Computer Vision for Railway Maintenance

Bridging Deep Learning, Inspection Automation, and Asset Maintenance Workflows

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About the author

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- Over **13 years** of specialized engineering and design experience in complex railway infrastructure in the domain of Overhead Catenary Systems (OCS).
- Currently serving as **OCS Project Technical Manager** at Alstom and has been internally recognized as a "**World Class Engineering Expert**" in Overhead Catenary Systems (OCS).
- Currently pursuing **MTech in Artificial Intelligence Machine Learning**, BITS Pilani, Work Integrated Program
- **Core Engineering Expertise:** Led technical delivery for diverse electrification systems (25kV AC, 2x25kV, 750V/1.5kV DC) across Mainlines, Metros, and Freight corridors. With global project footprint includes India, Israel, Australia, Mexico, Philippines, Greece, Romania, and the Baltic region.
- **The Tech & Automation Edge**: Unlike traditional engineering management, I prioritize the development of software tools to reduce manual redundancy.
- **Current Focus:** Transitioning from traditional CAD Automation (AutoLISP/VisualLISP) to Python-based Machine Learning workflows for design optimisation.
- **Specialisation:** Rail Domain Engineering expertise, Project Engineering, Tender Technical Management, Interface Integration (ICDs), and Requirements Management (DOORs).

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- Elsevier
- RailFOD23 research team
- Drones4Safety consortium
- Hugging Face community
- Ultralytics YOLO project
- GitHub open-source contributors

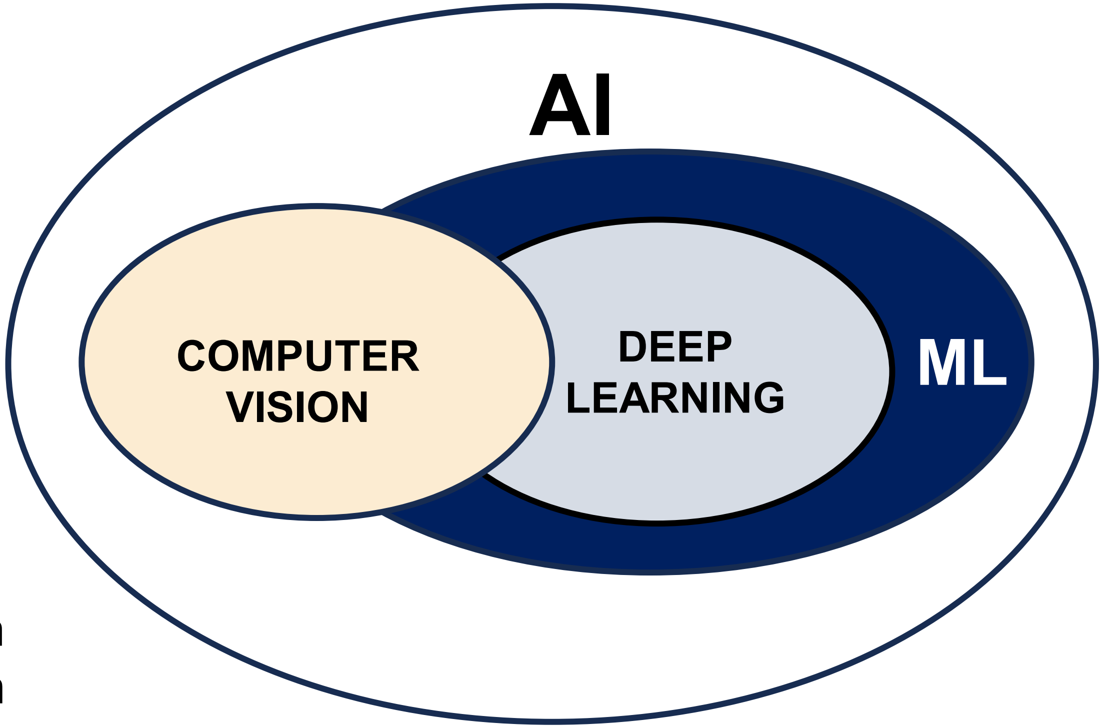
What is Computer Vision?

- **Computer vision** is a subfield of **artificial intelligence** that empowers machines to process, analyze, and interpret visual information from the world.

- It enables computers and systems to derive meaningful information from **digital images**, **videos,** and **other visual inputs** and act on that information.

Computer Vision for Railway Maintenance : In railway maintenance, this means using **inspection images, video streams, drone footage, vehicle-mounted cameras, or LiDAR point clouds** to

- Detect defects,
- Measure infrastructure condition, and
- Support maintenance planning.

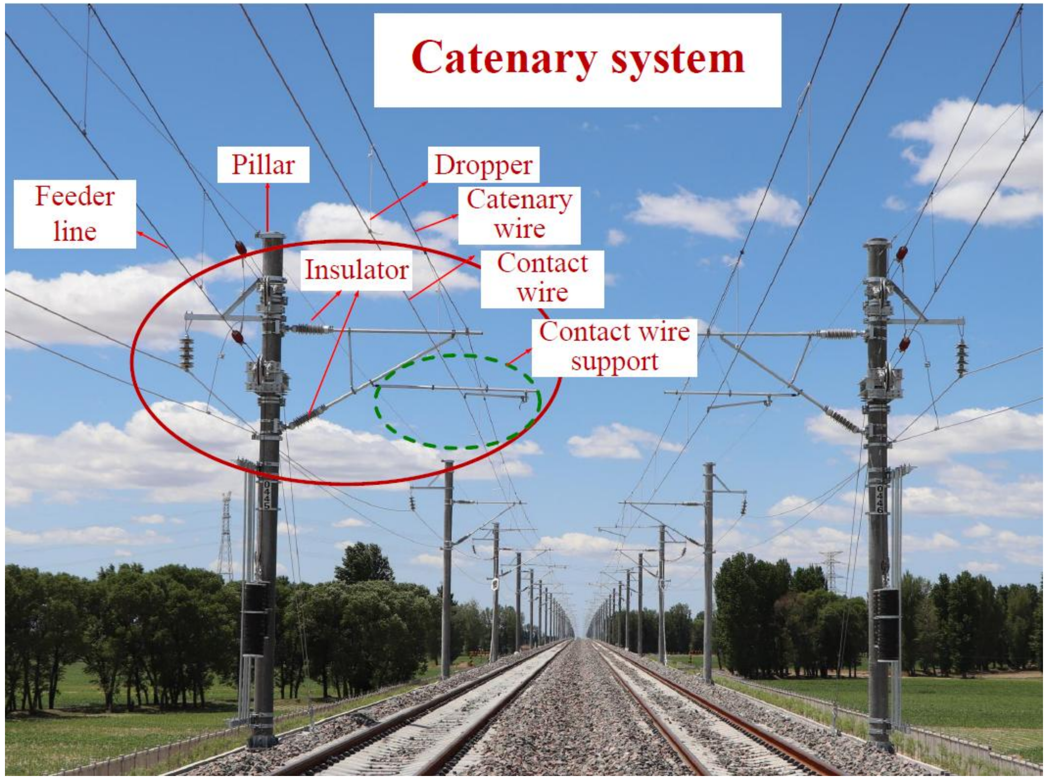


Computer vision is helpful in automating railway inspections workflows !!

Why Do Railways Need Automated Inspection?

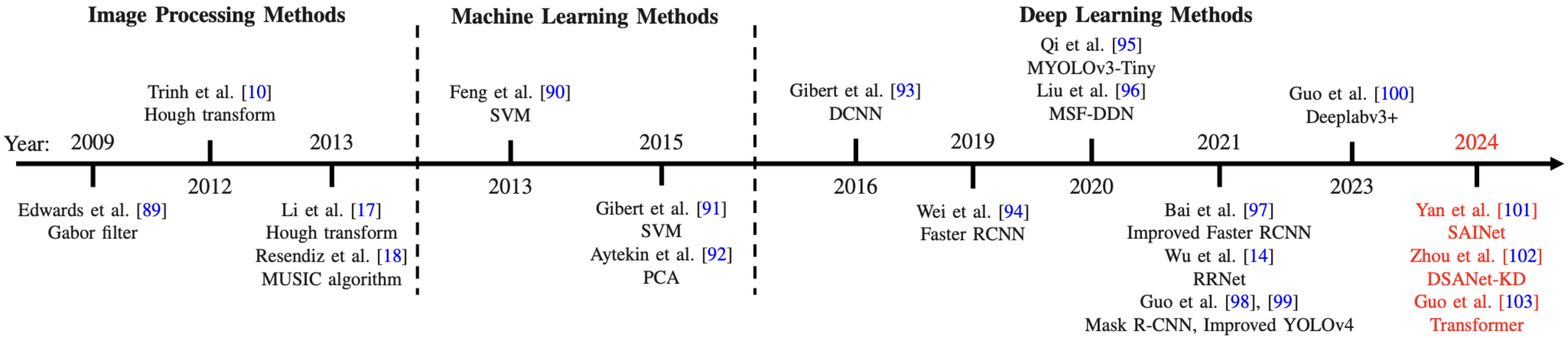
- Railway infrastructure spans across **hundreds/thousands of kilometers.**
- Indian rail network is **69,181kms (1,35,207 track length) – 4th largest rail network** across the world. (*Source: Indian Railways Annual Report & Accounts 2023–24 Ministry of Railways (Railway Board), Government of India)*
- Every kilometer of railway line consists of several assets of **electrical lines (OCS)** , **track systems**, **signaling systems** etc.., which keeps the several trains running daily.
- A typical Overhead Catenary System or OCS (electrical line which powers trains) on an average consists :
  - **6-8 insulators per 50mtrs**
  - **2-3 cantilever supports every 50mtrs**
  - **2-3 dropper clamp every 7-9mtrs**
  - **…and many more**
- **Thousands of assets per kilometer**, makes maintenance and monitoring of these assets a challenging task.
- **Modern inspection systems** generate **massive volumes of image and video data**. **Millions of inspection images** may be generated annually by **inspection vehicles, drones, and trackside monitoring systems**. Manual review becomes a bottleneck in maintenance workflows.
- Defects such as **cracks, deformations, loosened fittings and component wear** are difficult to detect consistently on such a large scale.

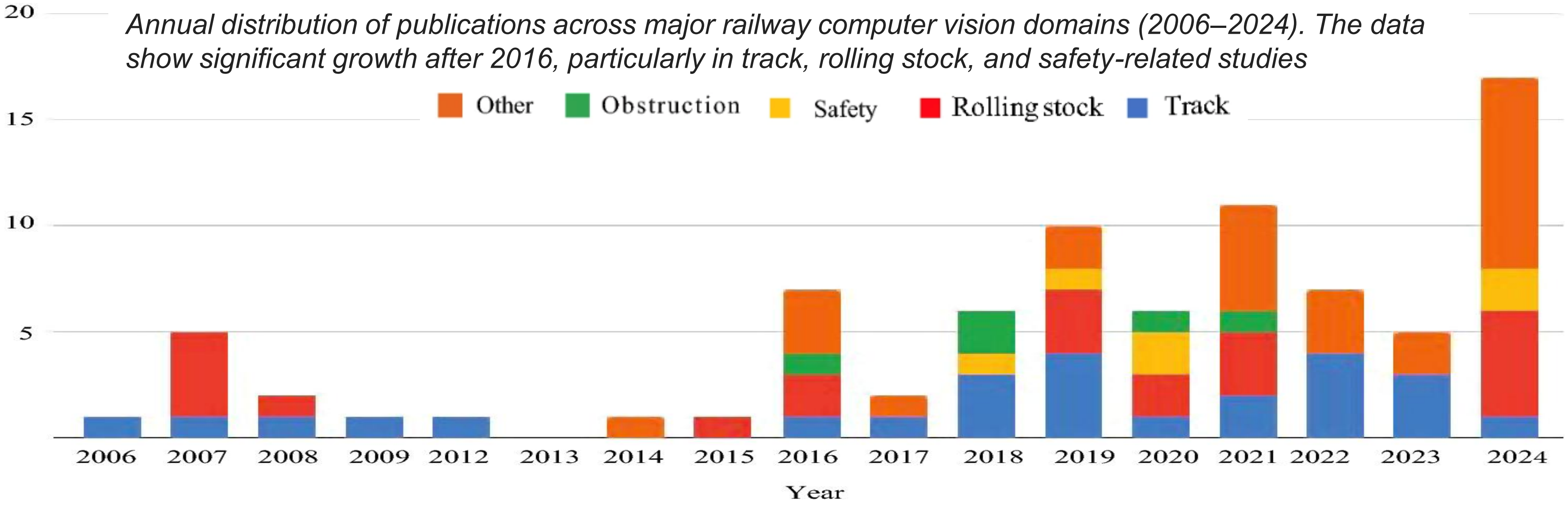
Railway line with Overhead Catenary System (OCS)



Source Publication (Image) : Wang, J.; Gao, S.; Yu, L.; Zhang, D.; Kou, L. Defect Severity Identification for a Catenary System Based on Deep Semantic Learning. Sensors 2022, 22, 9922. https://doi.org/10.3390/s22249922

Growth of Computer Vision in the era of Deep Learning

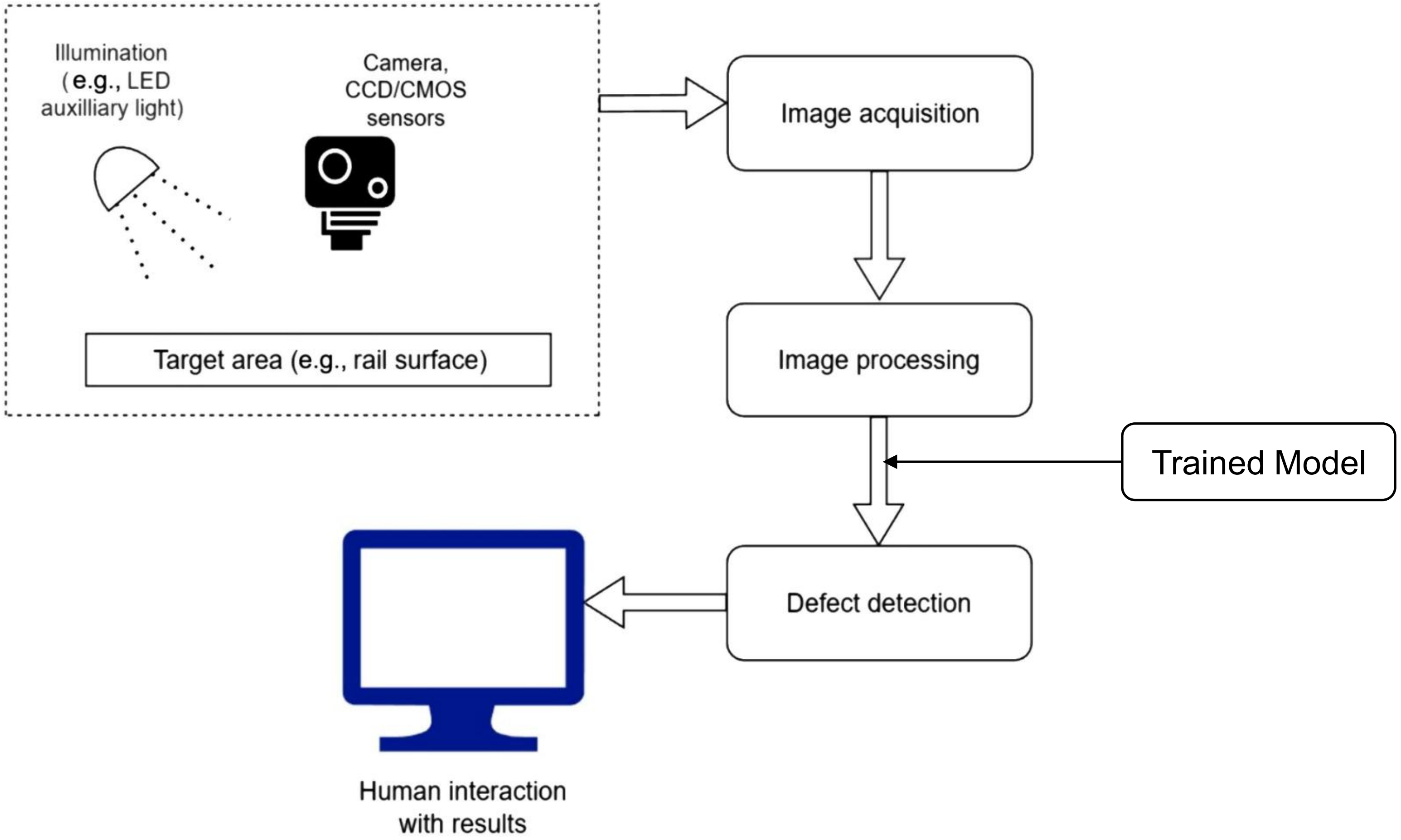




Annual distribution of publications across major railway computer vision domains (2006–2024). The data show significant growth after 2016, particularly in track, rolling stock, and safety-related studies

Figure reproduced from : Al Rabbani Alif, Mujadded & Tucker, Gareth & Hussain, Muhammad. (2026). Advances in computer vision for comprehensive railway engineering: from track inspection to rolling stock and safety monitoring. Railway Engineering Science. 10.1007/s40534-026-00434-7.

