Anomaly Detection in Drone Videos for Preventive Maintenance of Power Lines

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Guillaume Fourret[1,2], Marc Chaumont[1,3], Christophe Fiorio[1], Gérard Subsol[1], Samuel Brau[2]

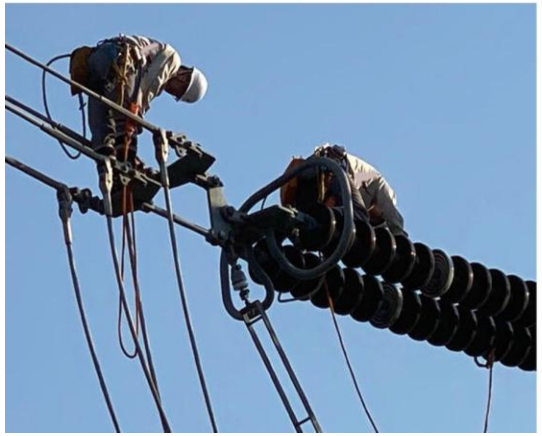
[1]ICAR, LIRMM, University of Montpellier, CNRS, France
[2]Drone Geofencing, Nîmes, France
[3]University of Nîmes, France

Contact: guillaume.fourret@lirmm.fr

1. UAS monitoring

Objective: Prevent power line shutdowns by analyzing their components.
Traditional inspection methods include:

Manual inspection



Robotic systems

Helicopter-assisted inspection

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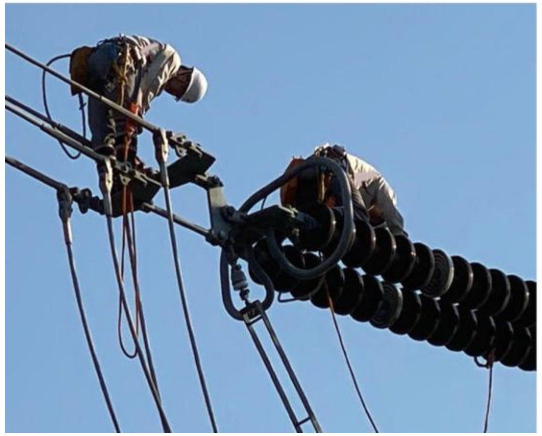


Robotic systems

Helicopter-assisted inspection

Unmanned **A**ircraft **S**ystems (**UAS**) have revolutionized the field:

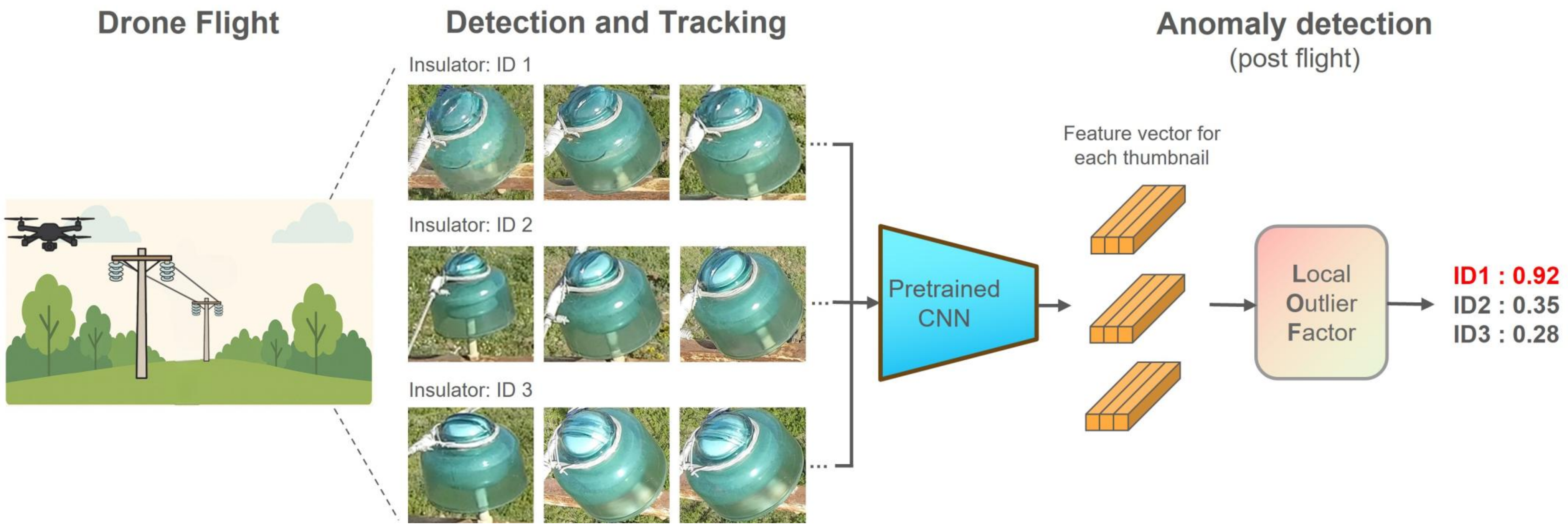
- Minimize risk to technicians
- Significantly lower operational costs
- Efficiently cover large and hard-to-reach areas
- Capture high-quality views of components from multiple angles

