Elongated Object Detection and Segmentation

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Artificial Intelligence &
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Elongated Object Detection and Segmentation

- **Introduction**
- Role of UAVs in elongated object detection
- Line segmentation
- Powerline detection and segmentation
- Pipeline detection and segmentation

Introduction

Elongated object detection: localization of instances of elongated structured objects inside an image.

- Powerline detection, referring to line detection.
- Pipeline detection, referring to linear structured object detection, such as cylinder.

Both object can be characterized as ***elongated linear objects*** because they extend in one direction (along one axis).

Introduction

Main goals of this presentation are:

- Provide the role of the UAVs in the problem of the elongated object detection.
- Present the most recent techniques used to locate and recognize elongated objects, specifically lines, power lines and pipelines.

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Role of UAVs in Elongated Object Detection

- UAVs can perform economic and faster asset inspection than the classic methods [LYU2019][SIN2019].

- For the visual inspection UAVs utilize RGB cameras, thermal camera and LiDAR sensors [LYU2019].

- UAVs external pipeline inspection constitutes a preferable replacement to in-pipe robots [AMI2016].

Applications on Industrial Environment

Applications of automatic linear elongated object detection by UAVs :

- Powerline visual inspection on electricity transmission and distribution networks [VAN2018].
- Pipeline external inspection on industrial environment [LYU2019].
- Autonomous tracking of pipelines and navigation of UAV in industrial environment [LYU2019].

Powerline Inspection

Powerline inspection tasks:

- Inspection and mapping of powerlines and its components (conductors and pylons) for damaged poles and crossarms and missing toppads [VAN2018].
- Monitoring for vegetation encroachment consists of: detection and classification of vegetation near the powerlines, estimation of height and distance from the powerlines [VAN2018].

Powerline Inspection

Powerline inspection tasks:

- Icing detection on the powerline and measurement of the icing thickness parameter [VAN2018].
- Disaster monitoring. Fast and accurate damage assessments on the powerlines to recover the power grid. [VAN2018].

Pipeline Inspection

5 types of pipeline failures to be inspected.

Causes	Distribution (%)
Mechanical failures	42
3rd party activity	24
Corrosion	18
Operational error	10
Natural Hazards	6

Possible pipeline failures [SIN2019][JAK2014]

Mechanical failures and corrosion are the 2 causes of failure which is aimed to be detected through UAV inspection.

Pipeline Inspection

- Mechanical failures [SIN2019]:
  - Open or misplaced insulation.
  - Rapture or puncture.
  - Leak.
- Corrosion [SIN2019][JAK2014]:
  - Internal: due to chemical or microbiological activity.
  - External:
    - Open insulation.
    - Manufacturing defects.
    - Location.

Pipeline Inspection


Corrosion damage [SIN2019].


Mechanical failure [SIN2019].