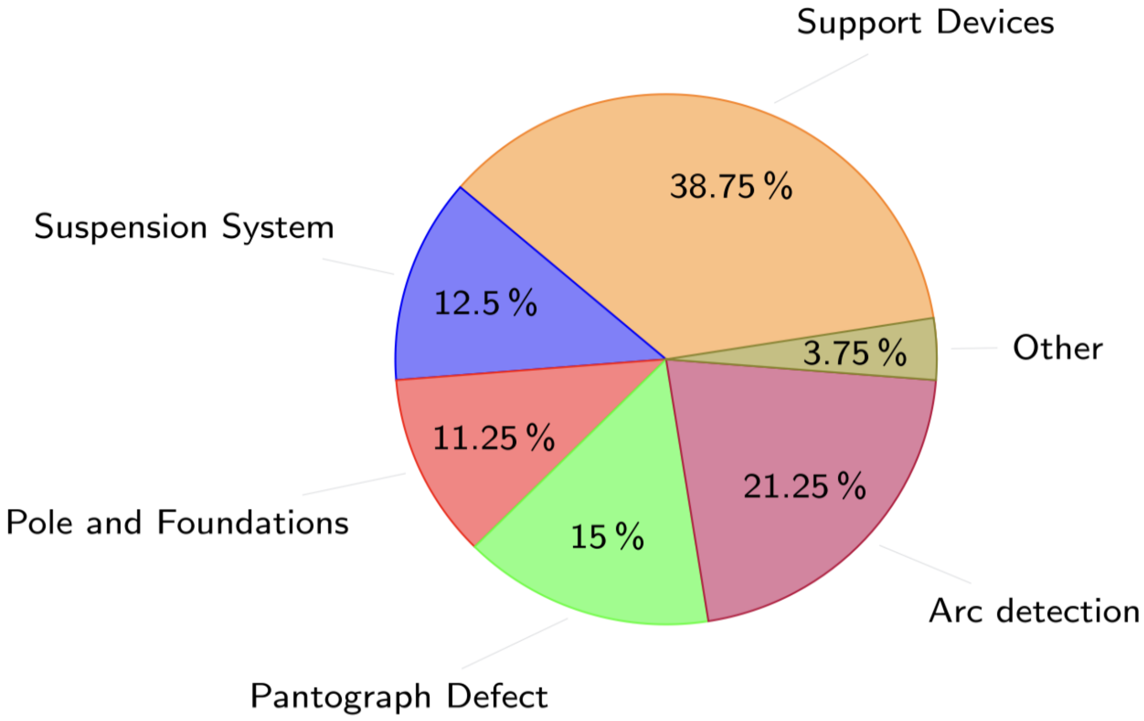
Typical Computer Vision Application for Defect Detection in Railway Systems



Source Publication : Kumar, A., & Harsha, S. P. (2024). A systematic literature review of defect detection in railways using machine vision-based inspection methods. International Journal of Transportation Science and Technology. https://doi.org/10.1016/j.ijtst.2024.06.006

Applications of Computer Vision in Overhead Catenary Systems

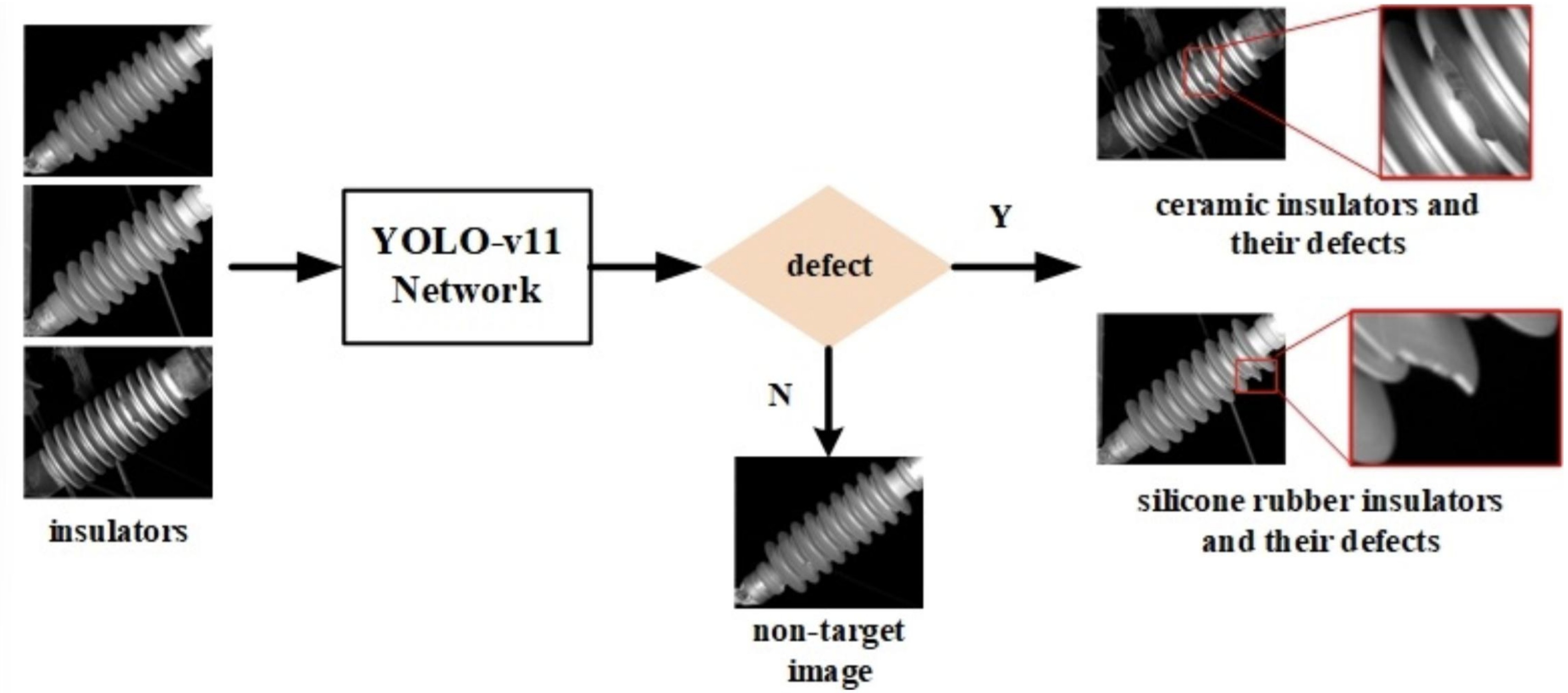
OCS Defect Detection using Computer Vision



Source Publication *"Jin He, Jinming He, Zhijian Gou, Fengmao Lv, Defect detection in railway catenary systems: a survey, Intelligent Transportation Infrastructure, Volume 4, 2025, liaf027, https://doi.org/10.1093/iti/liaf027"*

An Intelligent Approach Using YOLO-v11

Insulator Defect Detection and Classification

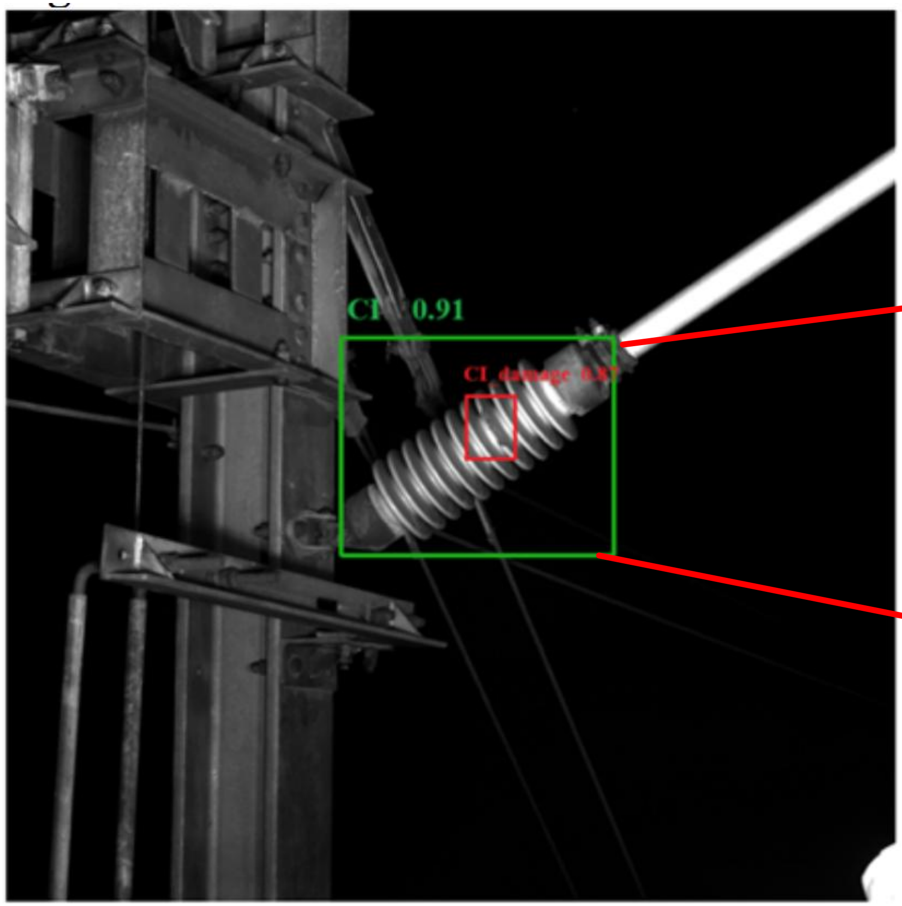


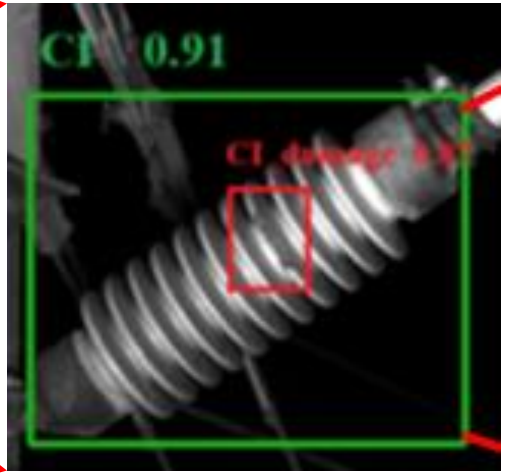
Source Publication :

X. Zheng, Y. Yan, N. Li, X. Li, and W. Huang, "Surface Defect Detection in High-speed Railway Overhead Contact System Insulators: An Intelligent Approach Using YOLO-v11," Journal of Engineering Science and Technology Review, vol. 18, no. 2, pp. 163-171, 2025

Surface Defect Detection in High-speed Railway Overhead Contact System Insulators

Insulator Defect Detection - Sample Results



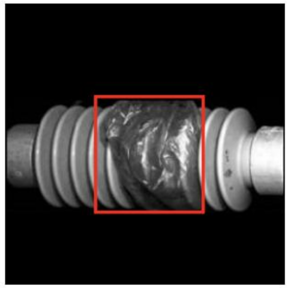
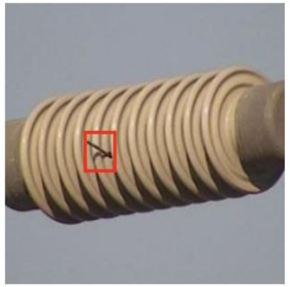


Defect detection – Ceramic insulator

Source Publication:
X. Zheng, Y. Yan, N. Li, X. Li, and W. Huang, "Surface Defect Detection in High-speed Railway Overhead Contact System Insulators: An Intelligent Approach Using YOLO-v11," Journal of Engineering Science and Technology Review, vol. 18, no. 2, pp. 163-171, 2025

Insulator Defect Detection & Captioning

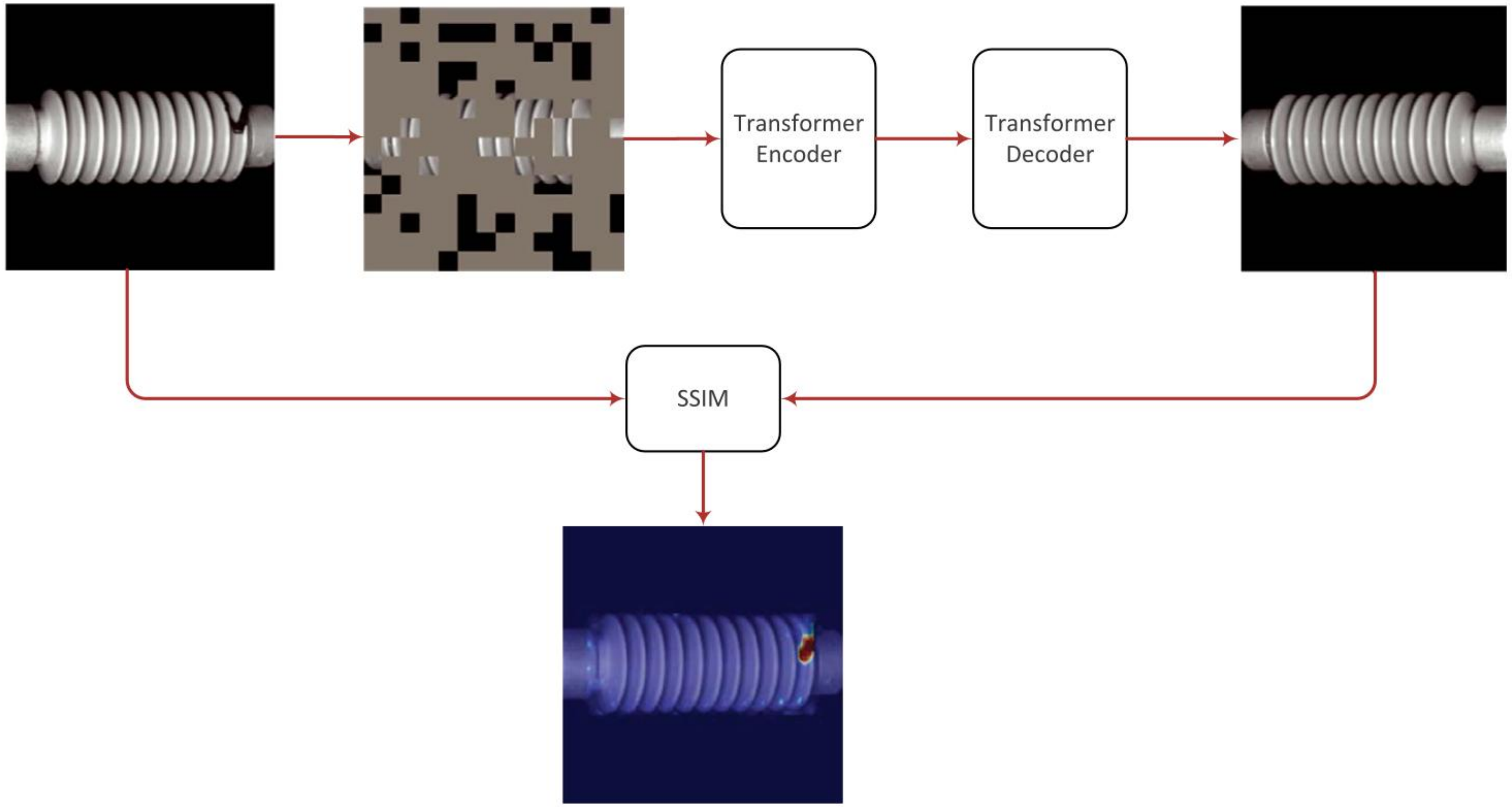
Defect detection & captioning using Co-InsCap

Image	Image Caption	Image	Image Caption
	**1.LSTM:** **caption:** "an insulator can be used **normally**" **2.LLaVA:** **caption:** "the insulator in the image has a piece of **plastic**, wrapped around it" **3.Ours:** **caption: "a black plastic bag on the insulator"**		**1.LSTM:** **caption:** "an insulator can be used normally can cause **problems**" **2.LLaVA:** **caption:** "the insulator in the image has **a hole** in it, which is a defect that can cause electrical issues" **3.Ours:** **caption: "an insulator damaged by wire have a problem"**

IEEE Publication :
Y. Chen, Z. An, and J. Zhou, "Co-InsCap: Collaborative Detection and Image Caption for Defective Insulator of High-Speed Railway Catenary," IEEE Transactions on Instrumentation and Measurement, vol. 74, 2025.

