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OBJECT DETECTION ALGORITHMS APPLIED ON LOW VOLTAGE GRID EQUIPMENT

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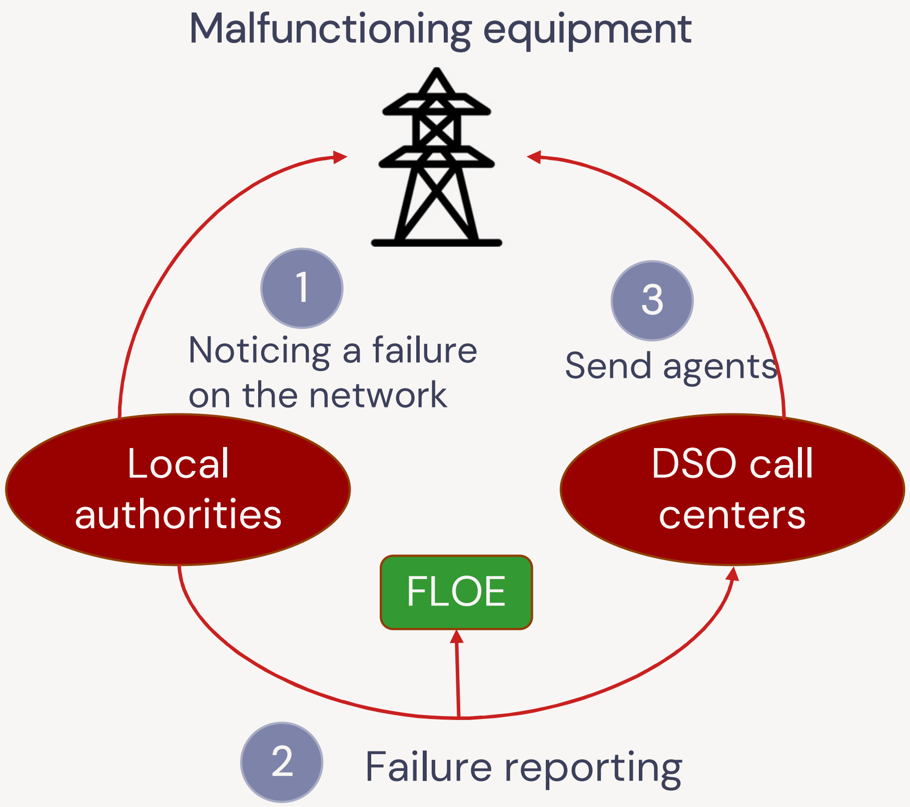
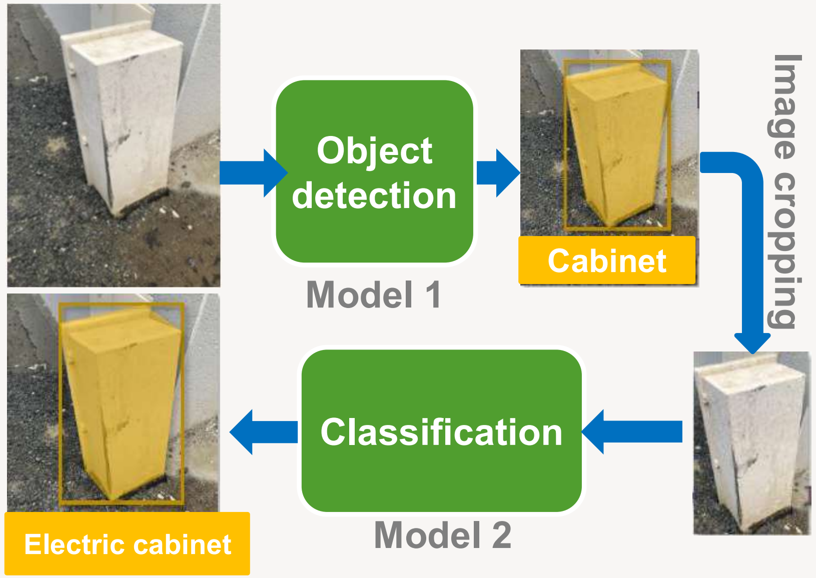
Introduction