1. Challenge of Real-World Anomaly Detection

- A large variety of components must be inspected
- Each component type can exhibit many visually distinct anomalies

Key Challenge: Supervised deep learning would require a vast amount of labeled anomaly data, which is often unavailable or costly to obtain

2. Our Pipeline for Unsupervised Anomaly Detection



1. A drone surveys the power line; analysis is done post-flight.

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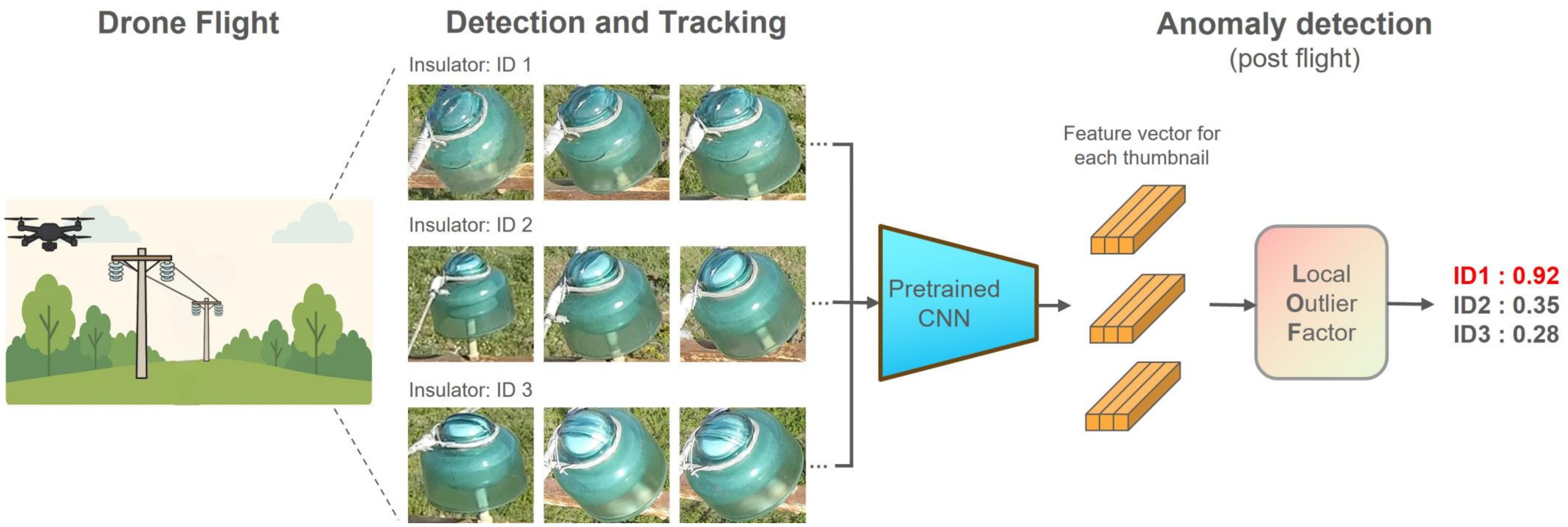

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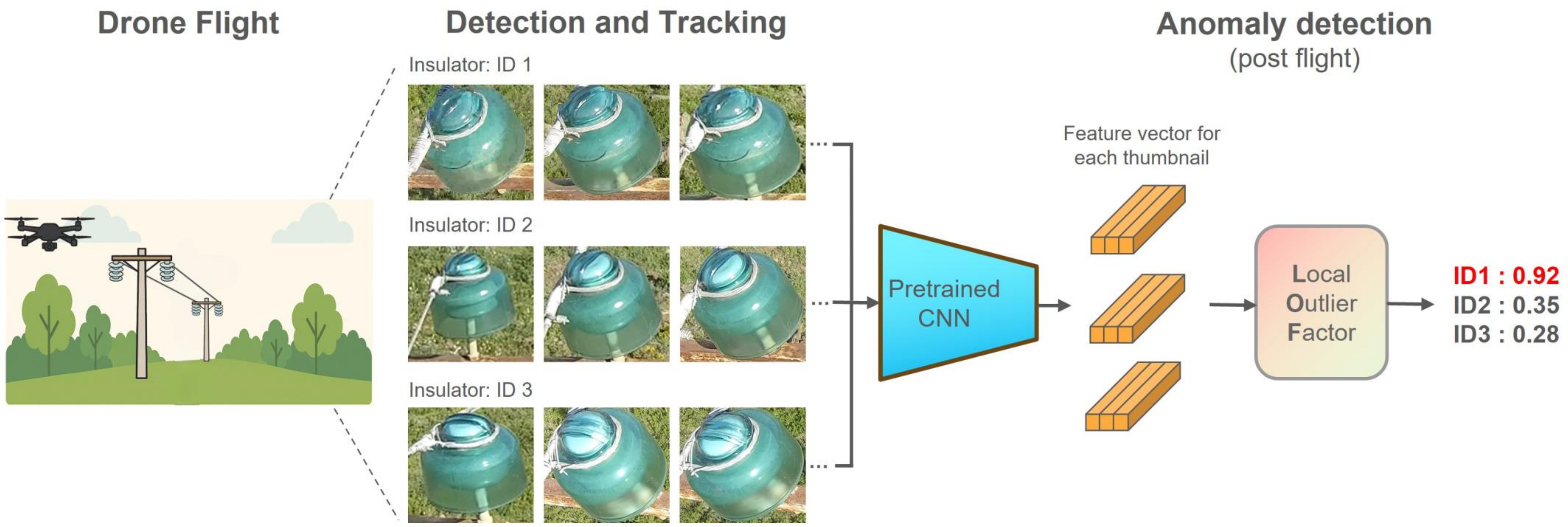