Insulator Anomaly Detection

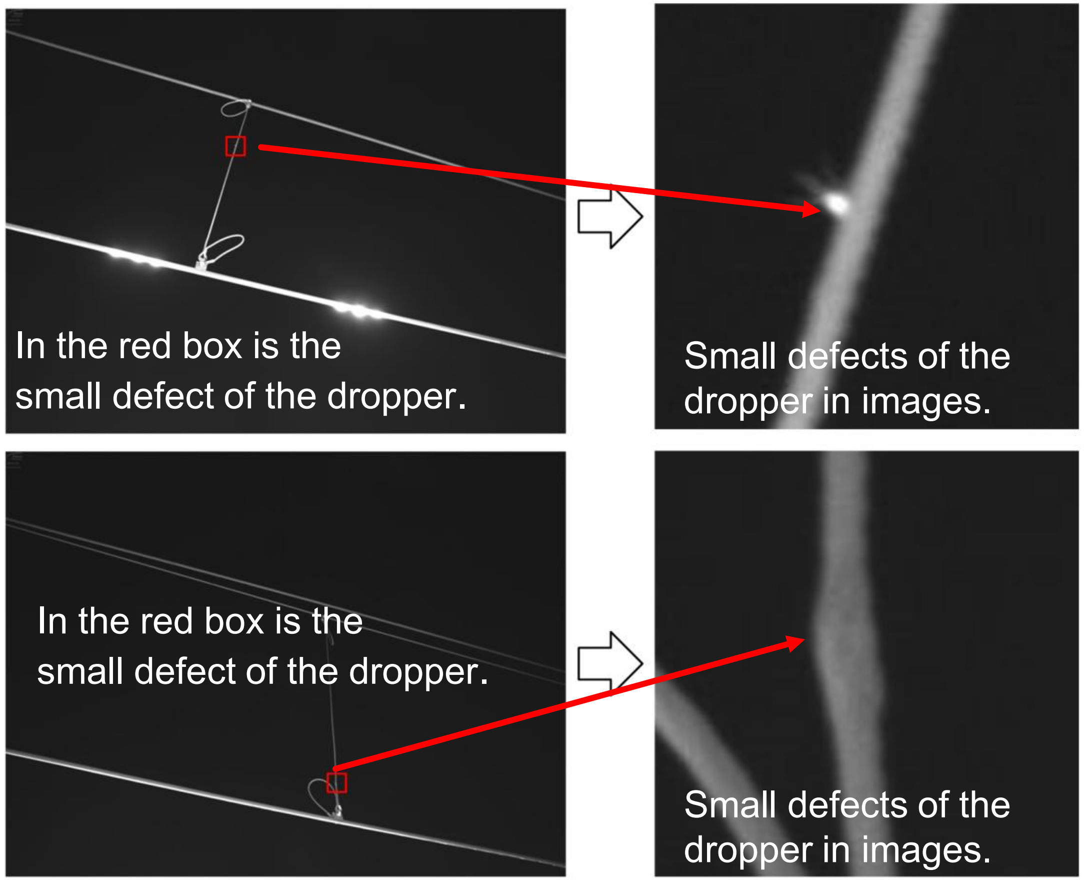
Masked Autoencoder (MAE) + SSIM



IEEE Publication Reference :
Catenary Insulator Defect Detection: A Dataset and an Unsupervised Baseline
T. Zhang et al., IEEE TIM, 2024

Detection of dropper defects

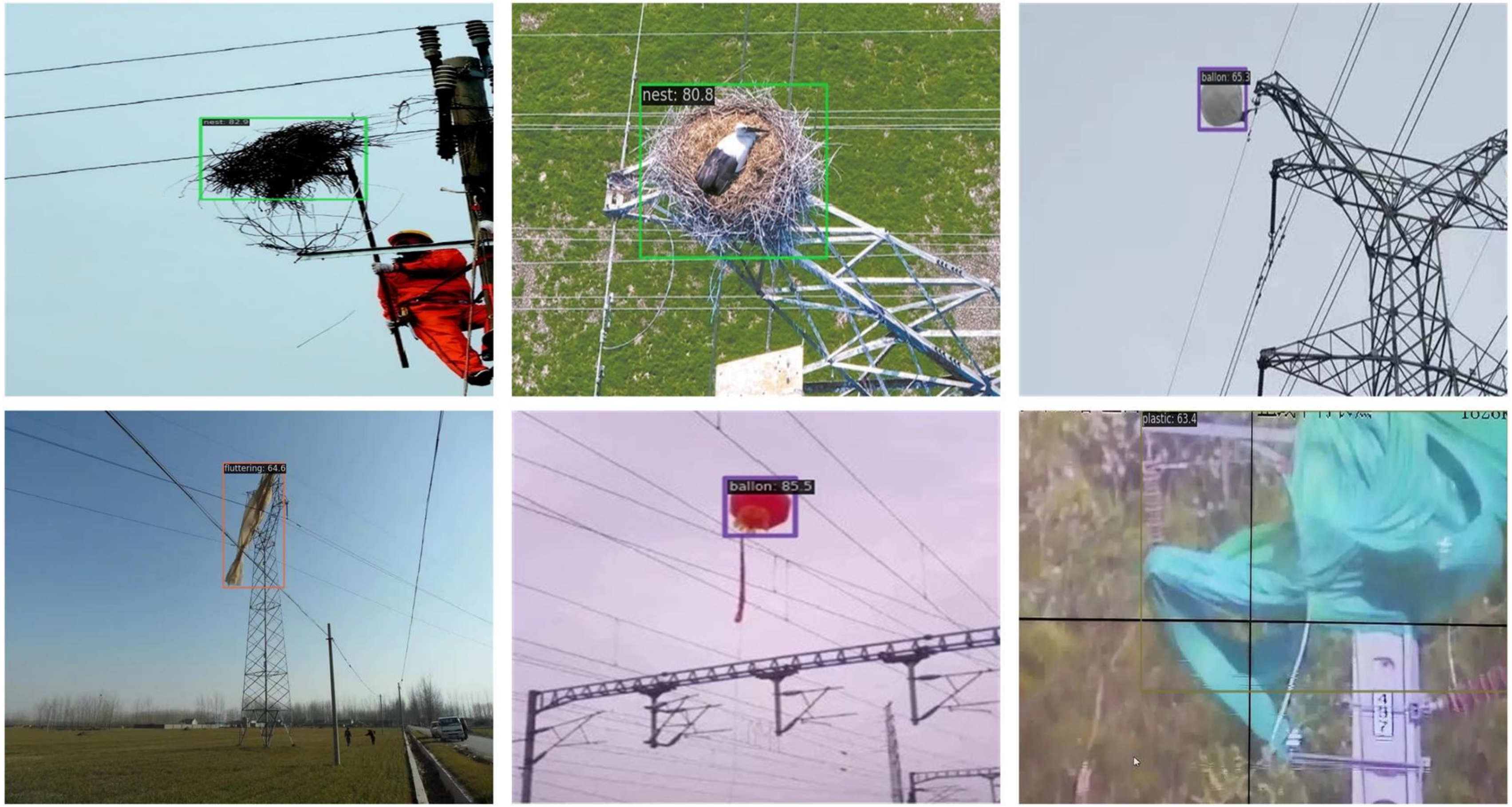
YOLO v5s + SK Attention Module



Source Publication :
Li Z, Rao Z, Ding L, Ding B, Fang J, Ma X. YOLOv5s-D: A Railway Catenary Dropper State Identification and Small Defect Detection Model. *Applied Sciences*. 2023; 13(13):7881. https://doi.org/10.3390/app13137881

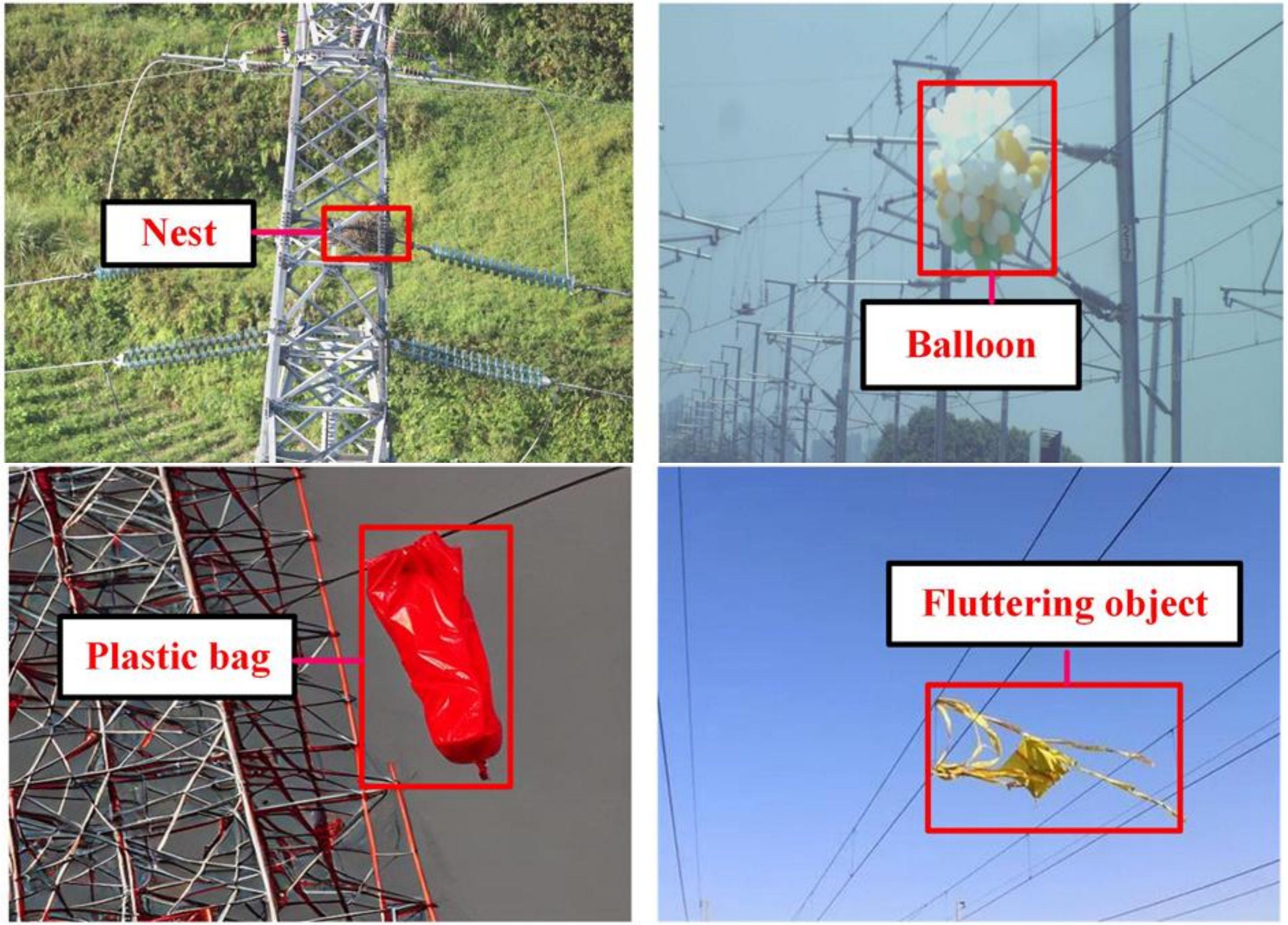
Foreign Object Detection

Foreign Object Detection on OCS Lines



Source Publication :
Chen, Z., Yang, J., Feng, Z. et al. RailFOD23: A dataset for foreign object detection on railroad transmission lines. Sci Data 11, 72 (2024). https://doi.org/10.1038/s41597-024-02918-9

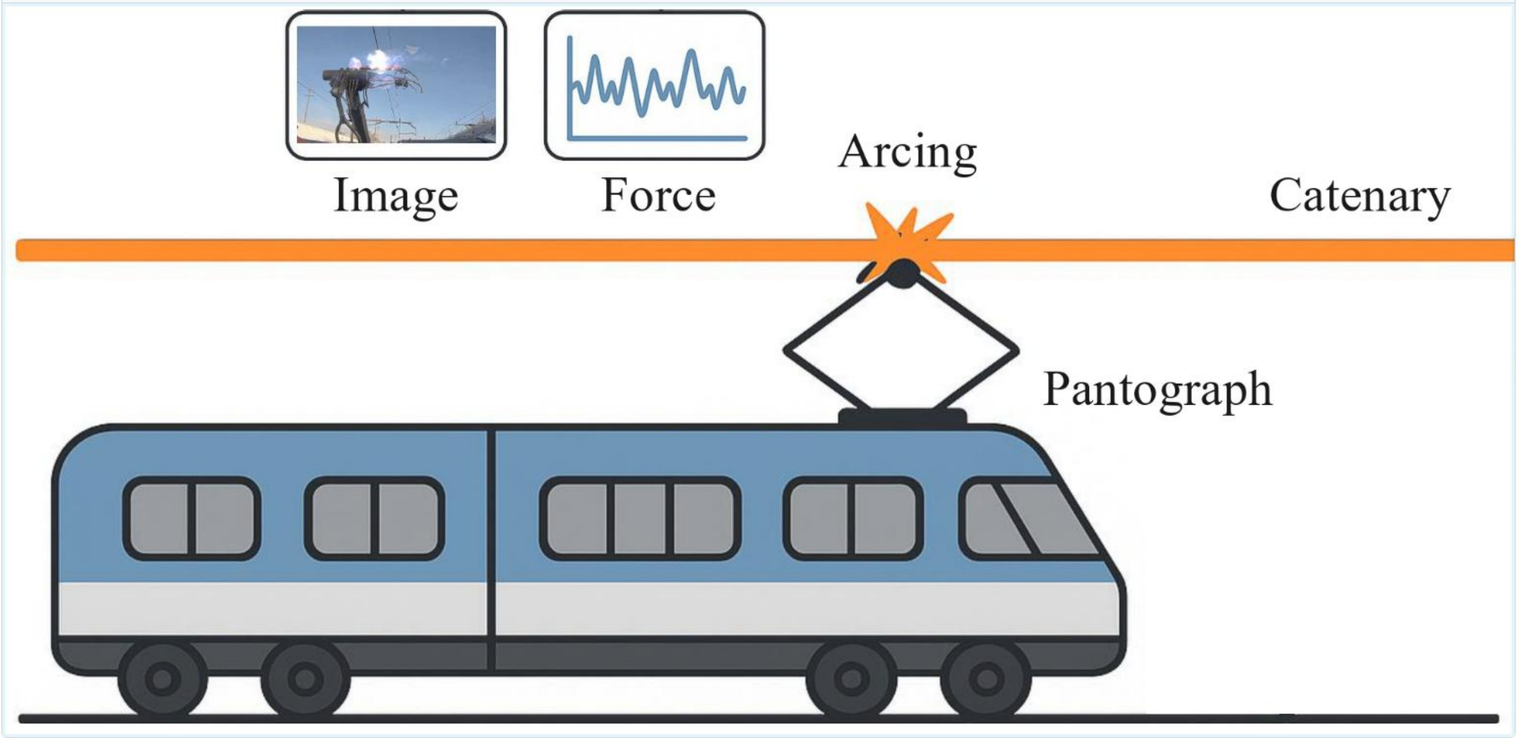
Foreign Object Detection



Source Publication :
Chen, Z., Yang, J., Feng, Z. *et al.* RailFOD23: A dataset for foreign object detection on railroad transmission lines. *Sci Data* **11**, 72 (2024). https://doi.org/10.1038/s41597-024-02918-9