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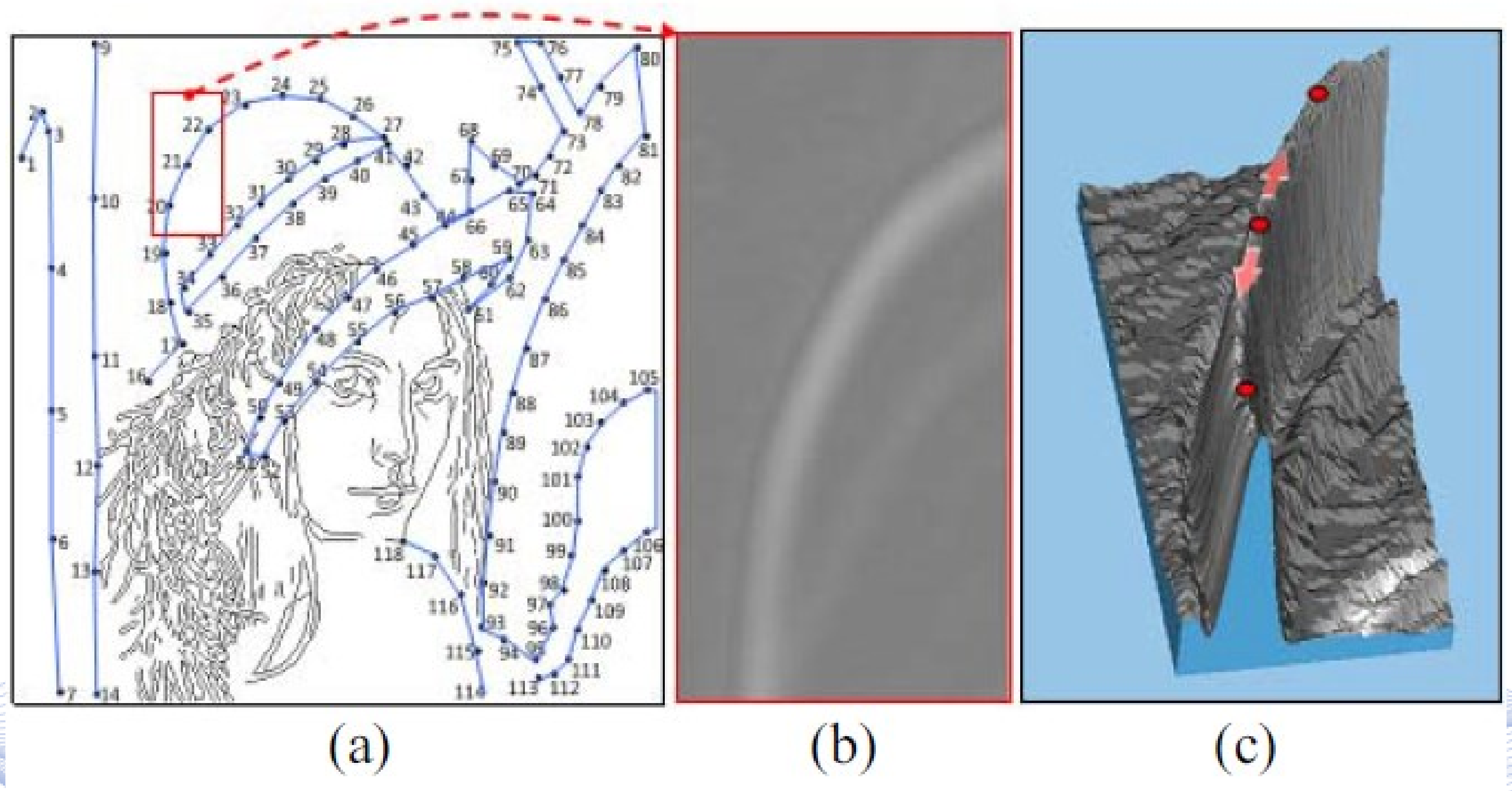
Line Segmentation

Edge Drawing Lines (EDLines):

- **Input**: RGB image
- **Output**: set of sharp, continuous, connected, chains of edge pixels, called edge segments.

- Implementation steps:
  - Edge Drawing: edge segments consisted of a chain of pixels corresponding to the edge.
  - Line Detection: “Least Squares Line Fittings” extracts lines from the edges.
  - Line Validation: uses the Helmholtz Principle

Line Segmentation



a) Edge map of Lena's photos. b) Part of the gradient map of the input image. c) The 3D illustration of (b) [YET2015].