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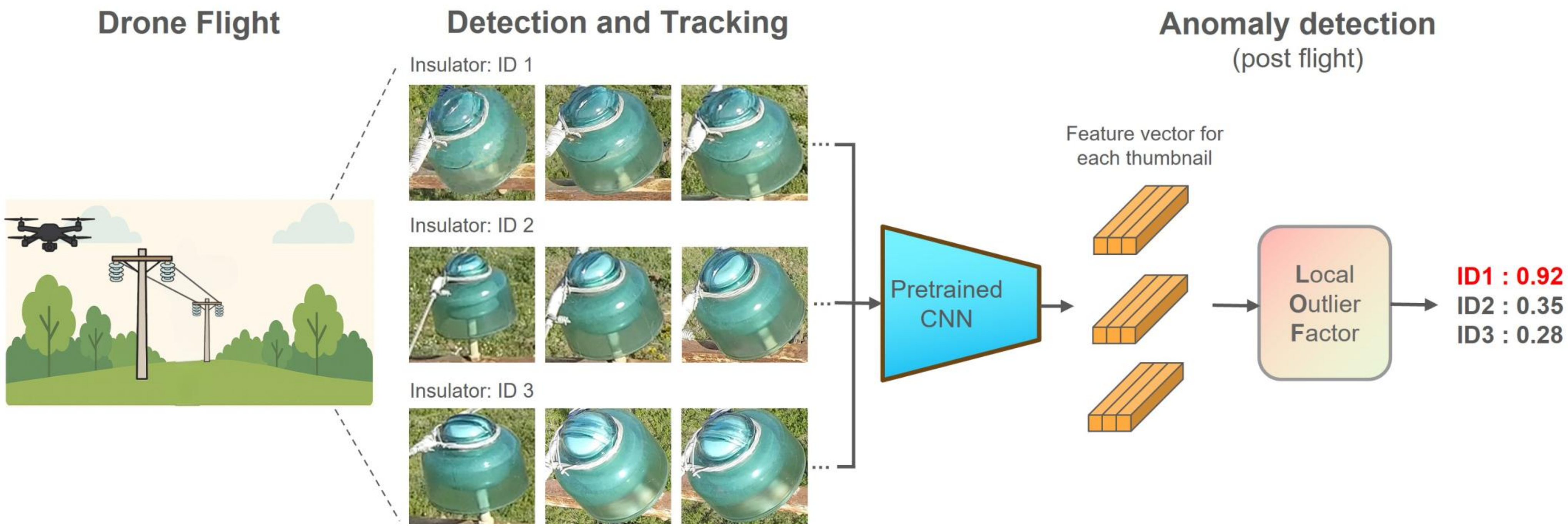

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2. An object detector with tracking extracts tracklets of components.
3. A pretrained CNN computes latent feature representations.
4. LOF (**L**ocal **O**utlier **F**actor) is used for unsupervised anomaly detection.

3. Object Detection and Tracking

Our main components of interest was the glass insulator:

- A YOLOv5m6[1] model was trained on 143 annotated insulators from various inspection mission.
- Training ran for 85 epochs with a batch size of 4 and a resolution of 1280x720 on an Nvidia RTX3070