Multimodal Learning for Arcing Detection in Pantograph-Catenary Systems

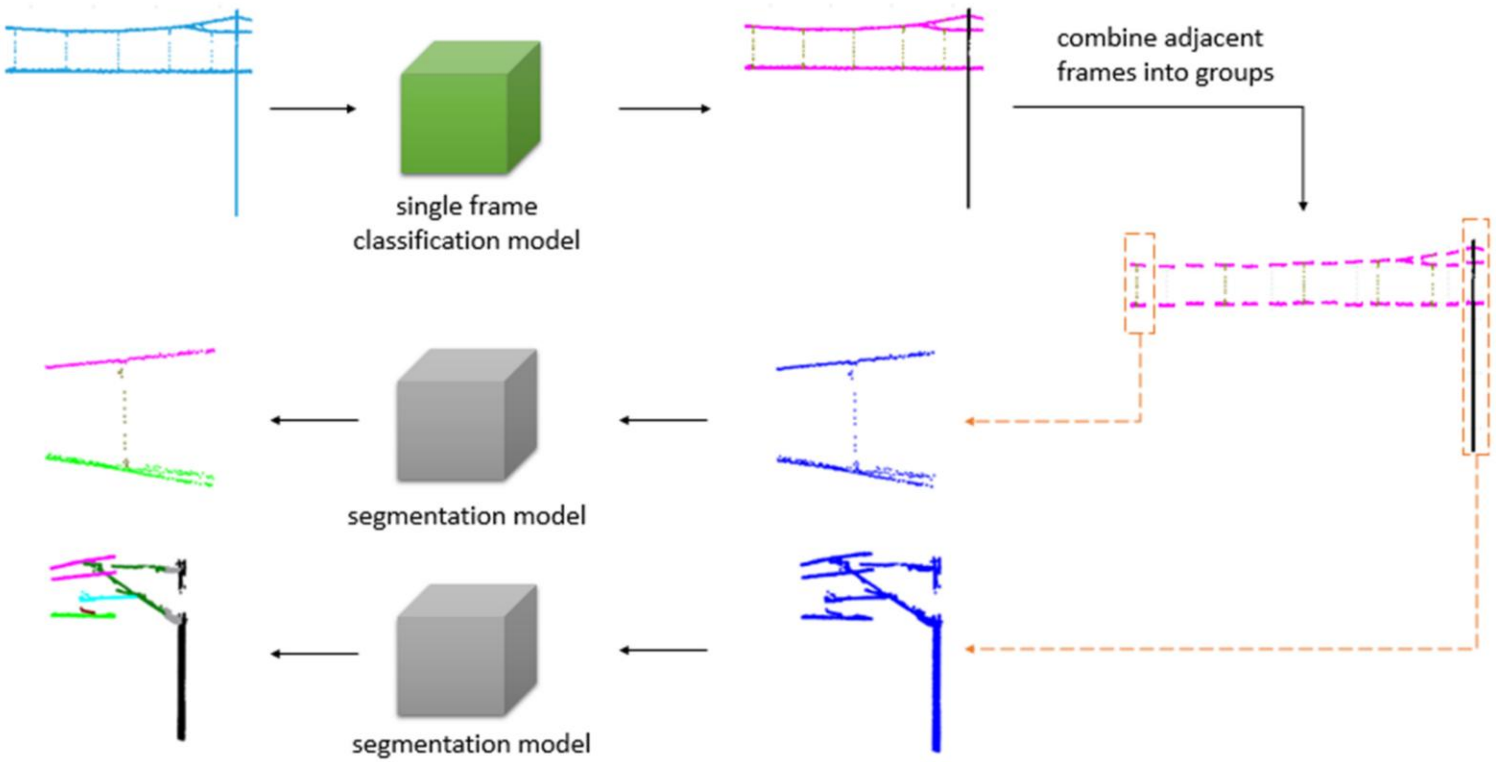
Arcing Detection in Pantograph-Catenary Systems



Source Publication :
Dong et al., Multimodal Learning for Arcing Detection in Pantograph-Catenary Systems, arXiv:2602.08792, 2026”
(Note : arXiv preprint currently under review at the time of release of this document)

Sematic Segmentation of 3D LiDAR point cloud data using Deep Learning Methods for automated OCS parameter measurements

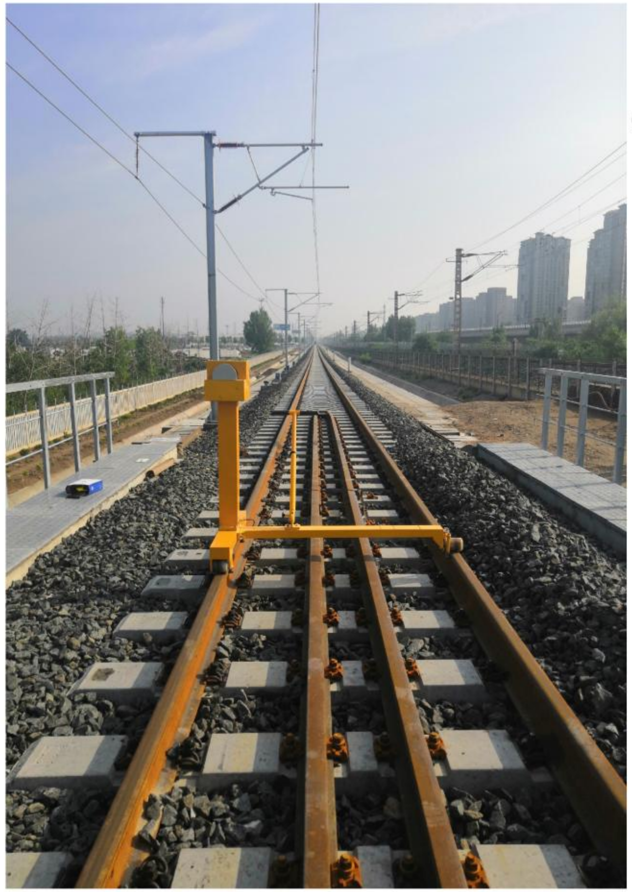
OCS Parameter Measurements using 3D Computer Vision

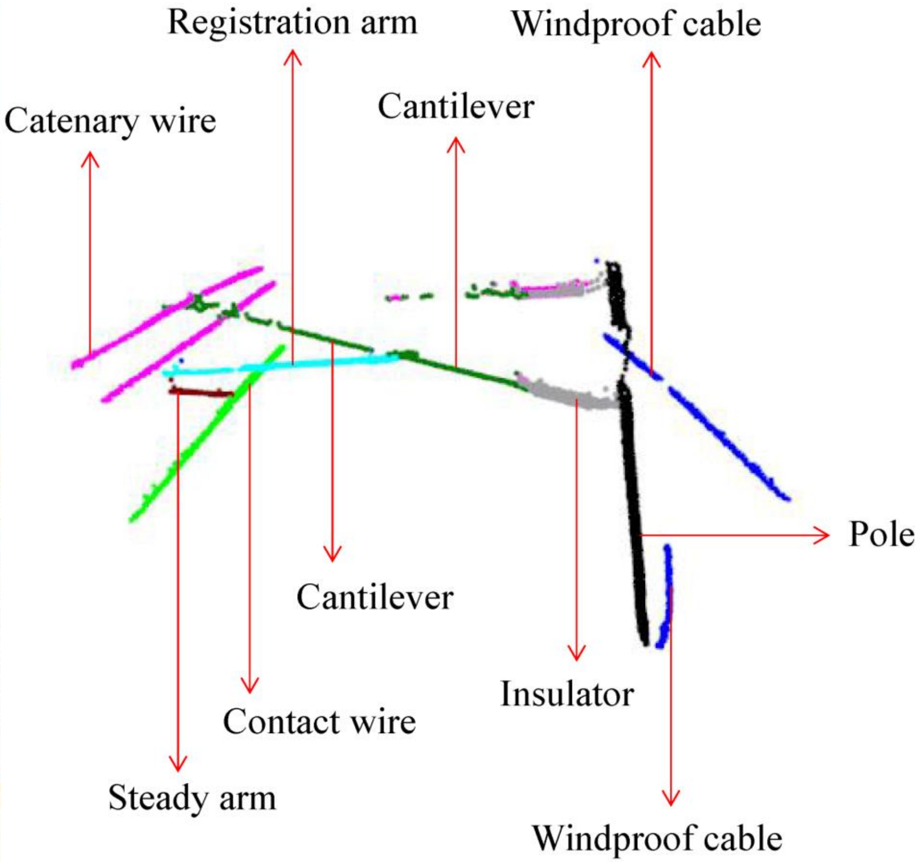


Source Publication :
Lin, S.; Xu, C.; Chen, L.; Li, S.; Tu, X. LiDAR Point Cloud Recognition of Overhead Catenary System with Deep Learning. Sensors 2020, 20, 2212. https://doi.org/10.3390/s20082212

OCS Parameter Measurements using 3D Computer Vision

Deep Neural Network for Overhead Contact System Recognition from LiDAR Point Clouds





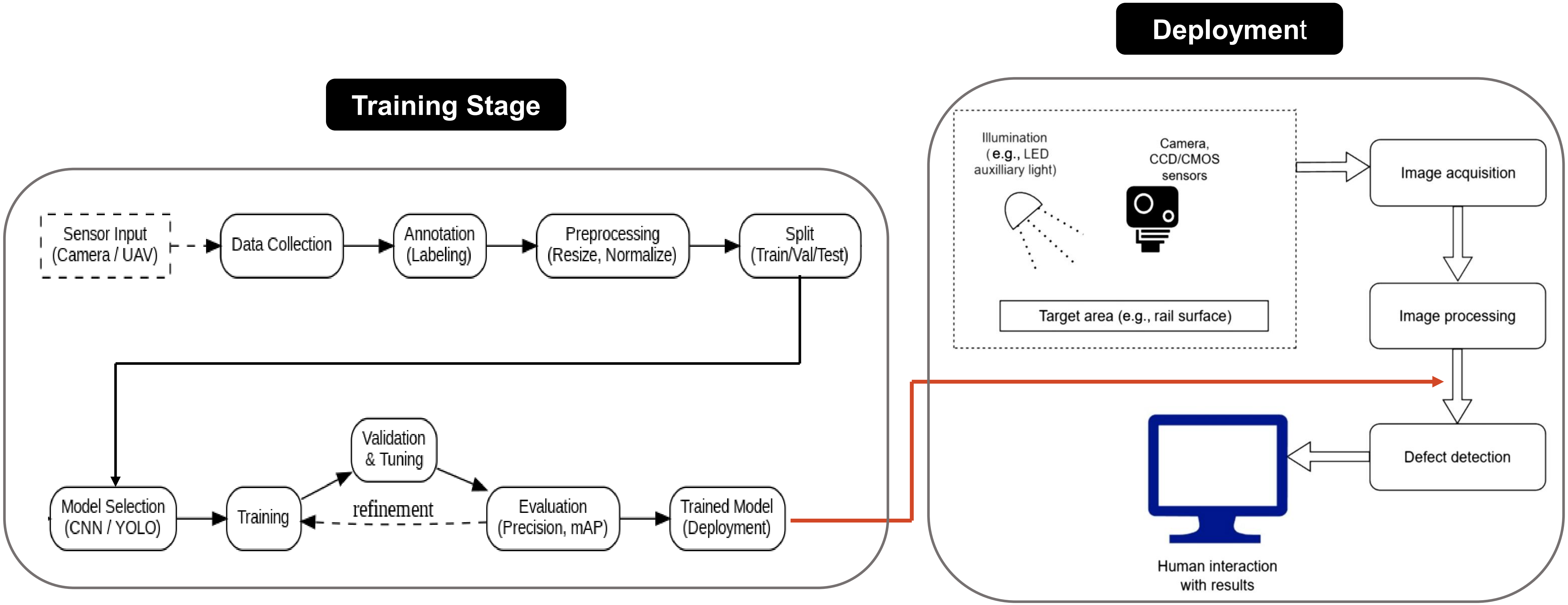
Inspection robot

Point cloud recognition

Source Publication :
Liu, S.; Tu, X.; Xu, C.; Chen, L.; Lin, S.; Li, R. An Optimized Deep Neural Network for Overhead Contact System Recognition from LiDAR Point Clouds. Remote Sens. 2021, 13, 4110. https://doi.org/10.3390/rs13204110

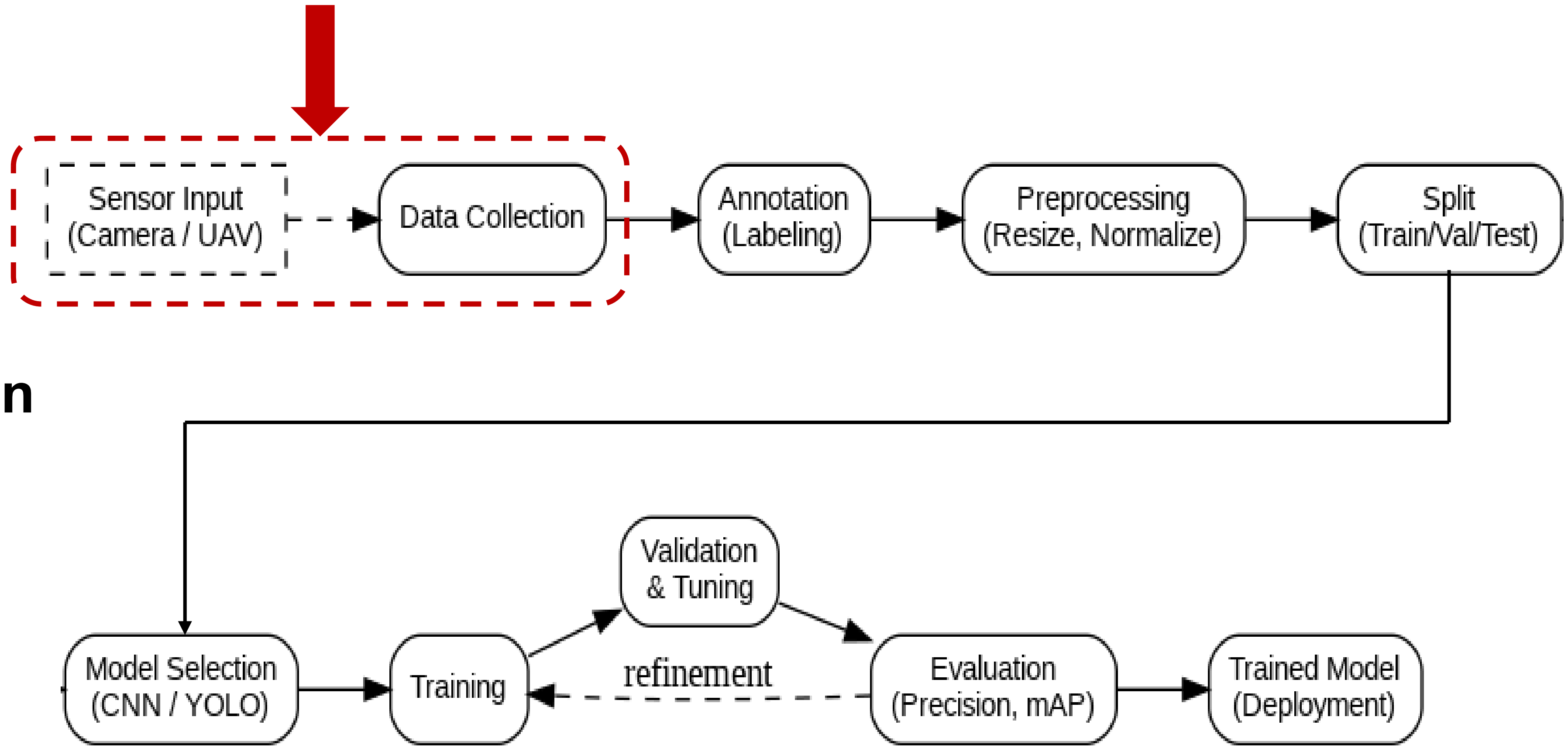
Computer Vision
Model Training & Deployment

