Automated Quality Control of Facade Elements

Tim - Fasada na Oko

1 Intro

KFK (Krov, Fasada, Konstrukcija) is a European leader in aluminum and glass facade systems. Each facade element must pass a quality control (QC) step before installation. Today, this process is manual: a worker visually inspects each element and compares it against specifications. This approach is slow, error-prone, and expensive—missed defects are often discovered only on-site, where repair or replacement costs are extremely high.

This project was developed during **NeoData Hackathon 2025**, organized by **Comminus**, with the goal of exploring an automated, scalable computer vision solution for defect detection on facade elements.

2 Approach / Solution

2.1 Dataset Exploration

We started by thoroughly exploring the provided dataset and available 3D models of facade elements. The first step was manual inspection of images to understand:

- Typical appearance of correct (positive) elements
- Common defect patterns in defective (negative) elements
- Variability in lighting, viewpoints, and background clutter

This step was crucial since the dataset contained **no predefined defect annotations**.

2.2 Early Experiments and Key Insight

We initially explored **SAM3** (Segment Anything Model v3) to directly localize defects. While SAM3 showed promising qualitative results, its performance was inconsistent without additional structural context.

> **Defect detection is significantly easier if the facade element type is known first.**

The dataset contains **three distinct facade element types**, each with different geometry and defect characteristics.

2.3 Macro Idea (Final System Design)

We defined the following high-level pipeline:

1. **Detect and classify the facade element** in the image
2. **Apply a specialized defect-detection strategy** tailored to that specific facade element type

This allowed us to trade a single, generic defect detector for **multiple precise, domain-specific methods**.

2.4 Dataset Limitations and Synthetic Data Exploration

The main challenge was the **small size of the real dataset**. We explored generating a synthetic dataset using the provided **3D models** by rendering realistic images with controlled defects. Although conceptually strong, this approach proved too time-consuming to implement robustly within the 24-hour hackathon.

As a practical compromise, we:

- Applied image rotations and simple augmentations
- Balanced classes to stabilize training

2.5 Facade Element Detection (YOLO)

We trained a **YOLO-based object detection model** to classify the facade element type.

- Primary metric: **accuracy**
- Rationale: downstream defect detection depends entirely on correct element classification

This model acts as the entry point to the pipeline.

2.6 Defect Detection (SAM3 + Heuristics)

After classification, we applied **element-specific defect detection strategies**, combining:

- Carefully designed **SAM3 prompts**
- Geometry- and context-aware post-processing

Here, **precision** was the dominant metric: false positives are costly in QC and directly penalized in evaluation.

2.7 3D Model–Based Defect Detection (Extended Exploration)

After classifying the facade element type using YOLO, we explored the use of the provided **3D CAD models** to extend the limited real-image dataset. The core idea was to generate synthetic training data by rendering the 3D models from multiple viewpoints and combining these renders with real images during training.

The intended pipeline consisted of rendering synthetic images across diverse viewing angles, merging synthetic and real data into a single training set, and using this augmented dataset to improve robustness to viewpoint and condition variability. This approach was primarily motivated by the small size and limited diversity of the real dataset.

To validate feasibility, we implemented an automated **Blender-based rendering pipeline**. Each facade model was rendered from **12–16 horizontal angles** and **3–5 elevation angles**, with dynamic lighting variations applied. In total, this process generated approximately **80 synthetic images per facade type**, resulting in around **240 additional training images**.

While the rendering pipeline was successfully completed, this approach was not fully integrated into the training loop within the hackathon timeframe. The main limitation was a noticeable **domain gap**: synthetic renders appeared significantly cleaner and more uniform than real production images. Bridging this gap would require additional techniques such as domain adaptation or style transfer, as well as careful tuning of the ratio between synthetic and real data.

By the end of the hackathon, we had a fully automated synthetic data generation pipeline and a proof of visual similarity between rendered and real facade elements. However, joint training, domain adaptation, and quantitative evaluation of performance gains remained out of scope.

Despite these limitations, this direction represents a strong long-term opportunity. With additional development focused on reducing the synthetic-to-real domain gap, 3D-based data generation could substantially improve model generalization and defect detection performance.

2.8 Productization

To make the solution usable, we implemented a **simple Streamlit UI** that:

- Accepts a single image or a batch of images
- Runs the full pipeline
- Generates a clear QC report per image

2.9 Why Now?

KFK is actively expanding its **Data Science and automation efforts**. This solution demonstrates a scalable path toward:

- Reducing manual QC costs
- Improving consistency and reliability
- Laying foundations for future data-driven quality assurance systems

The approach is modular and can evolve with more data and tighter integration of 3D models.

2.10 Product Demo

The final solution is wrapped in a lightweight **Streamlit application** designed for fast and intuitive QC inspection.