[1]Jocher, Glenn, Ayush Chaurasia, and Jing Qiu 2023, *YOLO by Ultralytics*

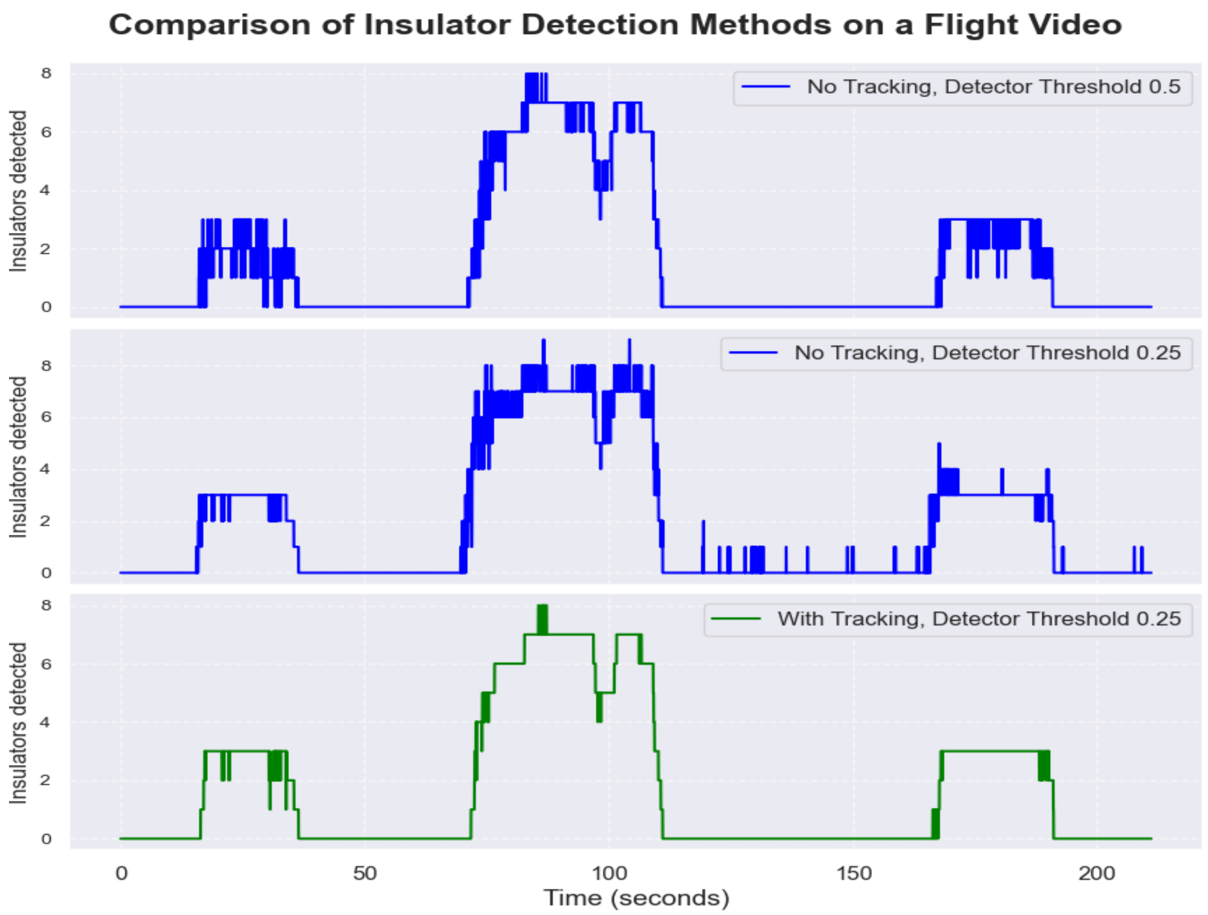
3. Object Detection and Tracking

Since our input is video, we enhanced the detector's robustness by integrating a tracking algorithm: **DeepSORT**[2]

DeepSORT combines a Kalman filter with deep feature matching to track detections across frames.

By integrating DeepSORT, we can:

- Lower YOLO's confidence threshold to improve component recall.
- Filter out false positives by only accepting detections that persist for at least 15 frames.



[2]Wojke, Nicolai, Alex Bewley, and Dietrich Paulus 2017. "Simple Online and Realtime Tracking with a Deep Association Metric".