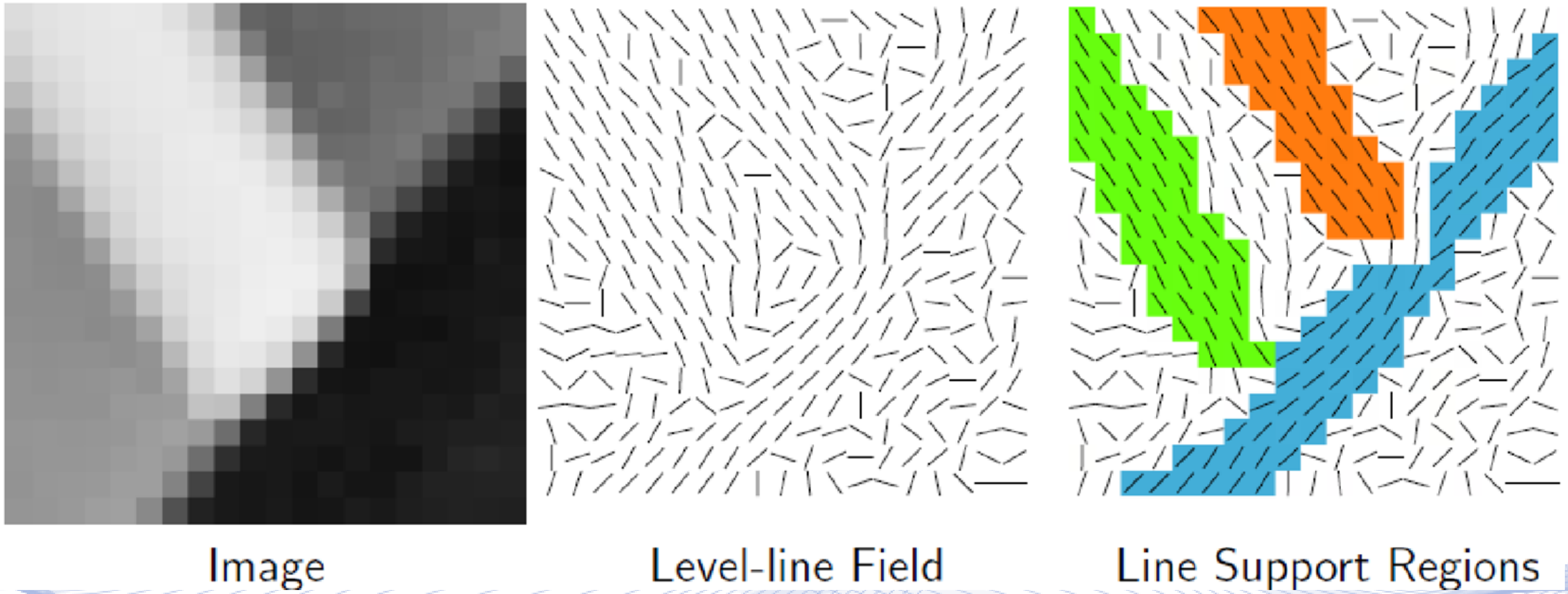
Line Segmentation

Line Segments Detector (LSD) [VON2012]**:**

- **Input:** Grayscale image
- **Output:** List of detected line segments

- Steps of LSD:
  - Produce level-line field
  - Line Support Regions (Region growing)
  - Associate a rectangle to each region
  - Helmholtz principle to consider ε-meaningful each rectangle