Computer Vision Model Training & Deployment Cycle



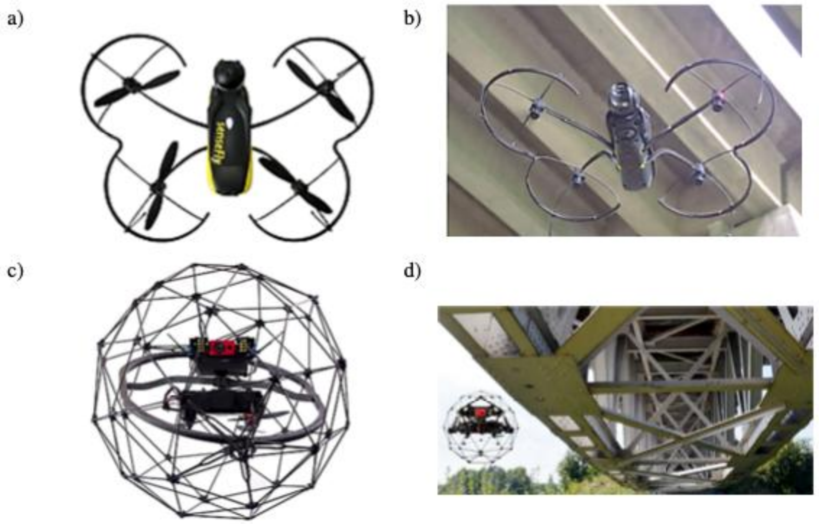
Training Stage

Data Collection/Acquisition

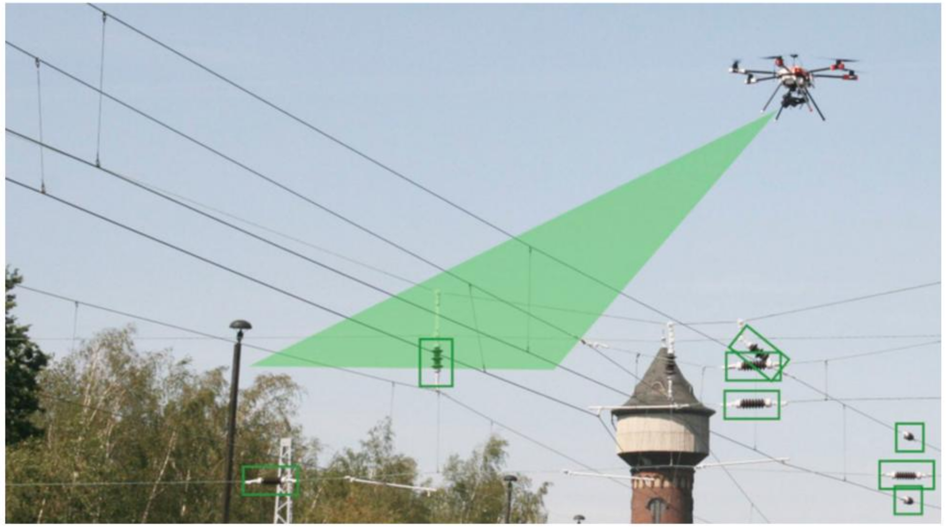


Data / Image Acquisition

Unmanned aerial vehicle cameras



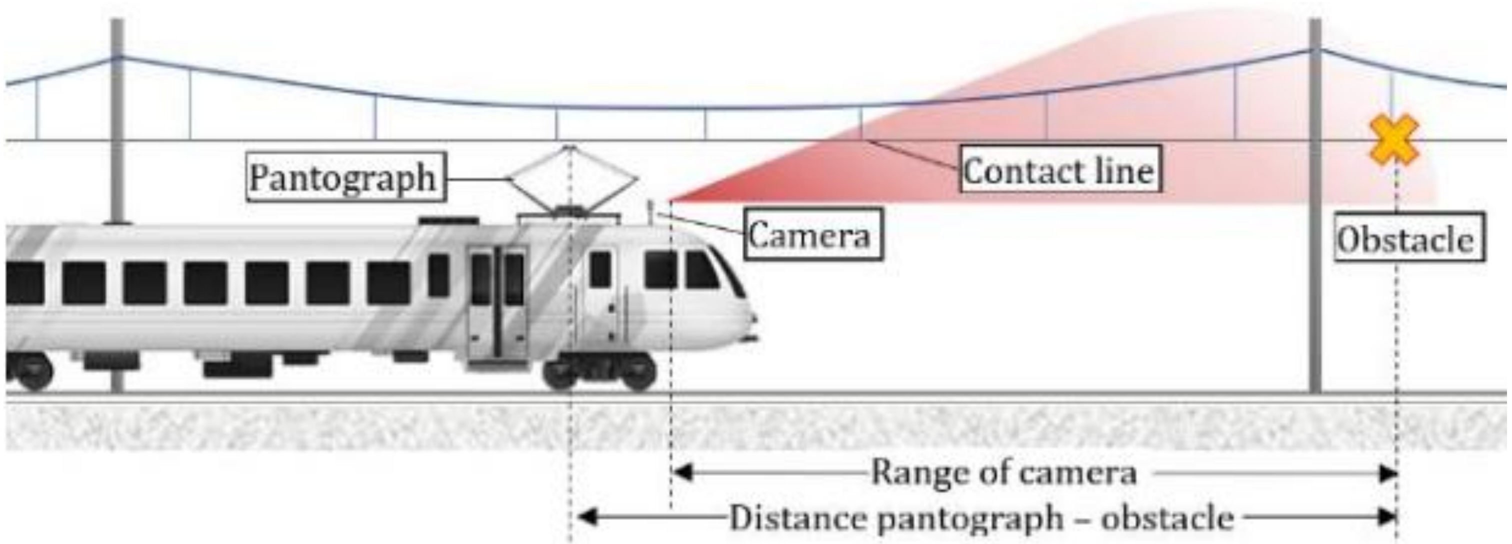
Source Publication : Lesiak, Piotr. (2021). Drones in the inspection of railway engineering facilities. Transportation Overview - Przeglad Komunikacyjny. 1-10. 10.35117/A_ENG_21_04_01.



Source Publication : Zschiesche, K.; Reiterer, A. Optical Measurement System for Monitoring Railway Infrastructure—A Review. Appl. Sci. 2024, 14, 8801. https://doi.org/10.3390/app14198801

Data / Image Acquisition

Vehicle-borne cameras (top mounted)

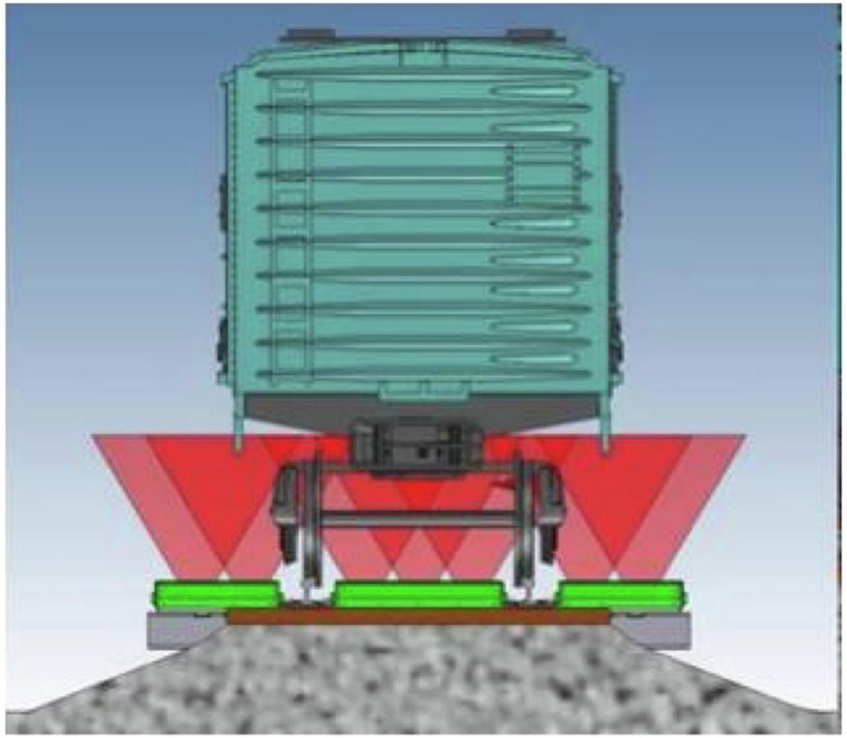


- OCS monitoring
- Pantograph – OCS interactions
- Arc detection

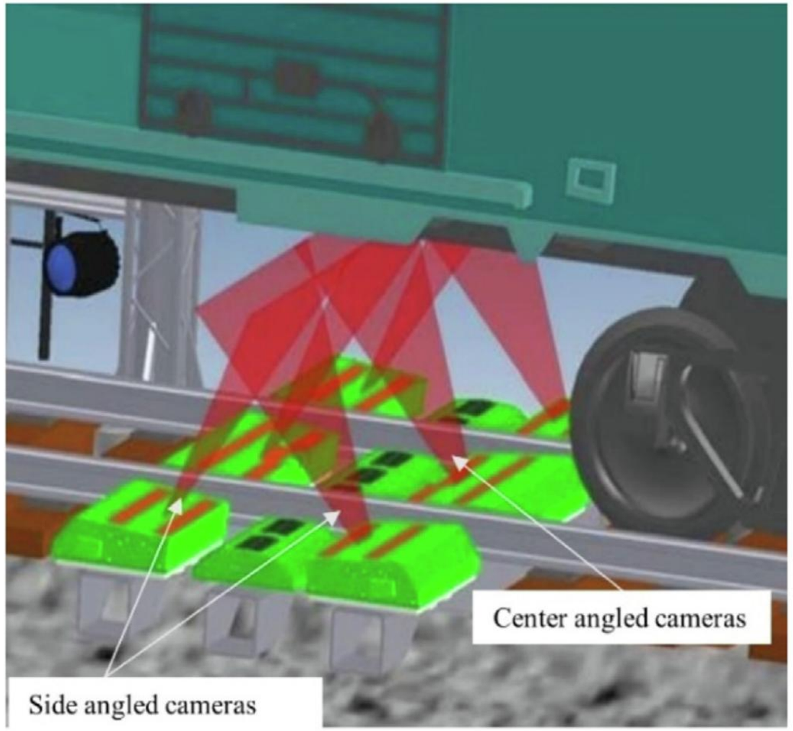
Source Publication : Romadoni, Achmad et al. “A Review in Automatic Visual Inspection for Railway Overhead Contact Line Systems based on Image Processing.” .

Data / Image Acquisition

Undercarriage Inspection system



Straight vertical looking cameras



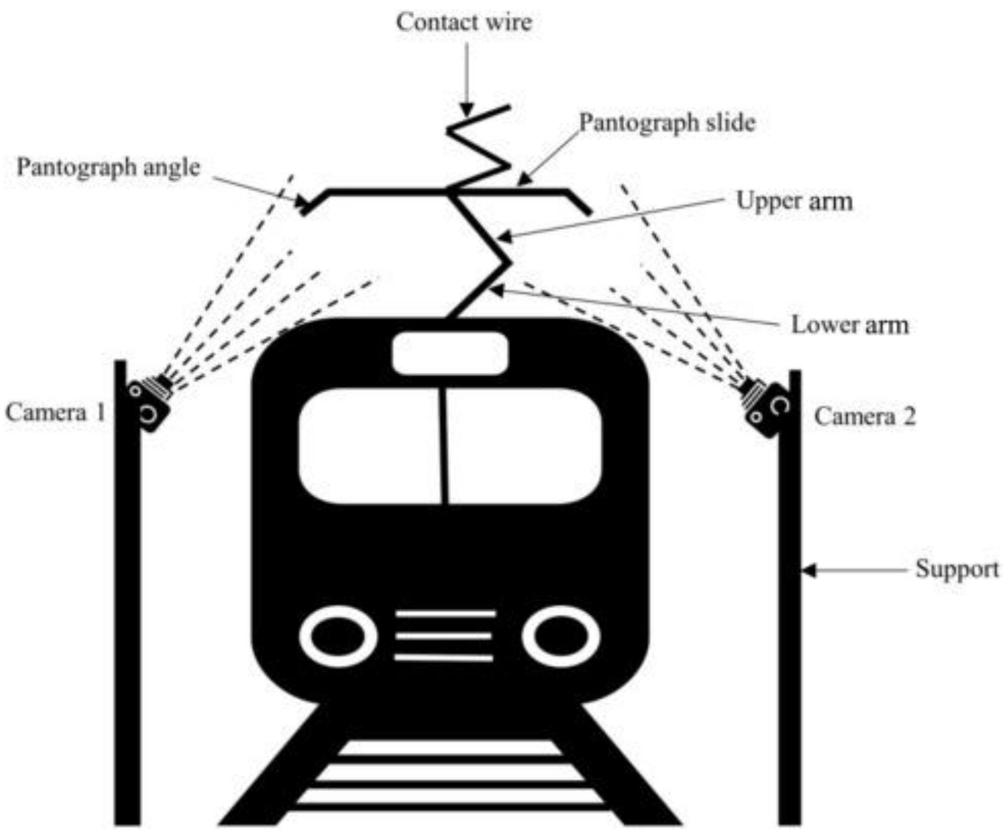
Angle-based camera placement

- Track/Rail Surface
- Ballast
- Sleepers
- Rail fasteners

Source Publication : Kumar, A., & Harsha, S. P. (2024). A systematic literature review of defect detection in railways using machine vision-based inspection methods. International Journal of Transportation Science and Technology. https://doi.org/10.1016/j.ijtst.2024.06.006