Similarities between electric equipment and other grid equipment

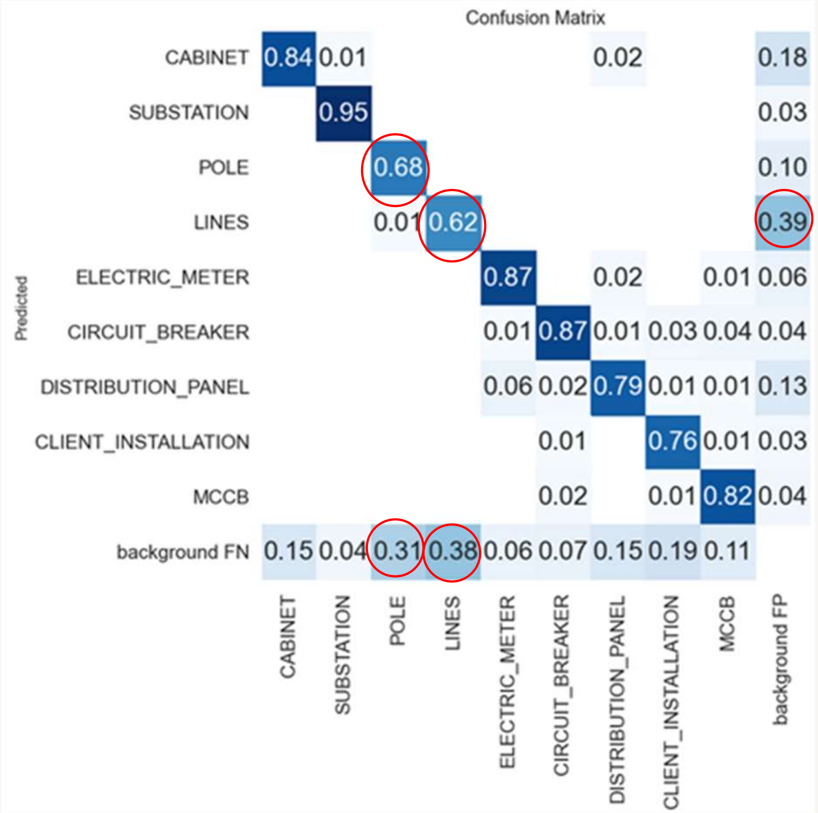
Approach

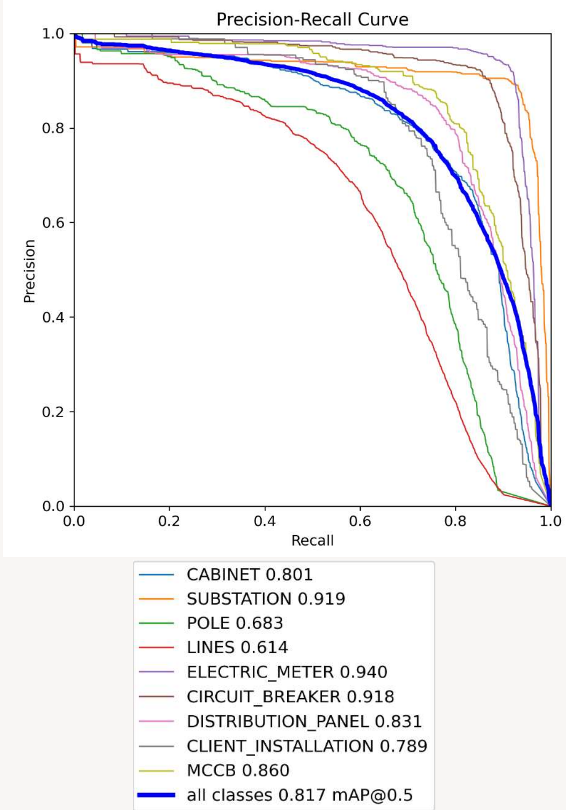
- Two-step approach: Object detection and image segmentation, followed by classification.
- For object detection, merge pictures of different grids for improved recall
- Afterwards, classification with a second model to distinguish between electric and non-electric equipment after initial steps.