3. LOF calculation

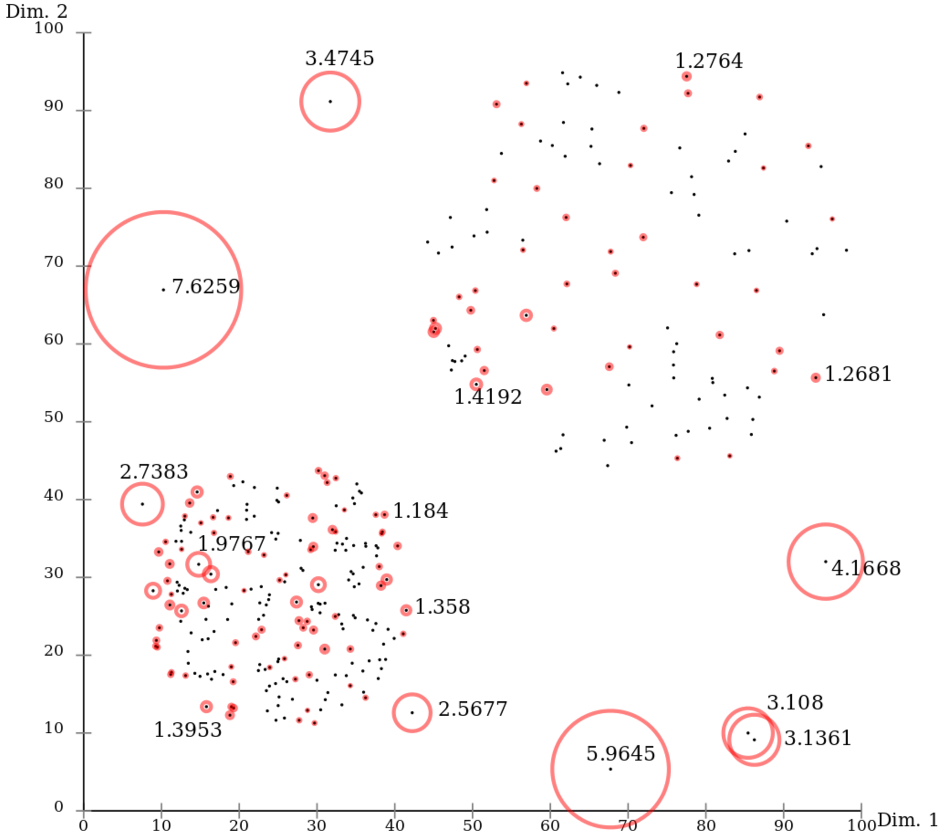
Local **O**utlier **F**actor (**LOF**)[3] is an unsupervised anomaly detection based on density analysis
Objective: Give a high score to isolated vector

- We start by computing the local reachable density of each vector:

$$lrd_k(\boldsymbol{X}_i) = 1/(\frac{\sum_{\boldsymbol{X}_j \in N_k(\boldsymbol{X}_i)} d_k(\boldsymbol{X}_i, \boldsymbol{X}_j)}{|N_k(\boldsymbol{X}_i)|})$$

- Then the LOF score is computed as a ratio with its neighborhood:

$$LOF_k(\boldsymbol{X}_i) = \frac{\sum_{\boldsymbol{X}_j \in N_k(\boldsymbol{X}_i)} lrd_k(\boldsymbol{X}_j)}{|N_k(\boldsymbol{X}_i)| \times lrd_k(\boldsymbol{X}_i)}$$