Line Segmentation



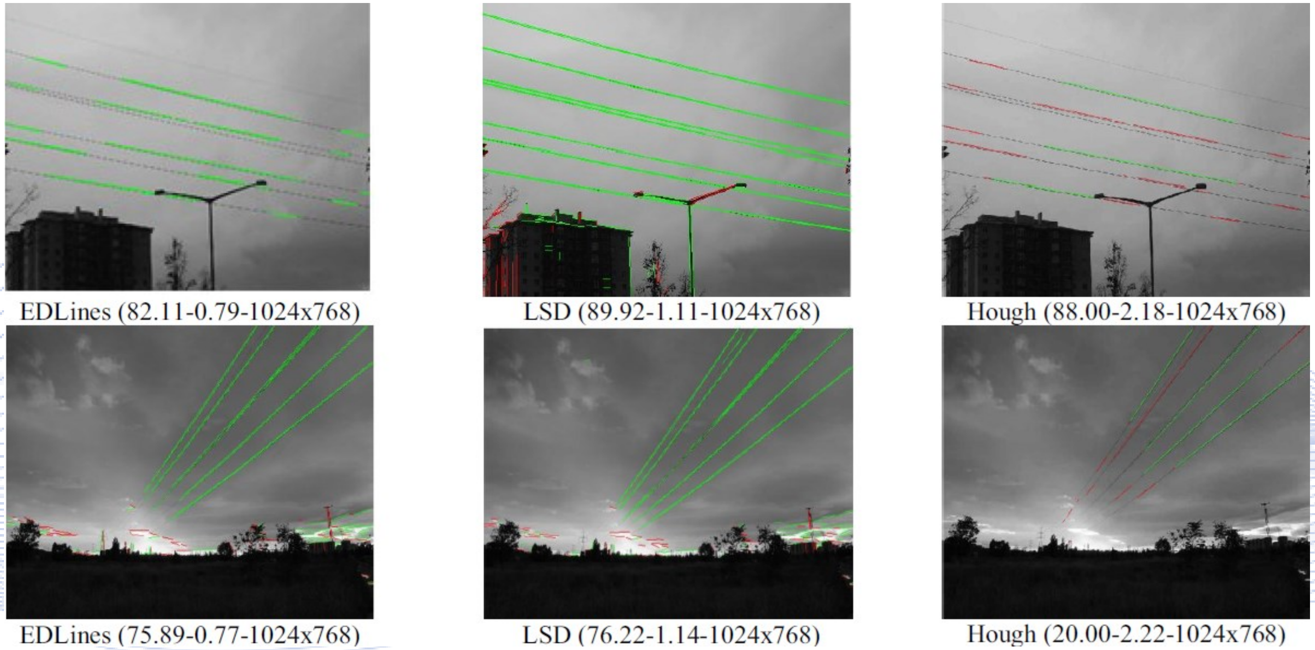
Vector field and region growing of the LSD algorithm [VON2012].

Line Segmentation

- Hough Transform has many variants and extensions, e.g. “Randomized Hough Transform”, “Elliptical Gaussian Kernel Hough Transform”, “Progressive Hough Transform” [YET2015] , etc..
- An edge map produced from edge detectors, such as Cunny, is required for the Hough Transform.
- The run times of these methods are long.
- The parameters of these techniques must be adjusted manually as they cannot be determined automatically.

Line Segmentation

Comparison of Edge Drawing Lines (EDLines), Line Segmentation Detector (LSD) and Hough Transform [YET2015].

