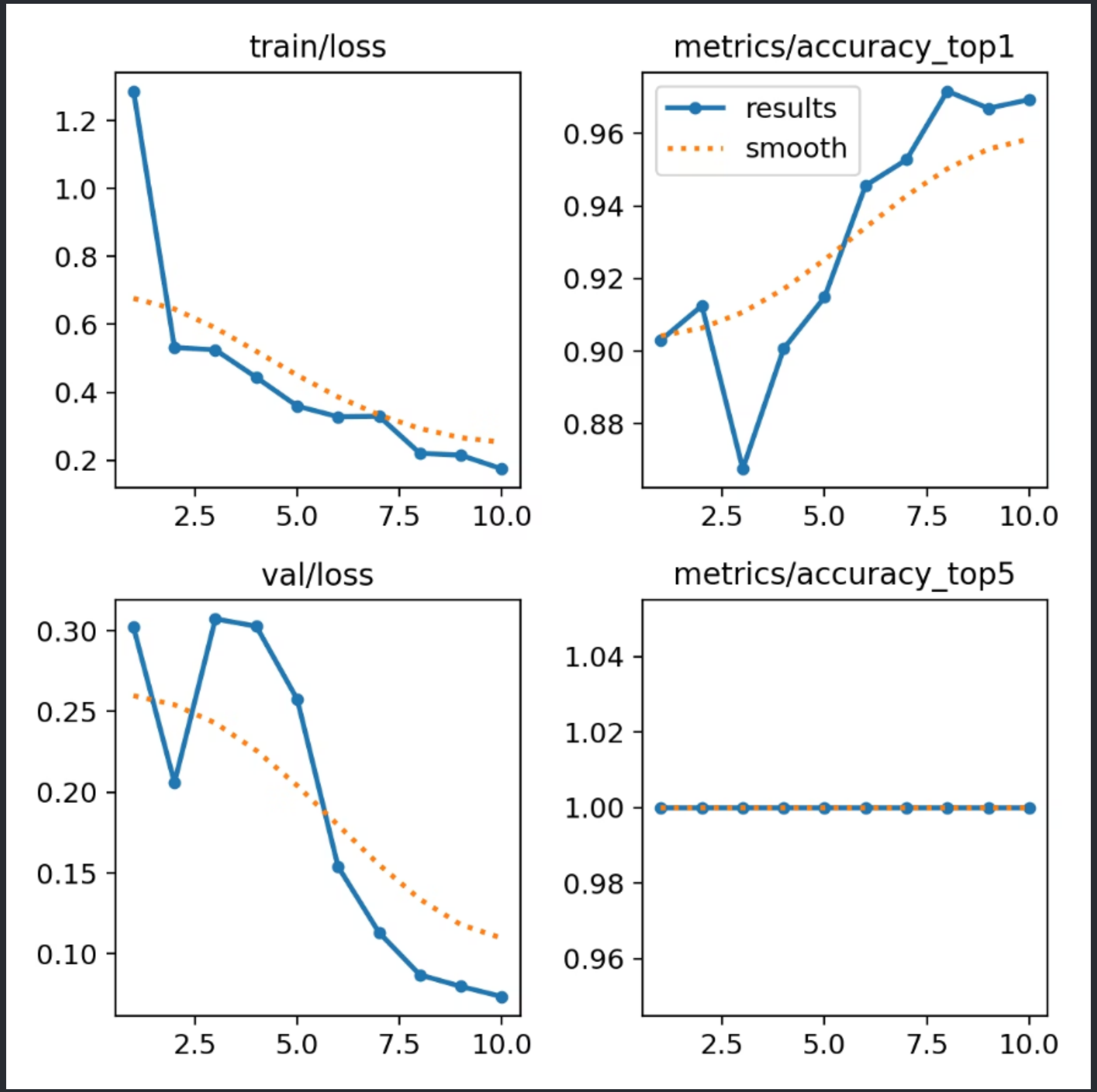


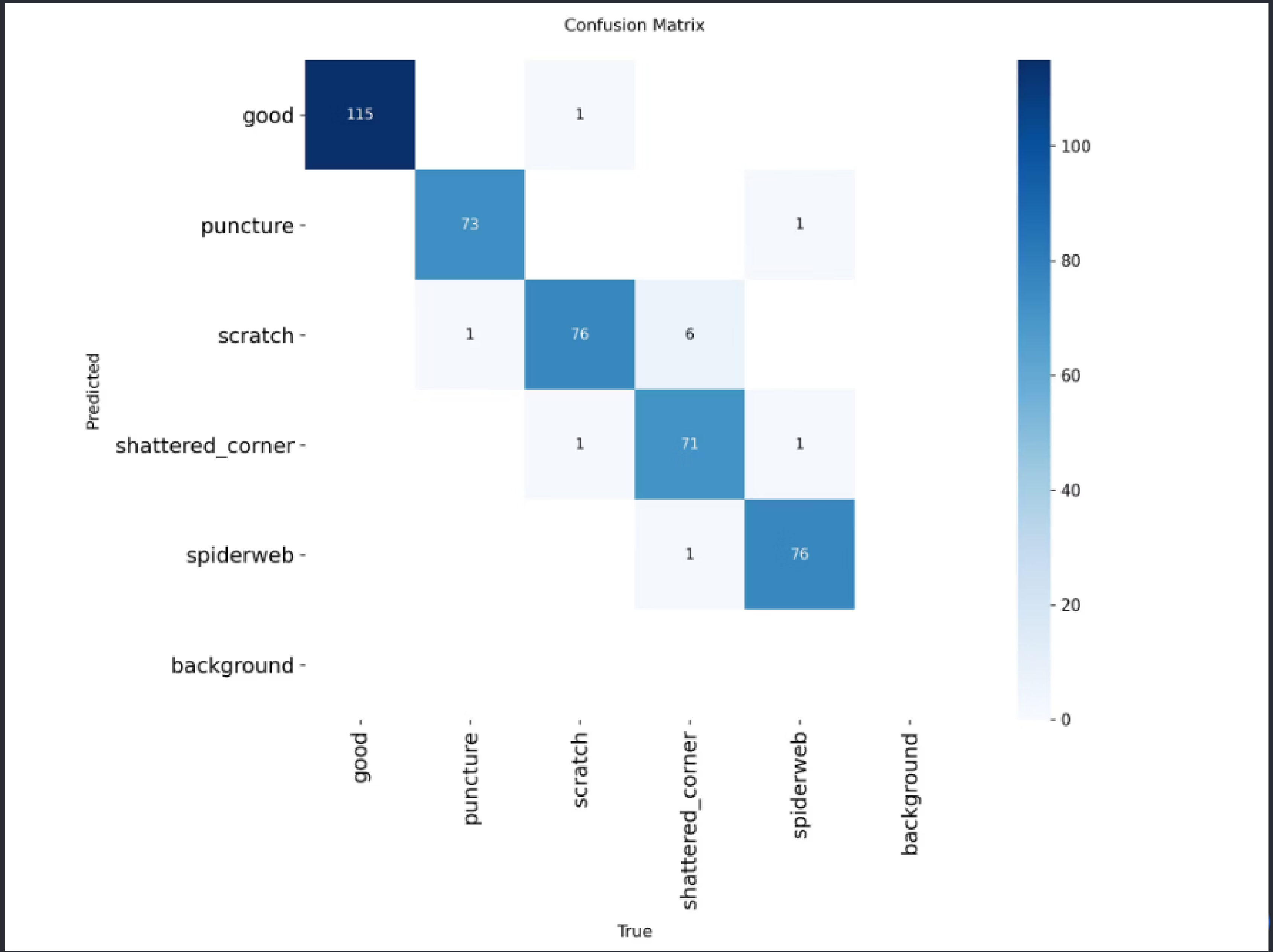
Training Results

Model Architecture: yolo11n-cls chosen for its speed and efficiency in image classification tasks.
Training Setup:

- Epochs: 10
- Image Size: 640x640
- Split: 80% Train, 20% Validation.

Recall of 0.966 and accuracy of 0.971






spiderweb 1.0
good 1.0
puncture 1.0
scratch 1.0
shattered_corner 1.0
shattered_corner 1.0
spiderweb 1.0
puncture 1.0
puncture 1.0
spiderweb 1.0
good 1.0
good 1.0
good 1.0
good 1.0
scratch 1.0
spiderweb 1.0

Project Plan & Technical Scope

Project Step	Technical Scope & Models Used	Expected Outcomes	Due Date
Pipeline Optimization: Masking & Realism	**Mask Refinement:** Fine-tuning the segmentation model to exclude TV stands to prevent inpainting artifacts. **Inpainting Tuning:** Adjusting generative parameters (Prompts, Strength, Guidance Scale) to ensure defects are realistic and clearly visible in all generated outputs.	An optimized pipeline producing accurate masks and realistic defects.	[hopefully before the final presentation]
Mass Dataset Generation	**Batch Processing:** Executing the optimized pipeline on a large scale. **Data Augmentation:** Utilizing varied prompts and random seeds to create a diverse range of defects and visual conditions for training data.	A large-scale, diverse synthetic dataset ready for model training.	[31/12/25]
Sim-to-Real Validation	**Model Training:** Training a detection model on the full generated synthetic dataset. **Inference Testing:** Testing the trained model on a separate set of *real* defective TV images to evaluate capabilities.	Validation metrics determining if the model can successfully detect real-world defects based on synthetic learning.	[hopefully before the final presentation]
Prepare Final Presentation	Aggregating results, visualizing "Synthetic vs. Real" comparisons, and summarizing the technical challenges and model performance.	Final presentation	[hopefully before the final presentation]