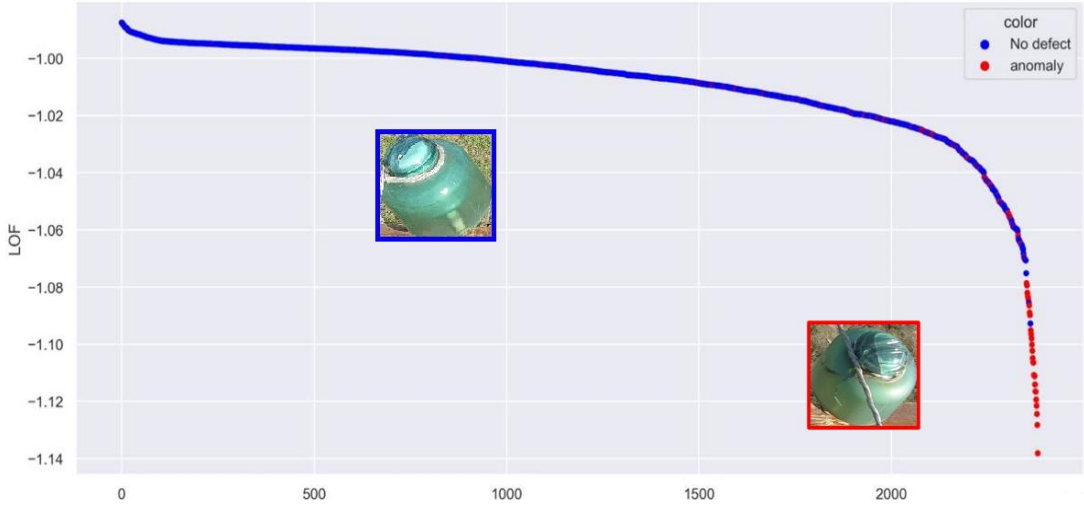
Example in a 2D space

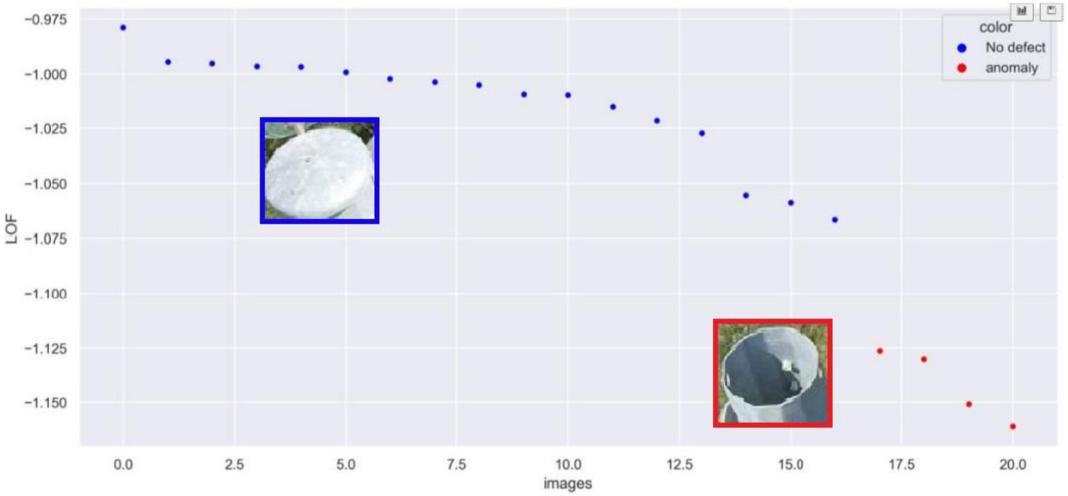
[3]Breunig, Markus M et al. 2000. "LOF: identifying density-based local outliers".

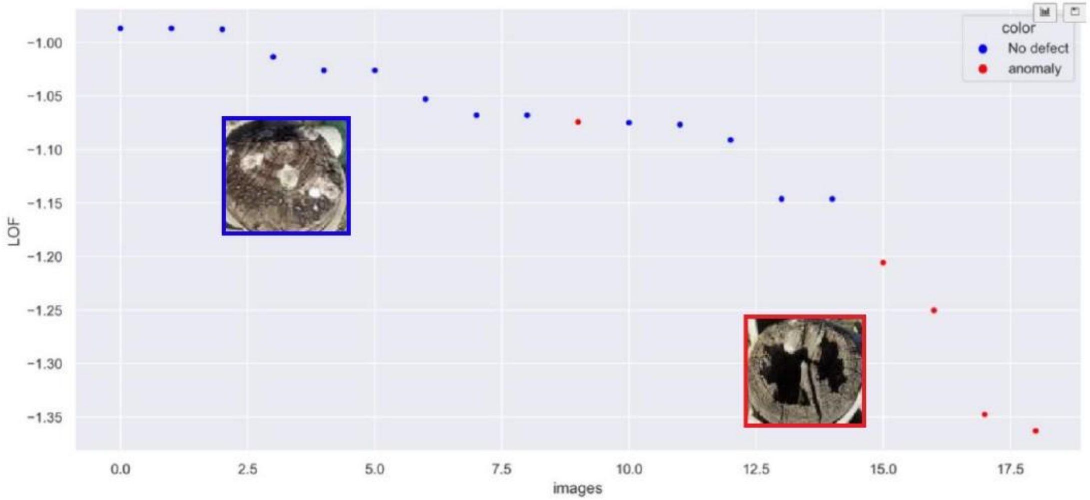
3. LOF calculation

Experiments were conducted on three components for defect detection: Glass insulator, Steel poles, Wooden poles

- We use a pretrained CNN feature extractor (VGG16-BN) trained on ImageNet.
- The extracted latent features are used as input to the LOF algorithm.
- The feature vectors corresponding to defective components are shown in red.