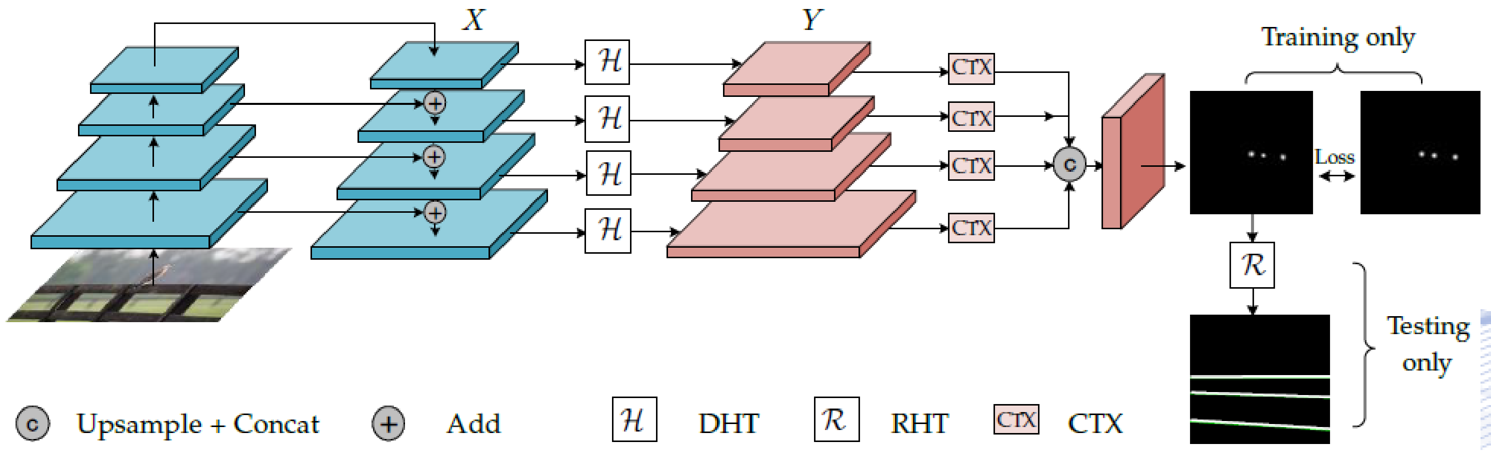


Comparison (Accuracy (%), Time (seconds), Size (row x column)) [YET2015].

Deep Line Segmentation

Deep Hough Transform for real-time semantic line detection.

- **Input:** RGB image
- Combination of feature learning capabilities of CNN with the Hough Transform technique [ZHA2021].



(DHT: Deep Hough Transform, RHT: Reverse Hough Transform, CTX: Context-aware line detection) [ZHA2021].

Deep Line Segmentation

Detection results from the Deep Hough Transform [ZHA2021].

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Powerline Detection

Tiny-Yolov3 model for power line detection [HYU2022].

- **Input**: RGB image
- **Prediction**: Bounding boxes for detection of continuous object.
- A line is labelled using several continuous boxes of constant size. The shape of the power line (U-shaped curve, straight line etc.) is broken to small straight fragments.
- Lines close to each other are labelled by the same bounding boxes.

Powerline Detection

Power line ground truth RoIs [HYU2022].

Powerline Detection

In tiny-Yolov3:

- Real-time implementation capabilities.
- It consist of seven convolution layers and six max-pooling layers.
- For the feature extraction 1 × 1 and 3 × 3 convolution layers were used.
- The continuous bounding boxes are predicted in two scales.
    - one 13 × 13 feature map and one 26 × 26 feature map
    - concatenation of upsampled 13×13 and 26×26 feature maps