Task 1 : Object detection

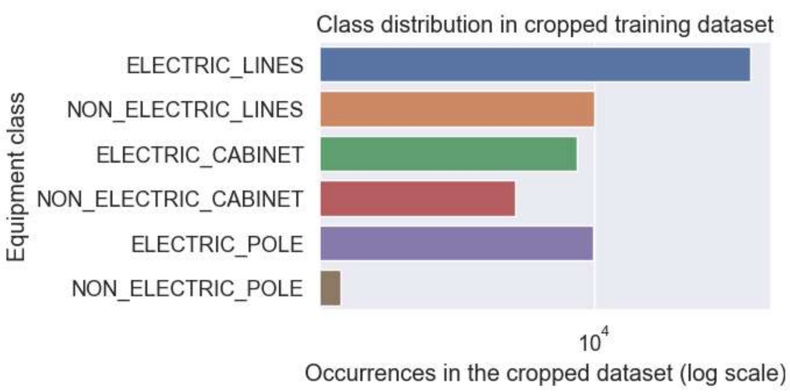
- The model performs well in detecting the majority of classes
- For poles are not centered in the images, the model tends to confuse them with trees, resulting in false positives or ignoring them resulting in false negatives. This explains the low recall rate for pole detection
- For lines, are extremely thin and often indistinguishable in noisy backgrounds





Task 2 : Classifier

Training data



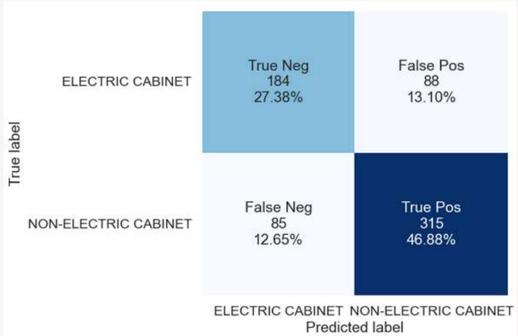
- The training dataset is highly imbalanced
- 3 models were trained to perform classification on each type of electric equipment and non-electric ones.

Classification results

Cabinets :

A recall of 74% and a **precision of 74%**. These results can be explained by:

- A **well-distributed** dataset: 59.6% of electrical cabinets and 30.4% of non-electric cabinets and an **acceptable volume of data**, 10 772 photos.
- This class has a **unique and easy form** to detect



Poles :

A recall of 65% and a **precision of 81%**. These results can be explained by:

- A lack of data and highly imbalanced dataset (84,6% vs 15.4%).
- Poles of different networks are similar and features that distinguish the two are almost impossible to be caught by a model

Lines :

A recall of 65% and a **precision of 62%**. These results can be explained by:

- The difficult and tiny shape of cables and noisy background of images make the task difficult

Results of detection

Ground Truth

Predictions

Conclusion

- Object detector achieved a mean Average Precision (mAP) of 81.7% on the testing dataset across all classes.
- Complex noisy backgrounds pose challenges for the object detector when poles and cables are not centrally positioned within the image.
- The classifier performs well for electric and non-electric cabinets but struggles with cables and poles due to data scarcity, low resolution, and shape/scale variation.
- The upcoming photos from the FLOE mobile application will enhance the dataset in terms of quantity and quality, further improving the model's performance.
- An interesting future perspective is to explore anomaly detection for electrical grids, requiring a diverse and sizable pool of annotated photos to achieve meaningful results.

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