Data / Image Acquisition

Way side camera mounting or train scanners

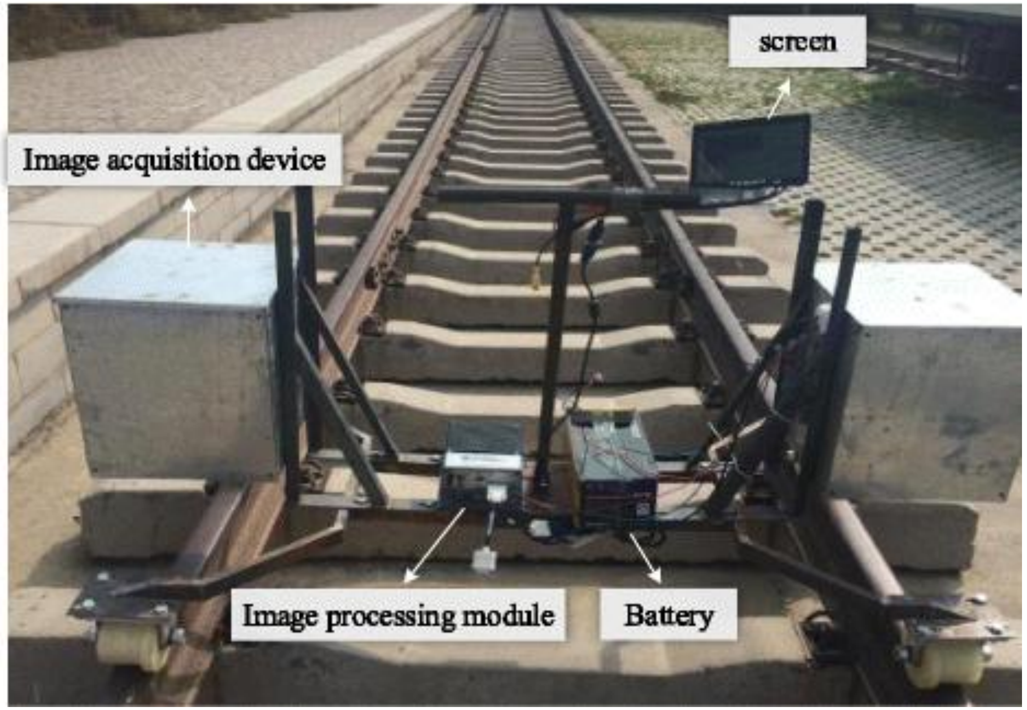


- Pantograph monitoring
- Train scanner
- Rolling stock inspections

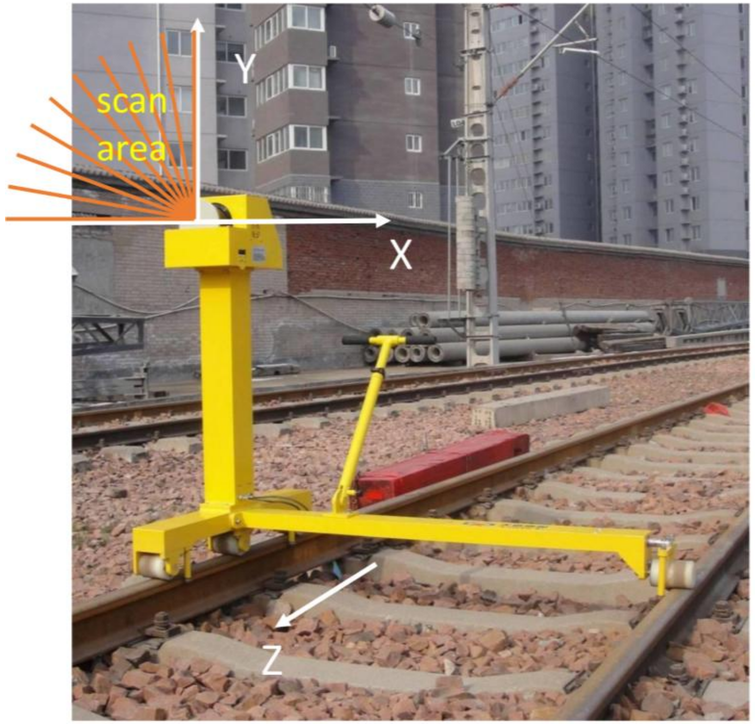
Source Publication : Kumar, A., & Harsha, S. P. (2024). A systematic literature review of defect detection in railways using machine vision-based inspection methods. International Journal of Transportation Science and Technology. https://doi.org/10.1016/j.ijtst.2024.06.006

Data / Image Acquisition

Inspection Trolley Mounted Image Acquisition



Real time detection system for rail surface defects based on computer vision



LiDAR equipment mounted on trolley

- Track inspections
- Way side inspections
- Point cloud construction using LiDAR

Source Publication : Min, Y., Xiao, B., Dang, J. *et al.* Real time detection system for rail surface defects based on machine vision. *J Image Video Proc.* **2018**, 3 (2018). https://doi.org/10.1186/s13640-017-0241-y

Source Publication : Lin, S.; Xu, C.; Chen, L.; Li, S.; Tu, X. LiDAR Point Cloud Recognition of Overhead Catenary System with Deep Learning. Sensors 2020, 20, 2212. https://doi.org/10.3390/s20082212

Data / Image Acquisition

Data from inspection car carrying sensor devices

Active rail inspection car carries instruments such as ultrasonic sensors, visual sensors, and laser sensors to actively detect the surface quality of the rail.

Source Publication : Wang, Y.; Miao, B.; Zhang, Y.; Huang, Z.; Xu, S. Review on Rail Damage Detection Technologies for High-Speed Trains. *Appl. Sci.* **2025**, *15*, 7725. https://doi.org/10.3390/app15147725

Data / Image Acquisition

Track robots equipped with cameras

(a)

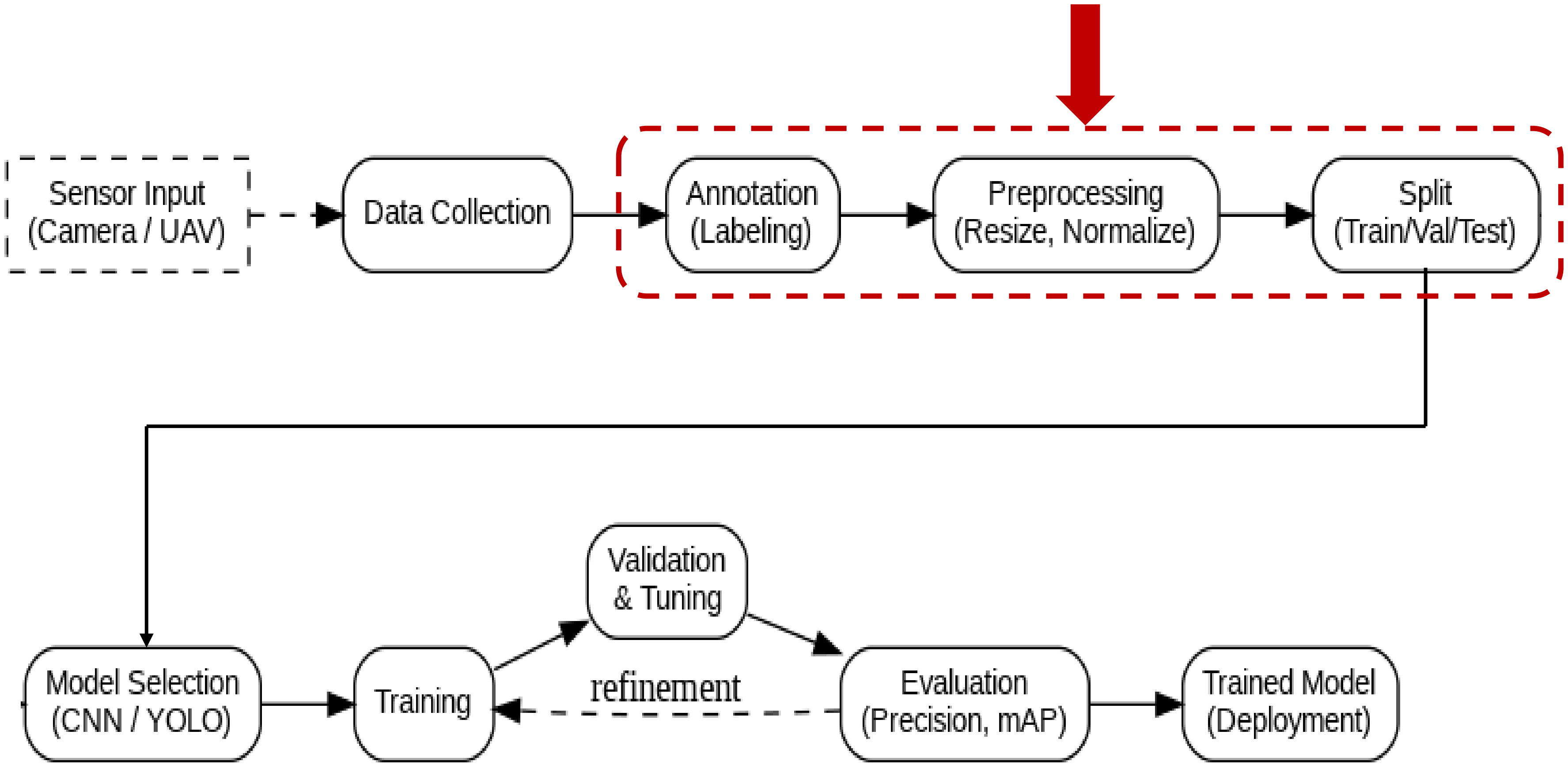
(b)

under vehicle inspection

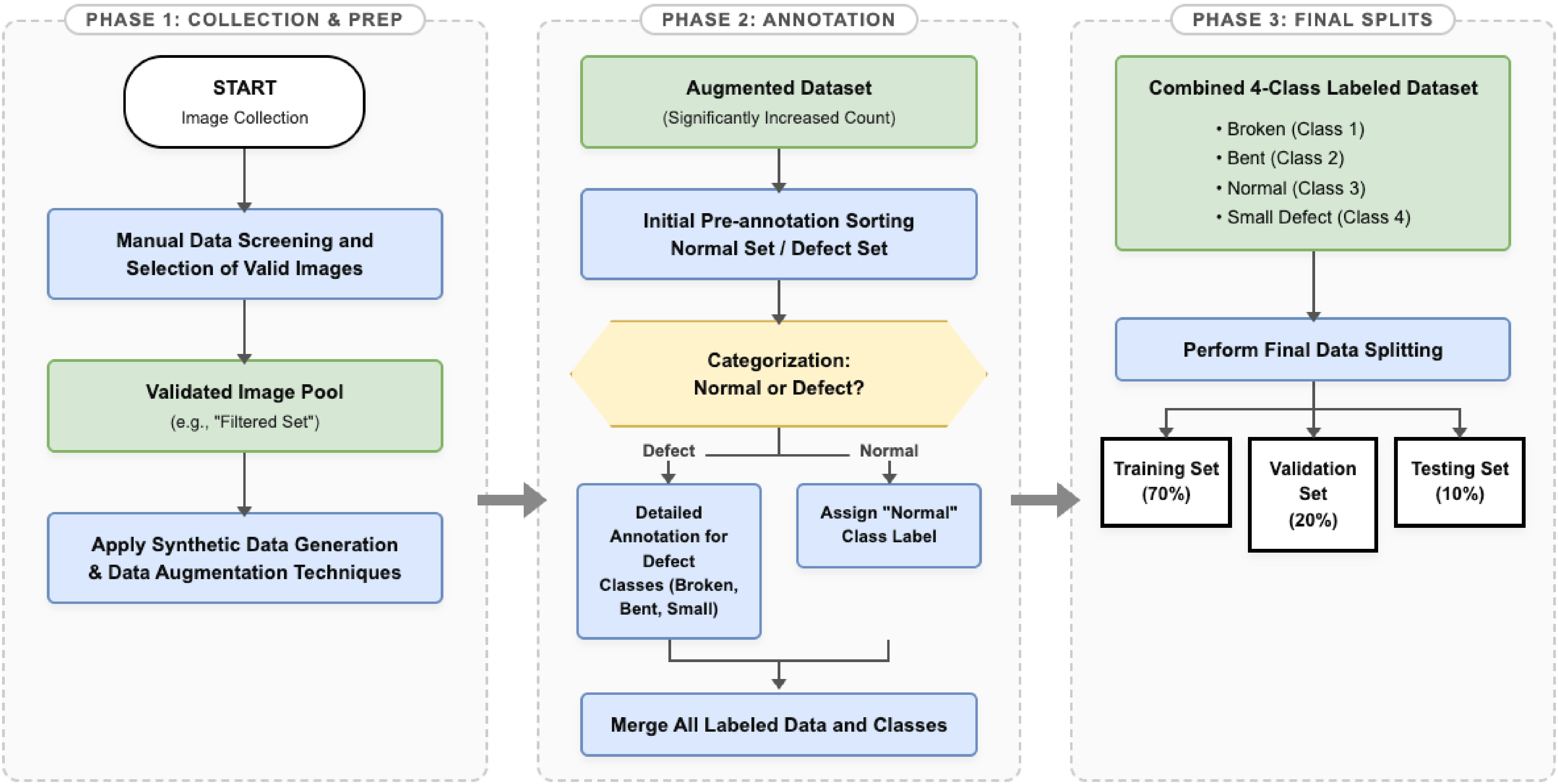
Source Publication : Kasch, J., & Ahmadian, M. (2024). Design and Operational Assessment of a Railroad Track Robot for Railcar Undercarriage Condition Inspection. *Designs*, *8*(4), 70. https://doi.org/10.3390/designs8040070

Training Stage

Annotation/ Labelling, Preprocessing & Data Split



Data labelling & Dataset Split (Train/Val/Test)



Case Study - Automatic Defect Detection of Dropper Suspension
Dataset Preparation & Labelling Example

Defect Categories

(a)broken dropper (dxdx) (b)bent dropper (wqdx) (c)normal dropper (zcdx) (d)small defect (xxqx)

Defect Categories

- Broken Dropper
- Bent Dropper
- Normal Dropper
- Dropper with Small Defects

Note :

1. These are not the only defects in droppers.
2. To cover more defect types, the model must be trained with additional datasets with additional defect type.

Source Publication : Li Z, Rao Z, Ding L, Ding B, Fang J, Ma X. YOLOv5s-D: A Railway Catenary Dropper State Identification and Small Defect Detection Model. *Applied Sciences*. 2023; 13(13):7881. https://doi.org/10.3390/app13137881

Case Study - Automatic Defect Detection of Dropper Suspension Dataset Preparation & Labelling Example

Image Acquisition

- Images collected using a high-speed railway catenary monitoring device.
- Initial dataset: 1,532 dropper images.
- After manual screening and removal of images without droppers:1,056 valid dropper images retained.

Challenge

- Dataset was highly imbalanced
- Majority of samples were normal droppers – 95%+
- Limited number of faulty droppers.
- Insufficient defect samples can lead to model overfitting and poor generalization.

Dataset Augmentation

- CycleGAN used to generate additional defect images.
- Further augmentation through image enhancement techniques.
- Final dataset size increased to 4,224 images:2,612 Normal droppers1,612 Defective droppers

1532 Images Collected
↓
Manual Screening
↓
1056 Valid Images
↓
CycleGAN + Data Augmentation
↓
4224 Images

| Normal 2612 | Defect 1612 |

↓
Annotation (Labeling)
↓
4 Classes:
Broken | Bent | Normal | Small Defect
↓
Train (70%) | Val (20%) | Test (10%)

Research team has not published the dataset as open source

Source Publication : Li Z, Rao Z, Ding L, Ding B, Fang J, Ma X. YOLOv5s-D: A Railway Catenary Dropper State Identification and Small Defect Detection Model. *Applied Sciences*. 2023; 13(13):7881. https://doi.org/10.3390/app13137881

Data Augmentation and Synthetic Data Generation

Challenge : Imbalanced Data Sets
(Eg : Majority images belong to normal class, Limited number of examples with defects, Insufficient defect samples can lead to model overfitting and poor generalization)

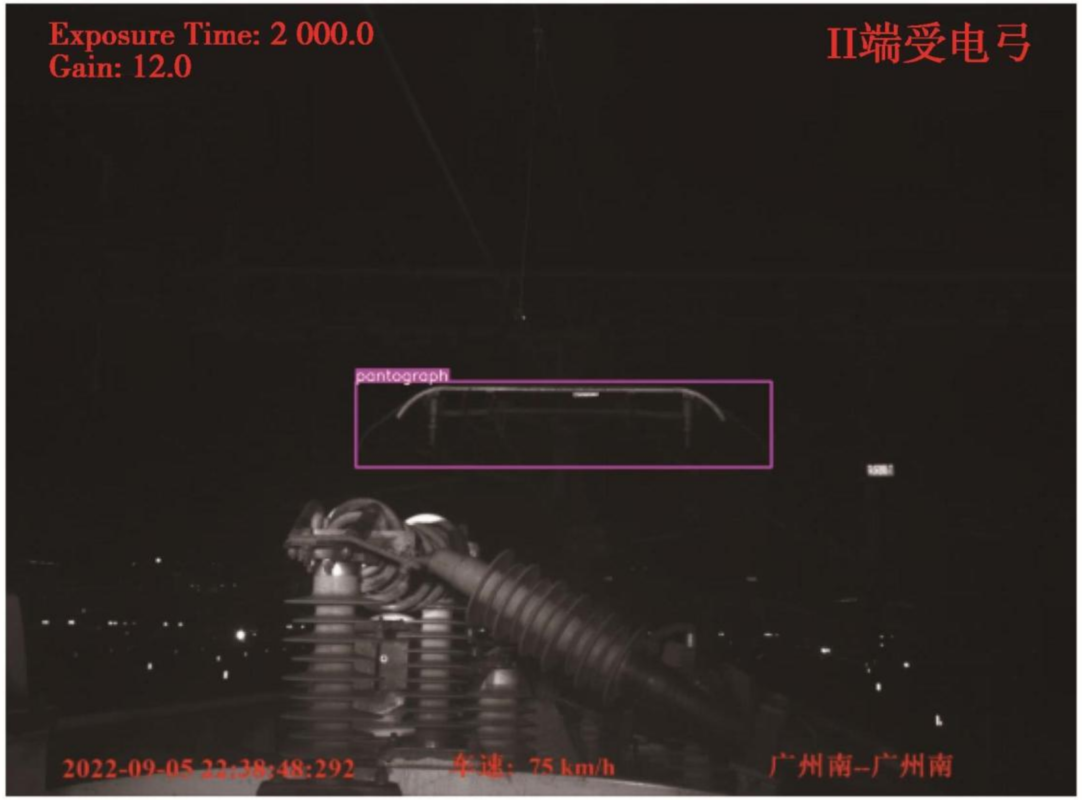
Dataset Augmentation
(Use available images and perform flip, rotate, blur, add noise to increase the number of image examples to improve model's generalization ability)