Powerline Detection

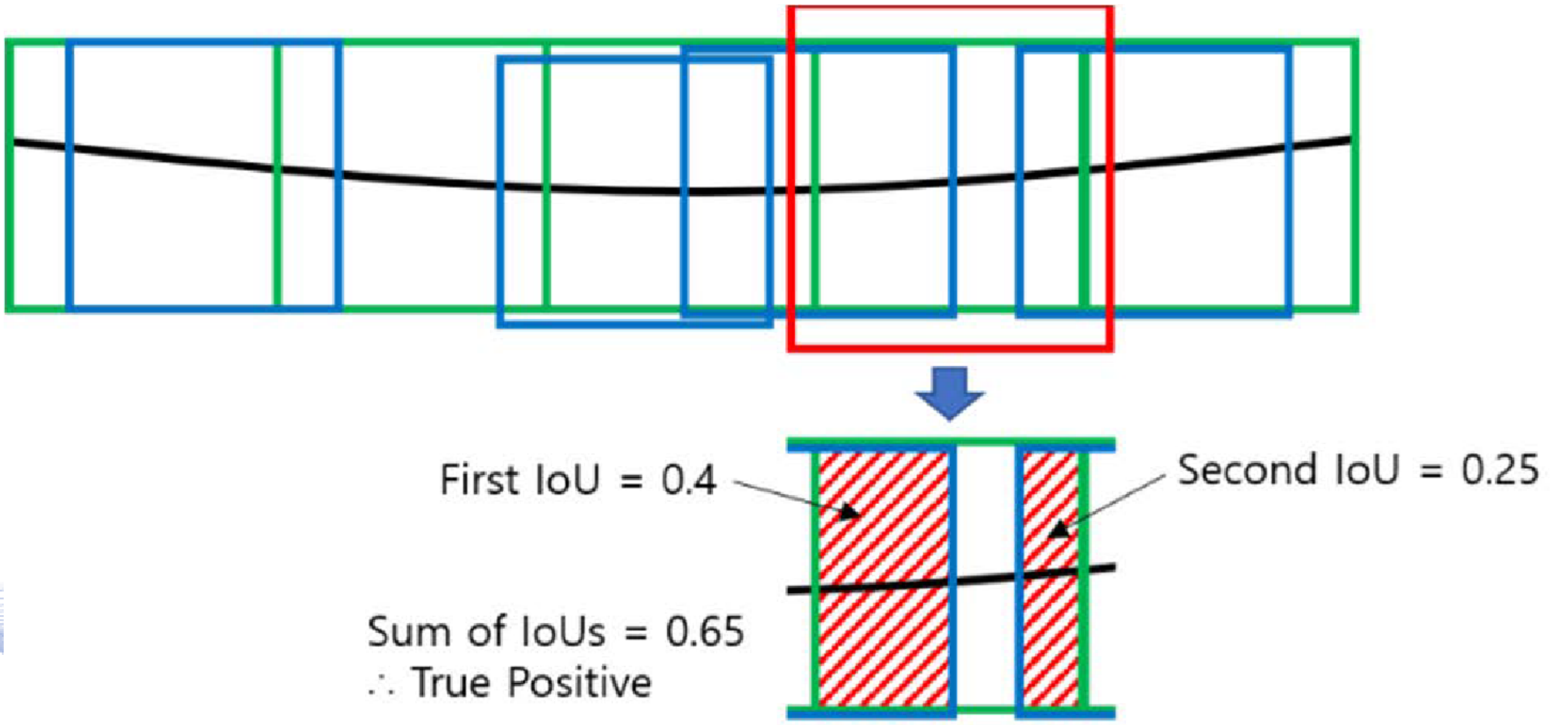
Evaluation metrics:

- ***Precision***, ***recall*** and ***Intersection over Union*** (IoU).

$$p(t) = \frac{\sum_{ij} n_{ij} z_{ij}}{\sum_{ij} n_{ij}}, \qquad r(t) = \frac{\sum_{ij} n_{ij} z_{ij}}{M}$$

$$J(\mathcal{A}, \mathcal{B}) = \frac{|\mathcal{A} \cap \mathcal{B}|}{|\mathcal{A} \cup \mathcal{B}|}.$$

