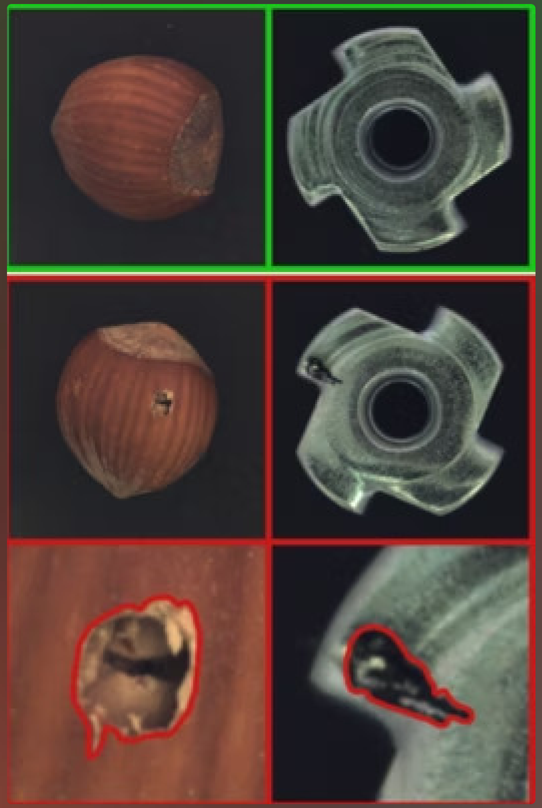
A Universal Feature Extractor with On-Site Adaptation for Industrial Anomaly Detection

A Flexible Two-Stage Framework for Few-Shot Novelty Detection in Manufacturing



The Problem We Solve

Traditional industrial anomaly detection requires training a separate, specialized model for each product category. When factories introduce new products, they face a painful choice: spend days collecting training data and retraining models, or deploy without proper anomaly detection. Our framework eliminates this bottleneck by introducing a universal feature extractor that adapts to new products in minutes using only a handful of golden samples.