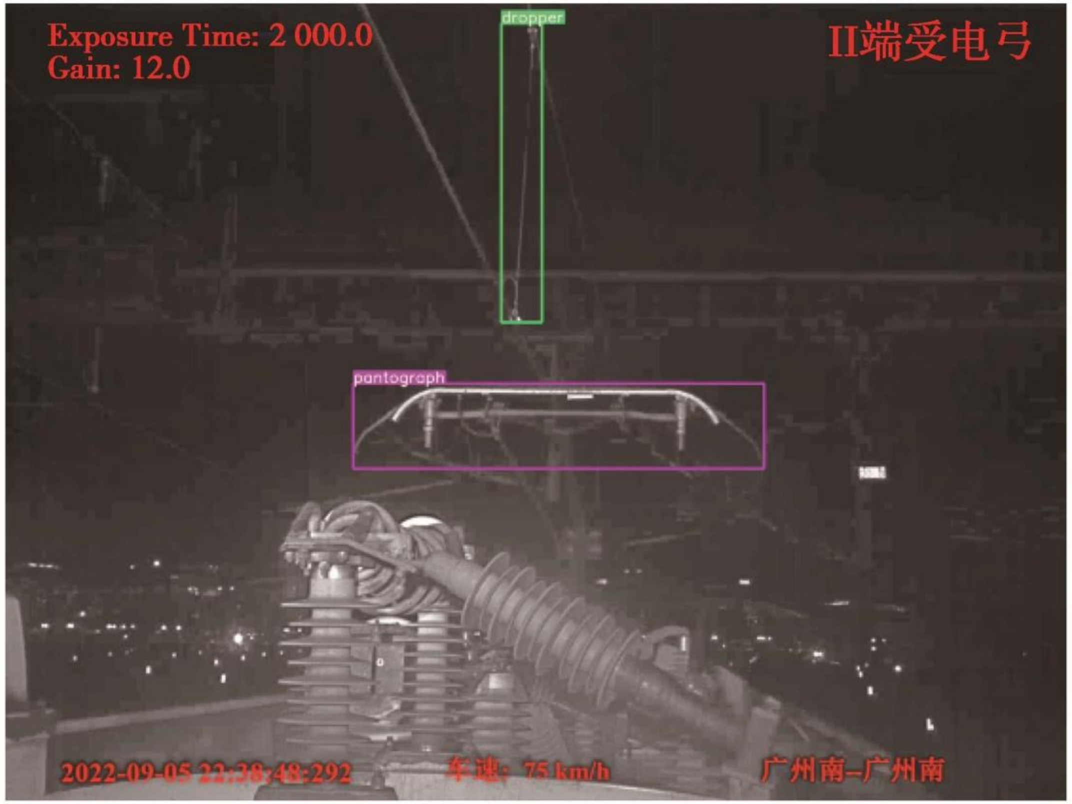
Synthetic Data Generation
(Generate new defect images with defects using available defect examples using specialized software)

Image pre-processing

Challenge : Uncertain Environment
(Eg : Fog, low light, night, rain)

Image processing using enhancement techniques
(Eg: Histogram equalization, normalization, noise filters, contrast stretching etc..,)





Source Publication : https://edl.csrzic.com/en/article/doi/10.13890/j.issn.1000-128X.2022.05.020/

Image pre-processing

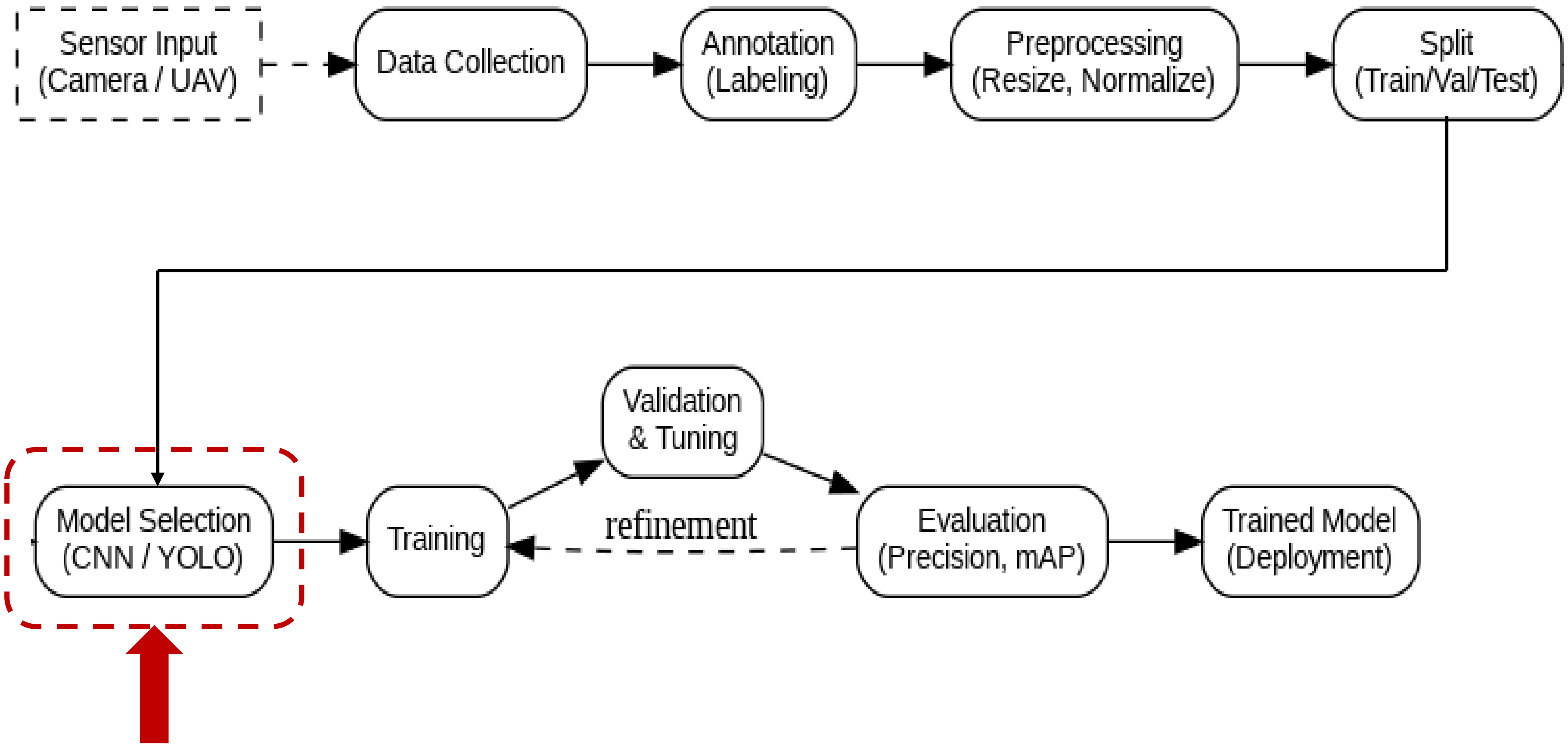
Challenge : Uncertain Environment
(Eg : Fog, low light, night, rain)

Image processing using enhancement techniques
(Eg: Histogram equalization, normalization, noise filters, contrast stretching etc..,)

Source Publication : https://edl.csrzic.com/en/article/doi/10.13890/j.issn.1000-128X.2022.05.020/

Training Stage

Model Selection



Model Selection

What is a “Model” in this context?
“A model is a trained decision-making AI neural network system that learns patterns from data.”

Question :
What about the models for specialized computer vision tasks?

- CNN → fast detection
- Transformer → context understanding
- Hybrid (CNN + Transformers) → best performance
- Multimodal → future systems

Types of Computer Vision Models (Railway Context)

CNN – based models

Usage : Traditional & widely used, computationally effcient

Best for: fast, real-time detection

Opensource models (few) :
- CNN (basic model)
- ResNet (pre-trained)
- VGG (pre-trained)
- EfficientNet (pre-trained)
- **YOLO (pre-trained, very popular in railway)**

Railway Use:
- Crack detection
- Fastener detection
- Real-time inspection

"CNN models look at small features like edges and patterns"

Types of Computer Vision Models (Railway Context)

Transformer-Based Models (Modern AI)

Usage : Computationally expensive

Best for: understanding full image context

Opensource models (few) :
- Vision Transformer (ViT), (Basic Model)
- Swin Transformer (pre-trained)
- DETR (pre-trained)

Railway Use:
- Complex defect patterns
- Large datasets
- Context-based detection

"Transformers understand the whole image like a big picture"

Types of Computer Vision Models (Railway Context)

CNN + Transformer (Hybrid Models)

Usage : Computationally moderate

Best for: Best performance in recent research

Opensource models (few) :
- ConvNext
- Swin + CNN hybrids
- DaViT (used in railway research)

Railway Use:
- High accuracy defect detection
- Combined local + global features

“Combines sharp detail (CNN) + big picture understanding (Transformer)”

Types of Computer Vision Models (Railway Context)

Multimodal Models (Advanced)

Usage : Computationally moderate

Best for: Best for future railway systems

Few Models :
- CLIP
- Vision + Sensor fusion models
- Vision + thermal + LiDAR models

Railway Use:
Combining:
- Image
- Infrared
- vibration

Detect hidden defects

"Uses multiple inputs like camera + sensors together"

Model Selection for OCS Defects – Research Survey

Component	Typical defect	Detection challenges	CNN-based	Transformer-based	CNN–Transformer hybrid	Multimodal models
Rod-insulator	Surface crack, flashover stain, breakage	Fine-grained texture, illumination variation	a Good on texture detail	a Captures long-range relation	b Combines local texture + global context	c Best: fuses visible + infrared info for temperature anomaly
Bird nest	Nest obstruction, foreign object	Irregular contour, weak contrast	a Limited generalization	b Better structural perception	**c Excellent contextual reasoning**	b Similar to hybrid
Dropper	Disconnection, deformation, detachment	Slender shape, small target	**d Sensitive to occlusion**	a Better geometry encoding	**c Best balance of local–global**	a Good but redundant
Bracing wire	Fracture, slackness, missing	Thin linear pattern, background confusion	**d Low contrast**	a Topology sensitive	**c Best for continuity and geometry**	a Similar but complex
Swivel Clevis	Looseness, corrosion, missing	Tiny metallic texture, cluttered background	a Texture detail	**d Poor small-target**	b Good compromise	**c Best: combines RGB + 3D info**

a Moderate performance advantage; b relatively better performance; **c best performance; d poor or unsuitable performance.**

Adapted from Source Publication, Table simplified and reformatted by author. : *"Jin He, Jinming He, Zhijian Gou, Fengmao Lv, Defect detection in railway catenary systems: a survey, Intelligent Transportation Infrastructure, Volume 4, 2025, liaf027, https://doi.org/10.1093/iti/liaf027";*

Model Selection for OCS Defects – Research Survey

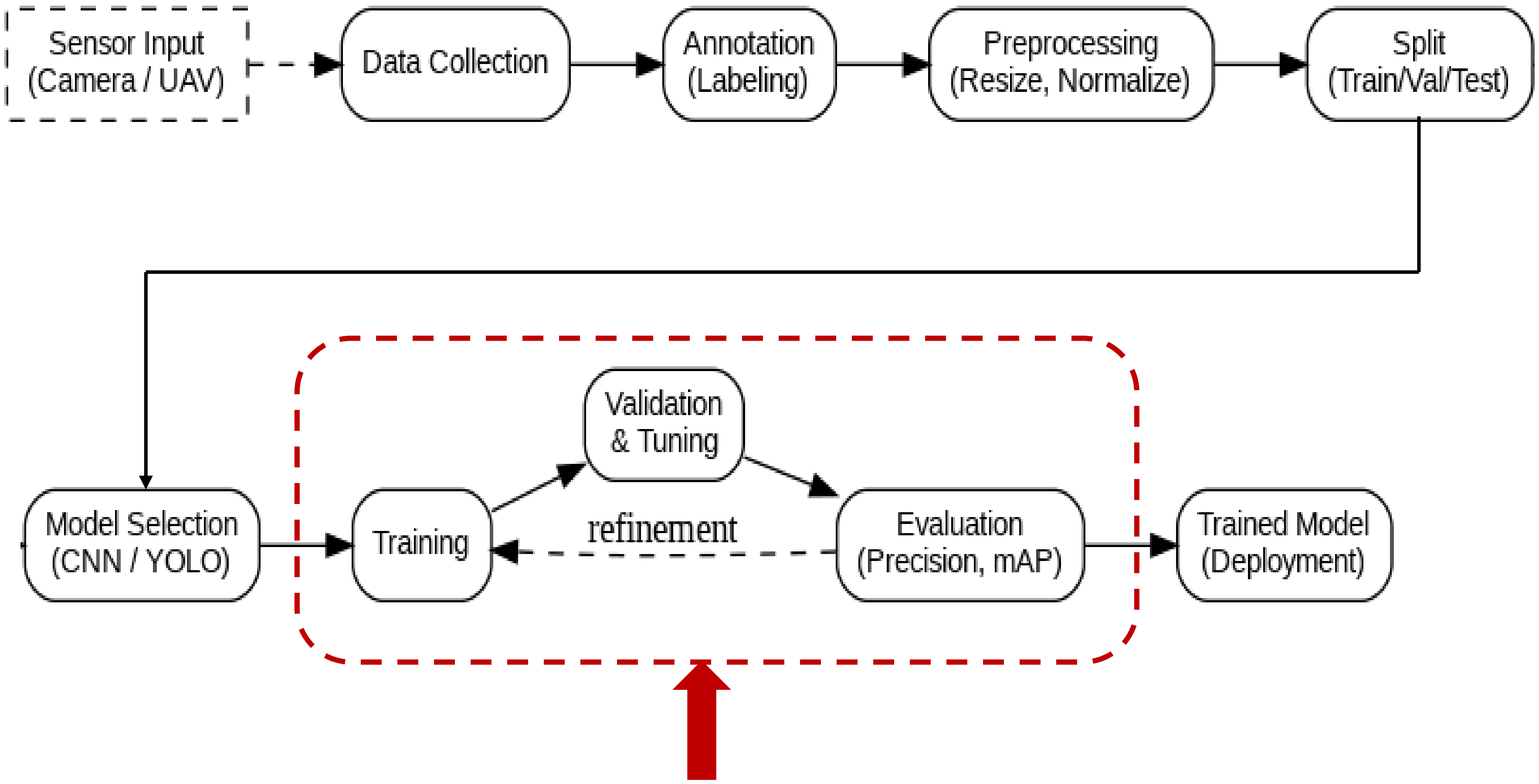
Component	Typical defect	Detection challenges	CNN-based	Transformer-based	CNN–Transformer hybrid	Multimodal models
Fastener	Looseness, crack, corrosion	Subtle texture, repetitive pattern	b High accuracy	a Stable but over-smooth	b Good structure	**c Best: integrates texture, force, and IR info**
Pantograph	Carbon strip wear, mechanical deformation	High-speed motion blur, temporal change	**d Motion blur sensitive**	b Sequence modeling	**c Structural temporal reasoning**	**c Best if video + vibration used**
Arc detection	Electric discharge, flashover arc	Short-time high-light emission	**d Hard for short transient**	a Temporal transformer effective	b Combines frame + context	**c Best: image + spectrum**
Split pin	Missing, looseness	Small-scale, low contrast	**d Miss detection**	a Fine structure learning	b Accurate	**c Best: fuses multi-sensor inputs**

a Moderate performance advantage; b relatively better performance; **c best performance**; **d poor or unsuitable performance.**