The app supports:

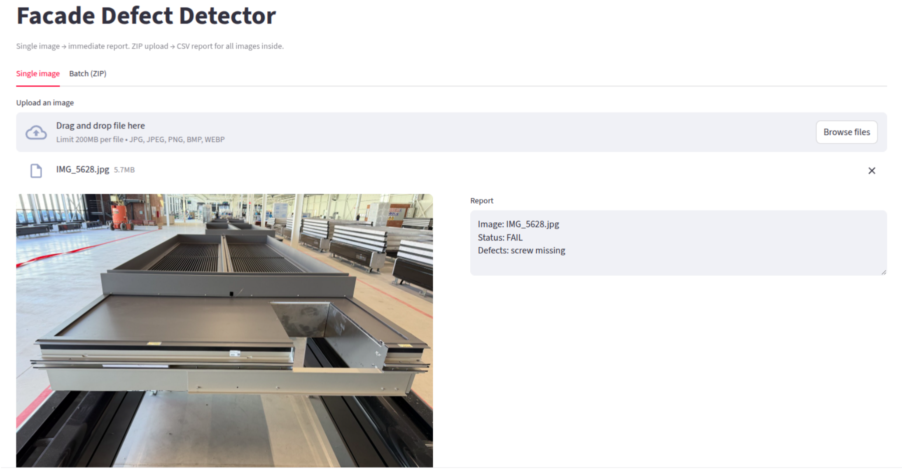
- **Single-image analysis** — upload one image and receive an immediate QC decision and defect report
- **Batch analysis** — upload a `.zip` archive of images and automatically generate a consolidated report for all elements

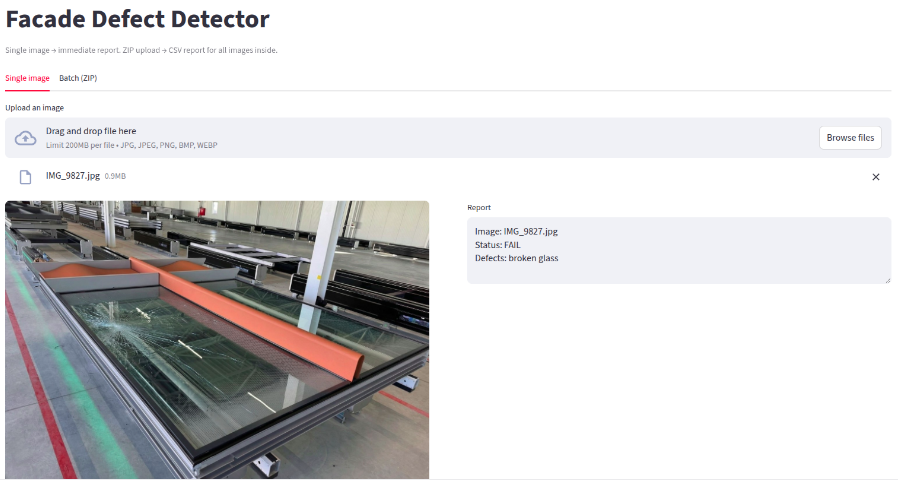
For each image, the application:

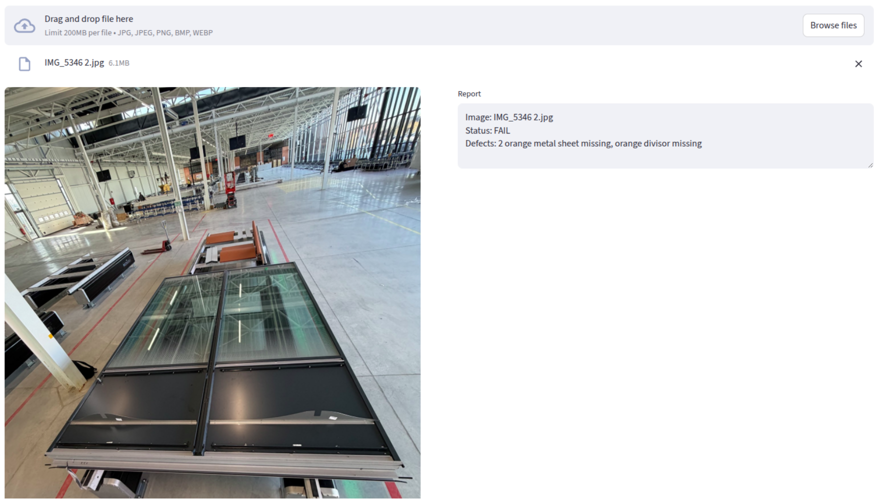
- Predicts the facade element type
- Runs the corresponding defect-detection pipeline
- Generates a structured QC report (PASS / FAIL with detected defects)
- **Visually highlights selected defects** directly on the image for easier interpretation

The demo includes screenshots of example usage for both single-image and batch workflows.

2.11 Demo Screenshots







2.12 Long-Term Vision

Although not fully implemented during the hackathon, **3D-model-based synthetic data generation** remains a highly promising direction. With sufficient time, this approach could enable:

- Large, realistic training datasets
- Controlled simulation of rare defects
- Strong generalization across projects and configurations

2.13 Team

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