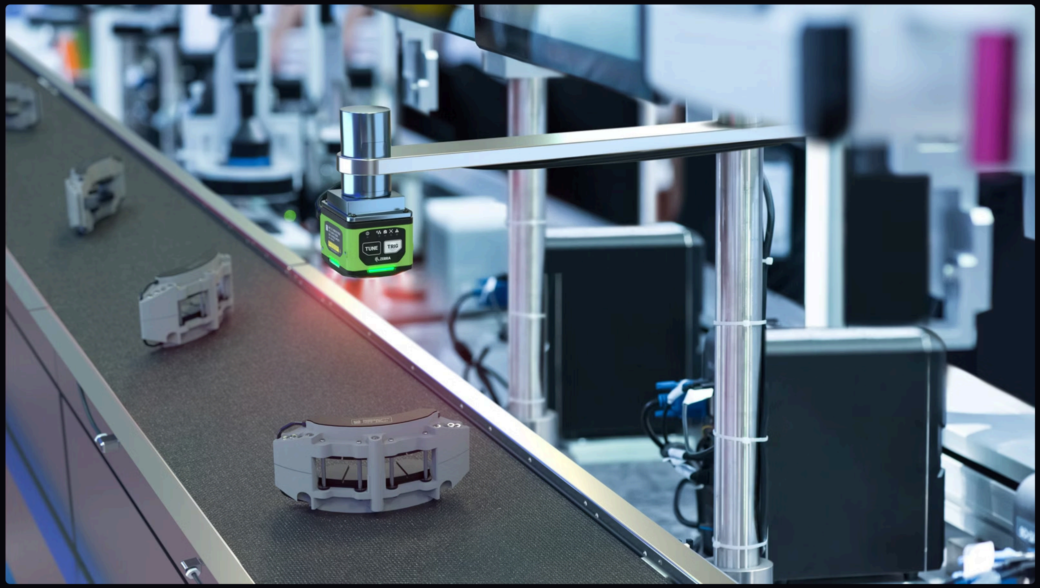
Core Innovation: Two-Stage Framework

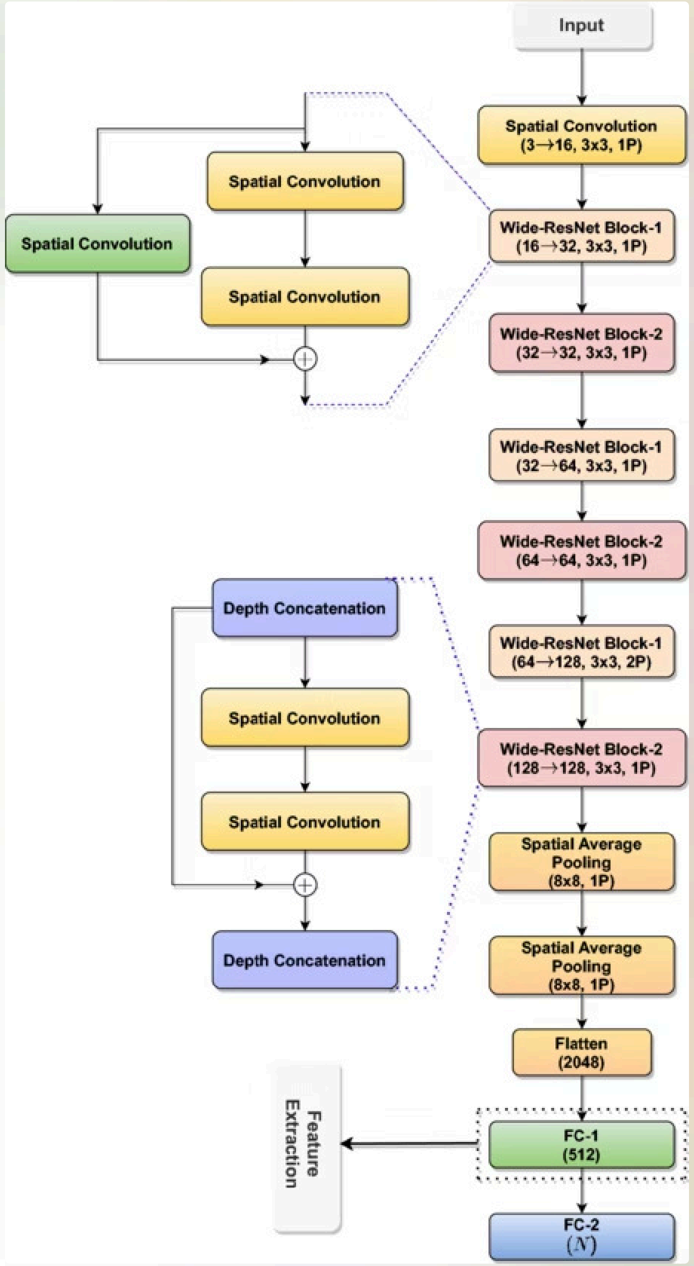
Traditional Approach

- Separate model per category (carpet, bottle, PCB)
- Requires large labeled datasets
- Retraining needed for each new product
- Days to weeks for deployment
- Not scalable to diverse manufacturing environments

Our Universal Extractor + Adaptation

- Single universal model trained once
- Learns from diverse industrial datasets
- On-site adaptation in minutes with golden samples
- Lightweight product-specific coreset files
- Practical, scalable for manufacturing deployment





Stage 1: Universal Feature Extractor Architecture

We employ a Wide ResNet-50 backbone pre-trained on a massive composite dataset (MVTec-AD and VisA) comprising thousands of industrial images. The model serves as a general-purpose visual language learner, not a classifier. Multi-scale feature extraction from layer2 (fine-grained texture details) and layer3 (structural context) are fused via upsampling and concatenation, creating rich representations capturing both minute defects and larger structural anomalies.