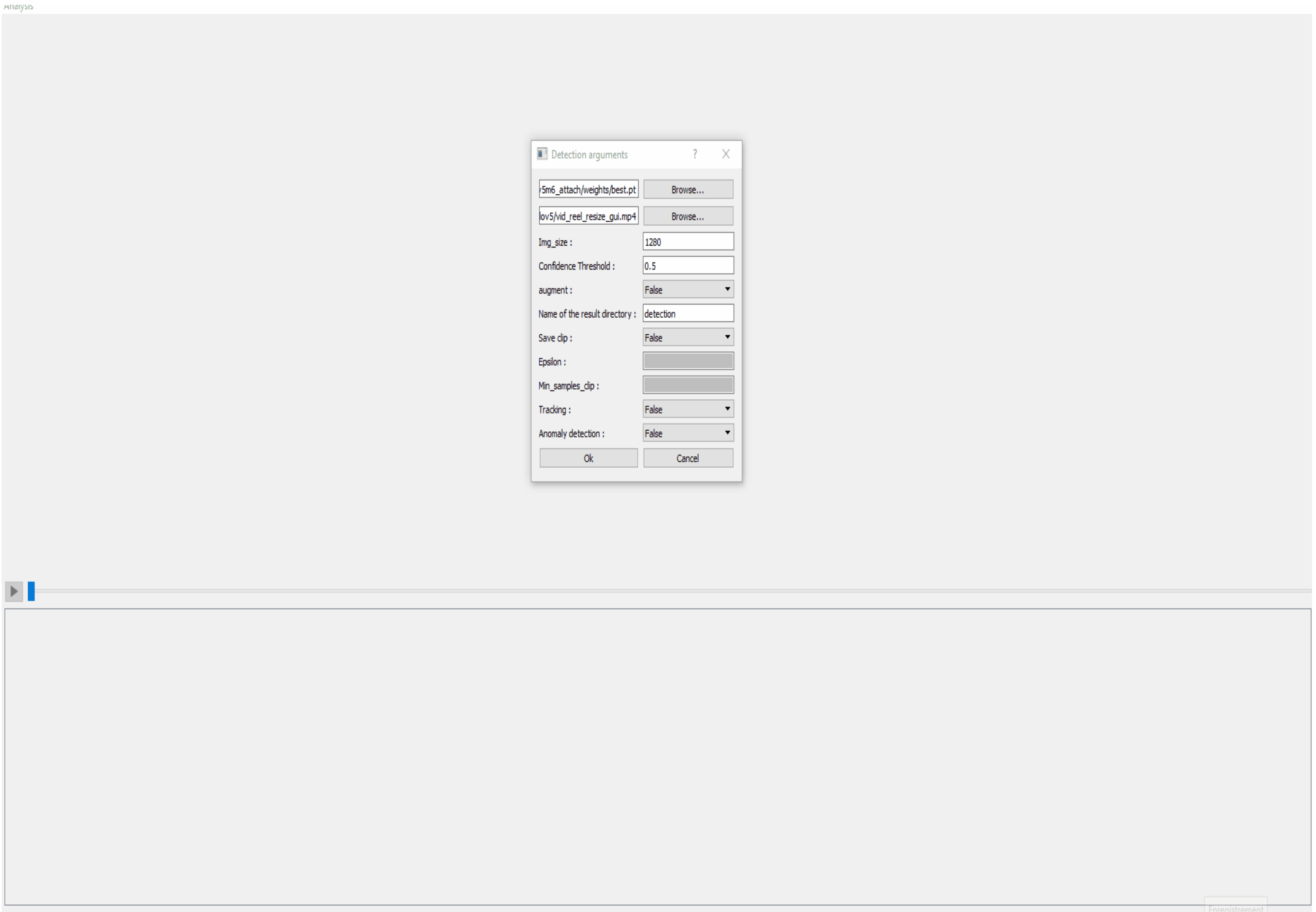




Note : For steel and wooden poles, crops were extracted manually since no detectors were available for these classes

4. Graphical User Interface

To help technicians use our method, we provide them a GUI by using PyQT5:



- Enables configuration of the detector's hyperparameters.
- Provides an interactive detection timeline, allowing technicians to quickly navigate to key moments.