Adapted from Source Publication, Table simplified and reformatted by author. : *"Jin He, Jinming He, Zhijian Gou, Fengmao Lv, Defect detection in railway catenary systems: a survey, Intelligent Transportation Infrastructure, Volume 4, 2025, liaf027, https://doi.org/10.1093/iti/liaf027";*

Training Stage

Model training & evaluation



Typical Model Training Methods

Model Training

Build a new model. Train from scratch

- Suitable for small tasks with less complexity
- Large datasets need bigger model and high budget

Select a pre-trained model. Train it for specific task

- Suitable for more complex tasks
- Taking advantage of pre-trained models reduces cost

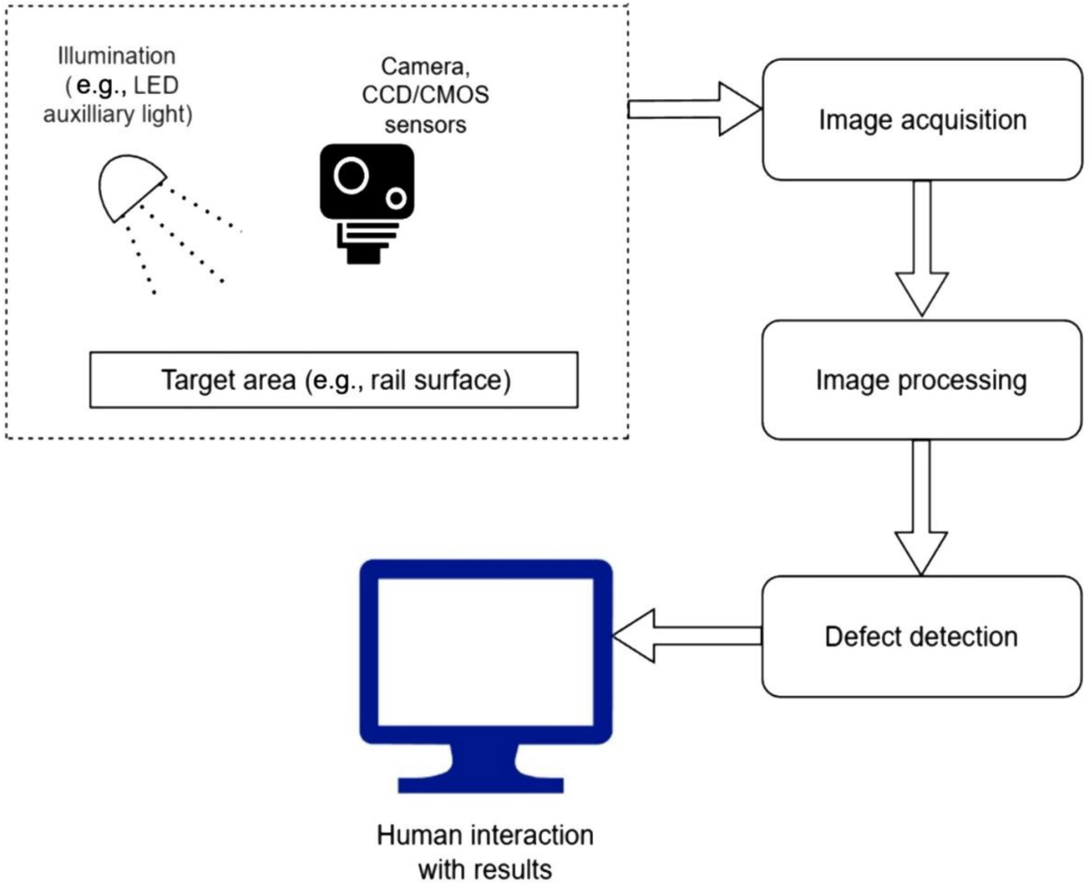
- Training a new model from scratch requires huge amount of data.
- A cost optimal approach is to consider open source pre-trained models trained on huge data and then train it to perform required task.

  Examples of pre-trained open source models :
  - YOLO, ResNet
  - ViT, CLIP, DINO
  - MobileNet,
  - EfficientNET etc..

"The barrier to entry for railway computer vision has dramatically reduced. Today, engineers can start from mature open-source models such as **YOLO, DETR, ViT, Swin Transformer, ConvNeXt, and CLIP** available through **Hugging Face** and **GitHub**, rather than developing neural networks entirely from scratch."

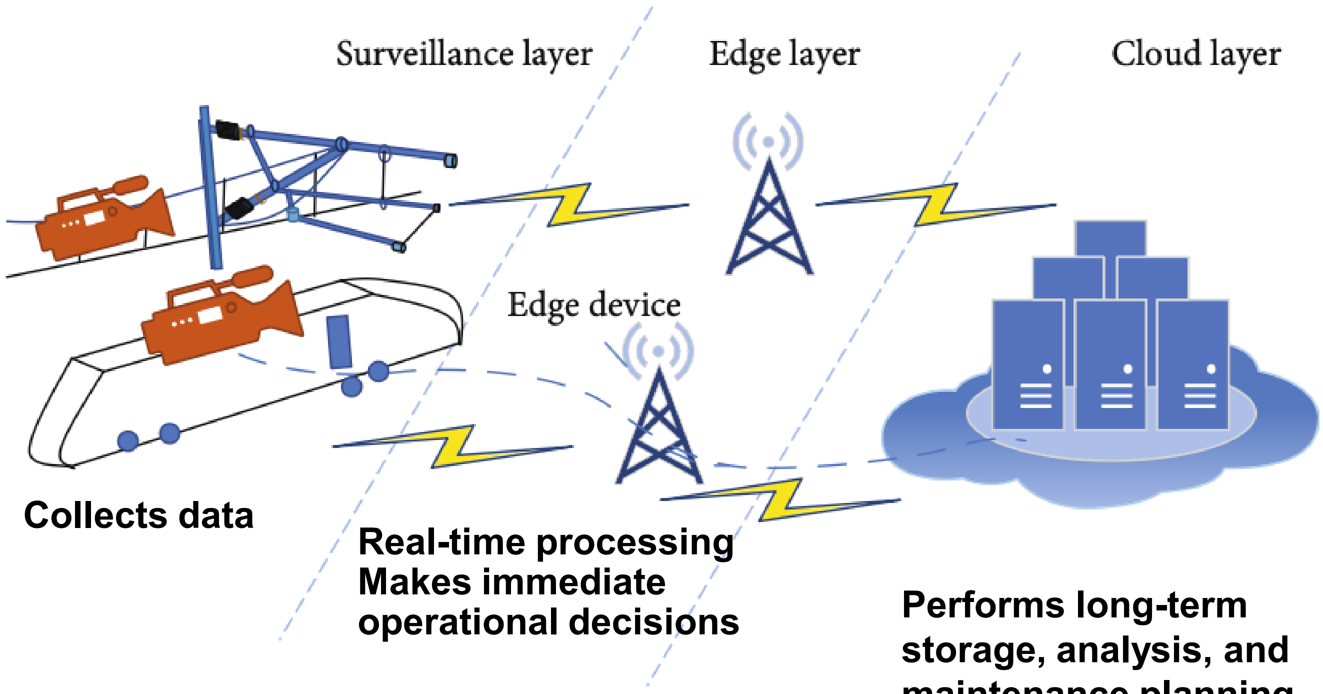
Deployment Stage

Model Deployment



Source Publication : Kumar, A., & Harsha, S. P. (2024). A systematic literature review of defect detection in railways using machine vision-based inspection methods. International Journal of Transportation Science and Technology. https://doi.org/10.1016/j.ijtst.2024.06.006

Computer Vision Model Deployment in Railway Infrastructure



Collects data

Real-time processing
Makes immediate operational decisions

Performs long-term storage, analysis, and maintenance planning.

- **Surveillance Layer:** Performs data and image acquisition using cameras and sensors installed on inspection vehicles or along the railway track.

- **Edge Layer:** Consists of onboard or trackside servers/GPUs that process images locally and perform real-time fault detection, enabling immediate alerts for safety-critical events.

- **Cloud Layer:** Consists of remote servers/GPUs used for long-term data storage, historical analysis, AI model training, and maintenance planning. Time-critical decisions are generally not performed in the cloud due to communication and data-transfer delays.

Time-critical fault detection should happen close to the asset, using edge processing.
Cloud systems are better suited for storage, long-term analysis, training improvement, and maintenance planning.

Source Publication : Shi, Xuetao & Zhao, Hongli & Jiang, Hailin & Zuo, Huijun & Zhang, Qiang. (2023). Edge Intelligence-Based OCS Fault Detection in Rail Transit Systems. Wireless Communications and Mobile Computing. 2023. 1-11. 10.1155/2023/8659679.

Challenges & Key Takeaways

Challenges

#	Challenge	Indicative Solution
1	Human Accountability	Maintain human oversight for validation and approval of critical AI decisions.
2	Limited Training Data	Start with high-value defect classes and continuously improve models using new field data.
3	Asset Visibility & Tagging	Use GPS-based defect tagging to enable localization without requiring a full digital asset model.
4	Cost Justification	Begin with targeted use cases, demonstrate ROI, and scale incrementally.
5	Regulatory Approvals (Drone Case)	Use ground-based inspection methods while parallelizing drone approval processes.
6	Operational Integration	Integrate AI outputs directly into maintenance workflows, with clear ownership, planning, and budget allocation.
7	Data Sovereignty	Keep sensitive rail data under local control through in-country storage, governance, and ownership.
8	Model Drift	Establish periodic retraining, validation, and performance monitoring as part of ongoing operations.
9	Explainability	Provide visual evidence and plain-language explanations for every AI-generated alert.

Key Takeaways

1. **This is operational today, not just research**. Network Rail, Deutsche Bahn, and BNSF are already running CV-based inspection in production — the technology has crossed from lab to field. **But these systems still need to be proven successful in industry.**
2. **No single model wins — match architecture to defect type.** CNNs for texture-level defects (cracks, corrosion), transformers for context-heavy cases (bird nests, obstructions), hybrids for the best all-round performance, multimodal for anything needing sensor fusion (thermal, LiDAR, vibration). **Take cost and resource efficient approach to design AI system by using multiple models.**
3. **Start from pretrained models, not from scratch.** YOLO, ViT, CLIP, DINO. No need to reinvent the wheel. **Good open-source models exist.**
4. **Data is the bottleneck, not the algorithm**. Any team starting this work should budget for data engineering, not just model selection.
5. **Deployment architecture determines whether it helps.** Time-critical faults need edge processing; training and planning belong in the cloud. **A state of art AI model without an efficient production system will eventually fails.**
6. **The real blockers are organizational, not technical.** accountability, explainability, cost justification, data sovereignty. Teams that treat this as "just buy a good model" tend to stall. **Rail operators need to own this product as their proprietary.**
7. **Human oversight stays in the loop.** Even at 95%+ accuracy, these systems are decision-support for critical infrastructure, not autonomous authority. **AI don’t replace human labor, rather they act as tools to improve system reliability and safety.**

Industry Case Studies (Information)

Computer Vision in Railway Maintenance

Swarm of drones (Drones4Safety)

Source : https://drones4safety.eu/d4s-media/

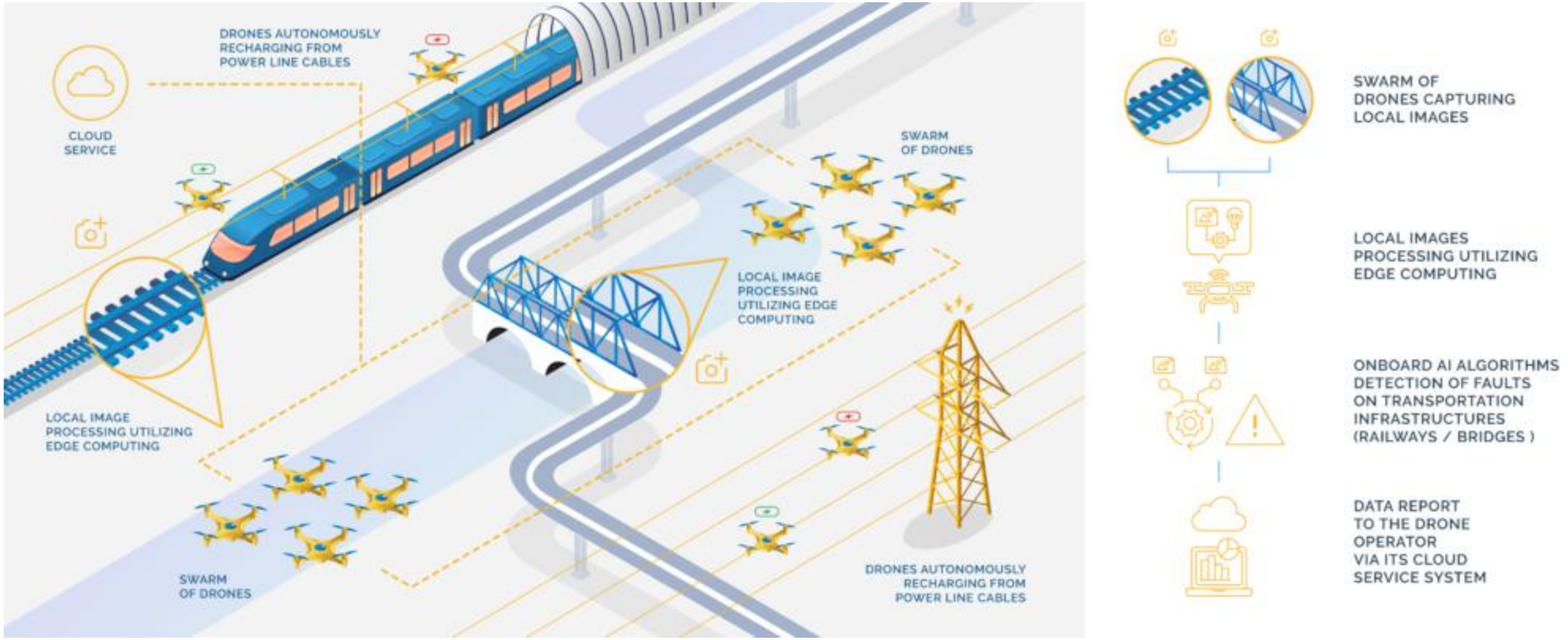


Image courtesy: Drones4Safety Project (EU Horizon 2020) : https://drones4safety.eu

The **Drones4Safety (D4S)** project is an EU-funded Horizon 2020 initiative developing a cooperative, autonomous, self-recharging, and continuously operating drone system. It aims to revolutionize the safety and efficiency of Europe's civil transportation infrastructure—specifically railways and bridges—by replacing conventional, human-led inspections with AI-driven, automated monitoring.

Computer Vision in Railway Maintenance

State of Practice Today

Network Rail (UK) — with heliguy™

CAA-approved BVLOS drone-in-a-box operations live at two sites (Gloucester & Romford). Automated DJI Dock 3 missions run daily with no on-site pilot, following 16 months of joint safety-case development.

Source: Network Rail / heliguy, May 2026

Deutsche Bahn (Germany) — with Dronehub

AI-driven anomaly detection across the 33,000 km network. Vendor-reported: >95% per-fastener defect accuracy, sub-15-minute report turnaround from drone landing to work order.

Source: Dronehub deployment case study, 2026 (vendor-reported figures)

BNSF & US Class I Freight Railroads

Computer-vision BVLOS track inspection running since 2015 (135-mile Clovis Subdivision). Expanding under the FAA/TSA's 2025 proposed BVLOS rulemaking for national-scale rollout.

Source: Railway Age, September 2025

Common pattern across all three: fixed-dock drone charging + edge/cloud AI inspection pipeline — not autonomous in-flight powerline recharging or drone swarms (see Drones4Safety example).

Thank You
Q&A Session