Stage 2: On-Site Adaptation Process

01

Golden Samples

Factory provides 10-20 "good" reference images of new product

02

Feature Extraction

Frozen universal extractor generates patch-level feature vectors

03

Coreset Subsampling

Greedy algorithm selects representative 1% subset of features

04

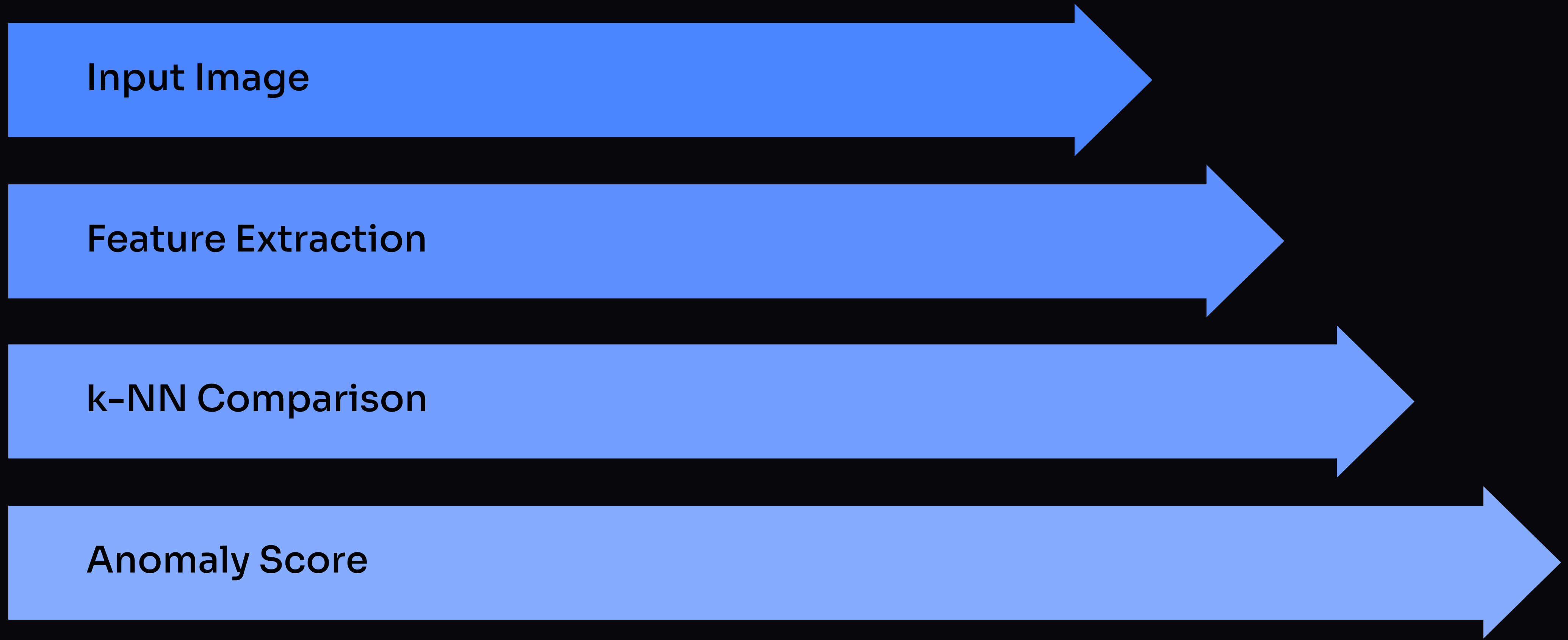
Lightweight Fingerprint

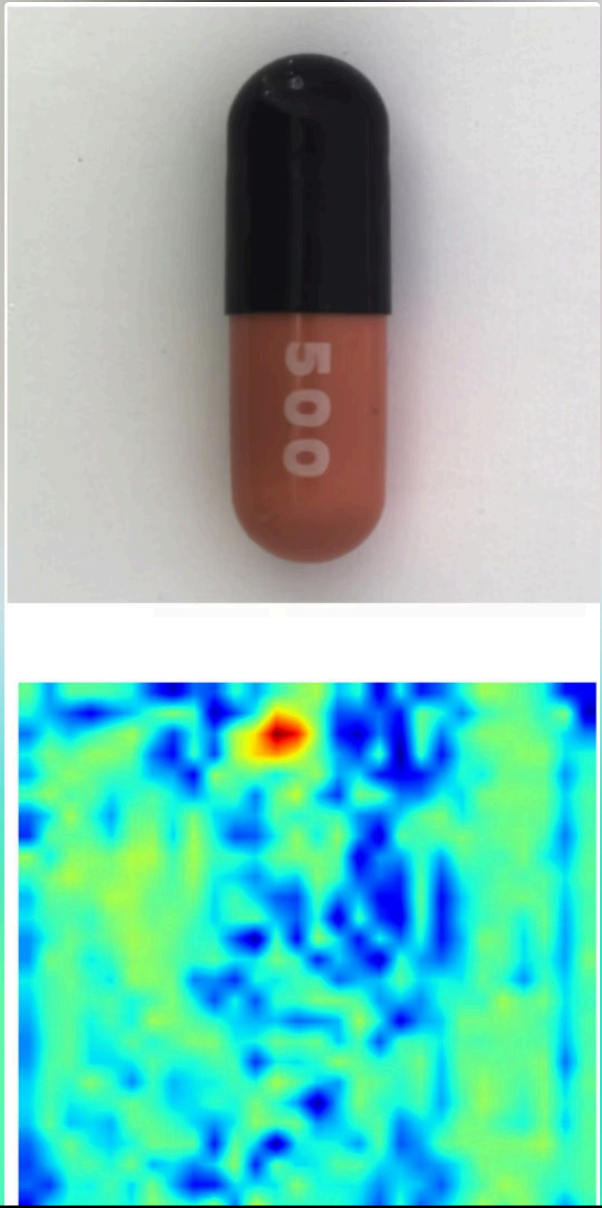
Product-specific .pkl file saved containing normalized feature memory

This adaptation occurs entirely offline using a provided fine-tuning script, requiring no deep learning expertise from factory personnel.