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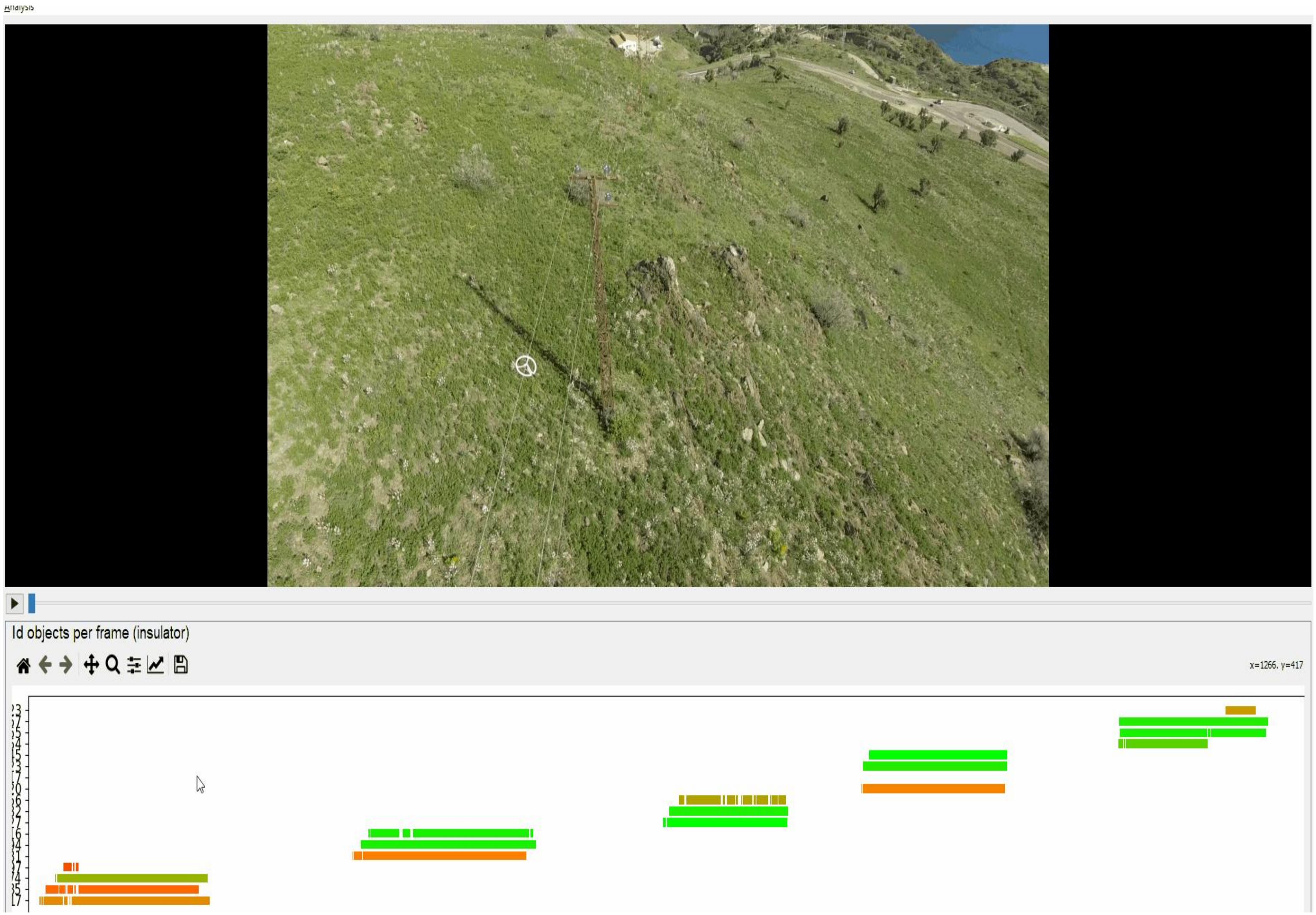
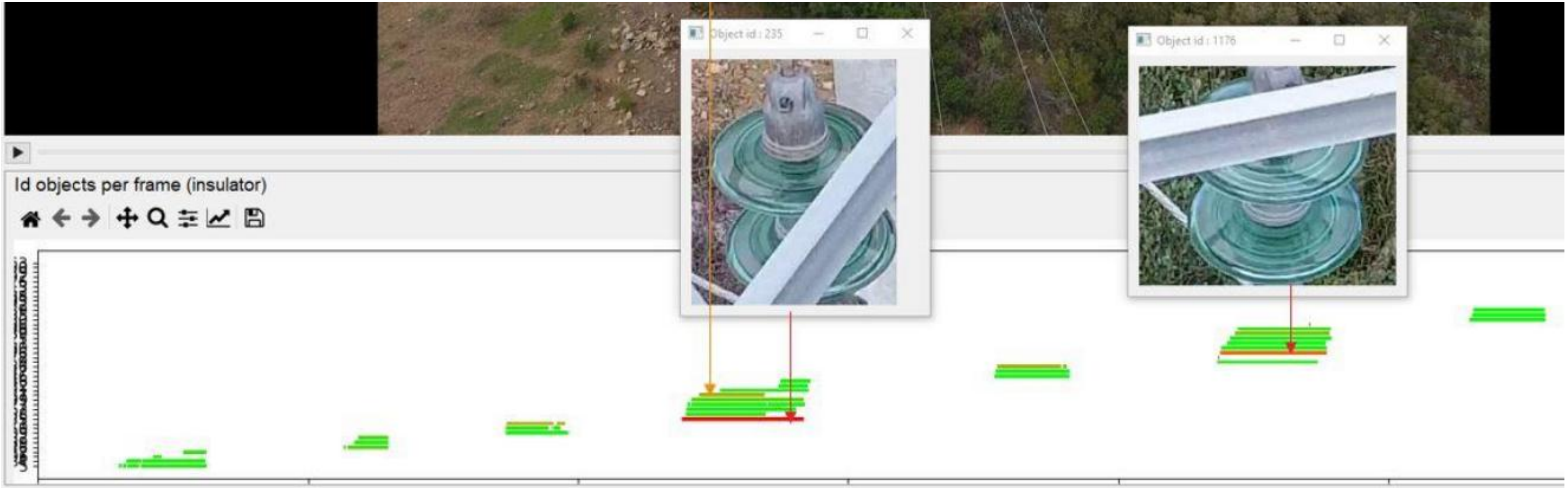


- With tracking and anomaly detection enabled, the GUI displays the appearance tracklet for each detected component.
- Tracklet colors reflect anomaly scores computed using the LOF algorithm.
- Technicians can inspect a component by clicking on its tracklet.

5. Conclusion

To conclude, this work:

- We proposed a generic pipeline for defect detection on power line components.
- Integration Few-Shot Object Detection (FSOD) could further reduce data requirements in the initial detection stage
- Occluded objects often yield high anomaly scores, detecting and handling occlusions could improve pipeline robustness.



Thanks for your attention!
Questions?