Real-Time Inference Pipeline

During deployment, test images are passed through the same frozen universal extractor. Patch-level features are compared against the product's coreset using k-Nearest Neighbors (k-NN) search in high-dimensional feature space. L2-distance to the nearest coreset feature becomes the anomaly score: low distance indicates normalcy, high distance signals potential defects. This metric-learning approach enables real-time detection without computational overhead.





Anomaly Localization and Segmentation

Heatmap Generation

Per-patch anomaly scores reshaped into 2D spatial grid

Bilinear Upsampling

Low-resolution grid interpolated to match input image dimensions

Morphological Refinement

OpenCV thresholding and morphological operations clean noise

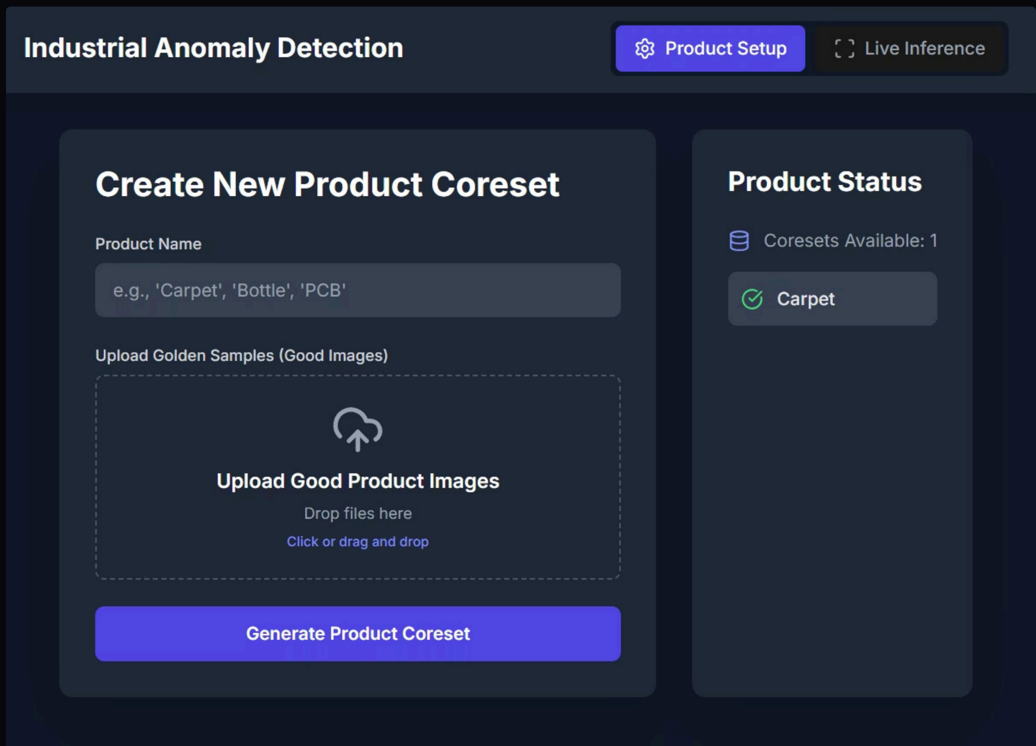
Defect Localization

Contour detection precisely marks anomalous regions on image

System Architecture and Implementation

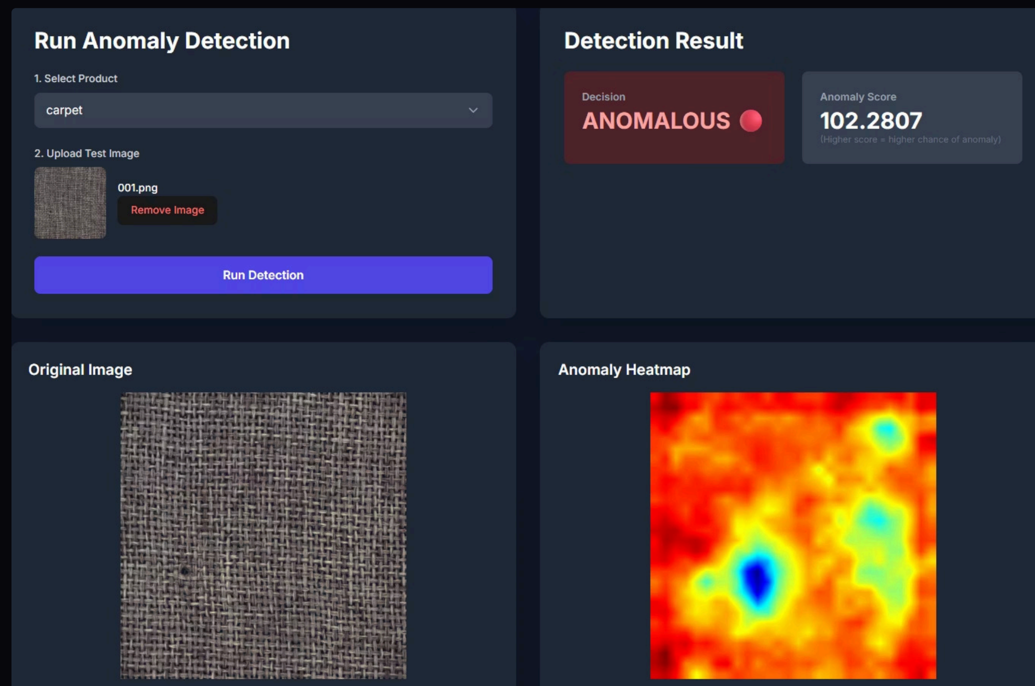
Backend Infrastructure

- Flask (Python) server managing universal extractor model
- RESTful API endpoints for setup and inference
- Product-specific coreset (.pkl) caching and versioning
- Asynchronous job processing for batch detection



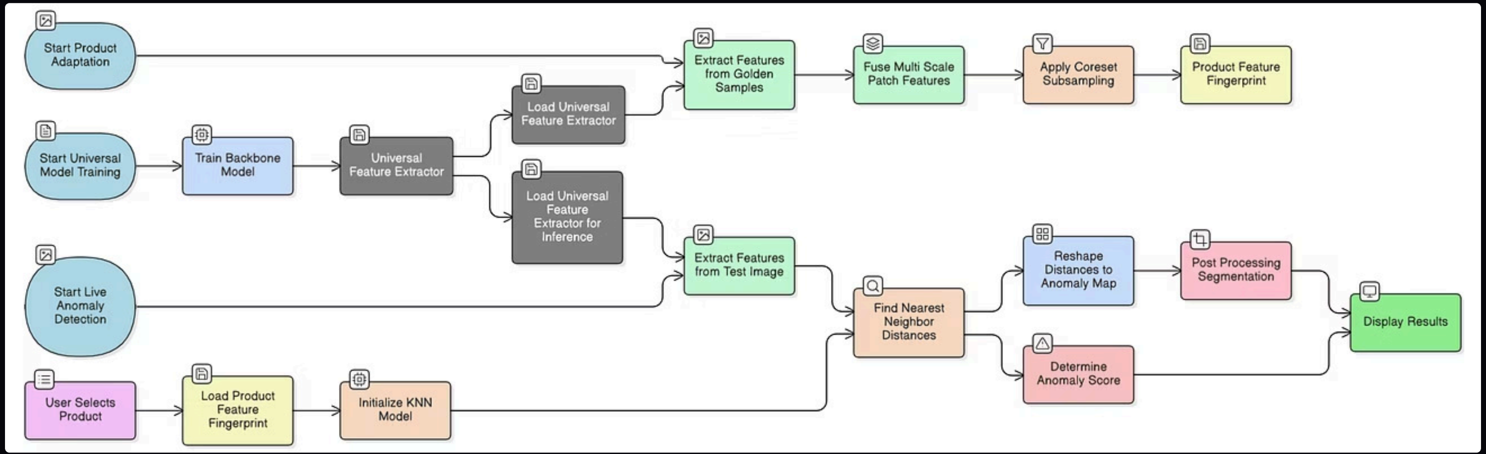
Frontend Interface

- React (Vite) application for factory engineers
- Product management dashboard
- Batch image upload and processing
- Interactive heatmap visualization and analytics



Training Data and Experimental Foundation

The universal feature extractor was trained on two large-scale industrial anomaly detection datasets. **MVTec-AD** contains 5,354 high-resolution images across 15 product categories including textiles, metal, and electronic components. **VisA (Visual Anomaly)** provides 10,821 images of industrial products in natural environments. Together, these datasets comprise diverse manufacturing contexts: textures, structural defects, contamination, and component misalignment, enabling robust generalization to novel factory products.



Conclusion: Practical Scalability for Manufacturing

This framework successfully decouples universal feature representation from product-specific adaptation, overcoming the critical limitation of traditional per-category models. By combining deep learning for rich representation and metric learning for fast adaptation, we deliver a practical solution for dynamic manufacturing environments. Factory engineers can deploy anomaly detection for new products in minutes using only golden samples—no retraining, no deep learning expertise required. This hybrid approach balances accuracy, efficiency, and real-world deployability.

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