Powerline Detection

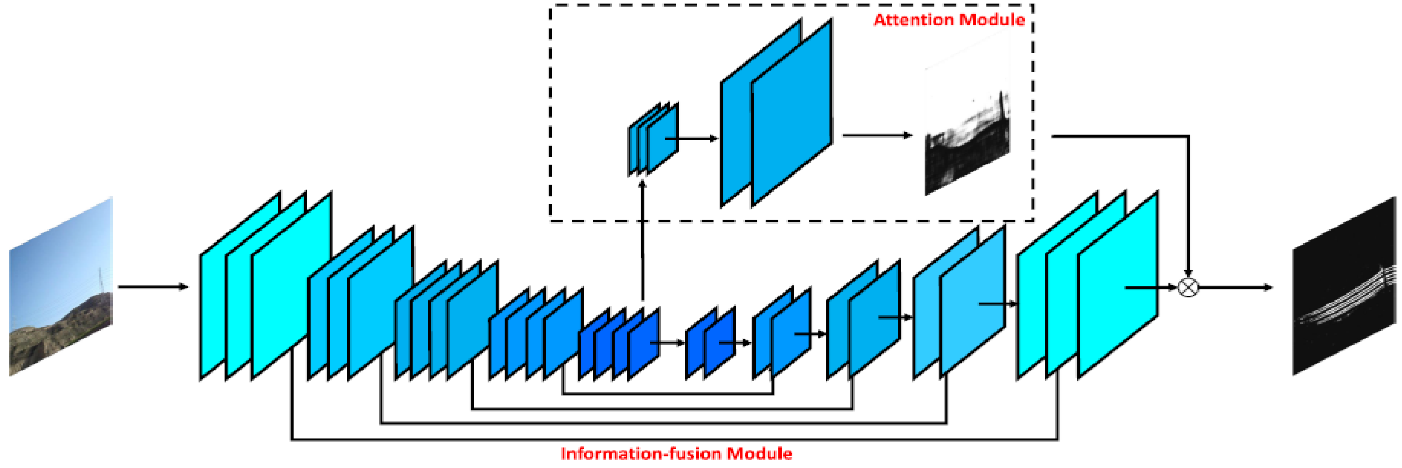


Example of a case of a true positive in [HYU2022].

Powerline Segmentation

End-to-end convolutional architecture for pixelwise power line detection.

- Encoder-decoder CNN with information fusion
- Attention sub-brand creates high-resolution attention mask from the deep feature
- **Output**: a score for each pixel $Y(x)$.



Architecture of the attentional power line detection [LIY2019].

Powerline Segmentation

For the pixelwise detection of a powerline it is needed:

- Semantic information for the identification of the powerlines.
- The localization information for detecting the position of the powerline.

Powerline Segmentation

Information Fusion Module [LIY2019]

- **Output**: Probability score map.
- The convolution layers and the upsampling provides semantic information.
- Lateral connections from the shallow to the corresponding deep layers (same spatial scale) provides the needed localization information.

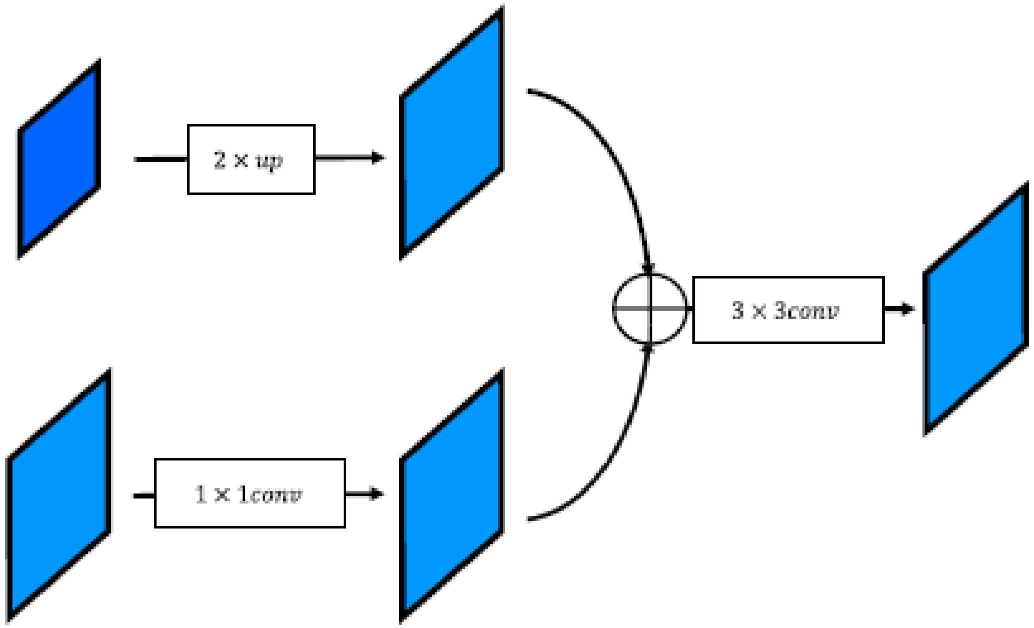
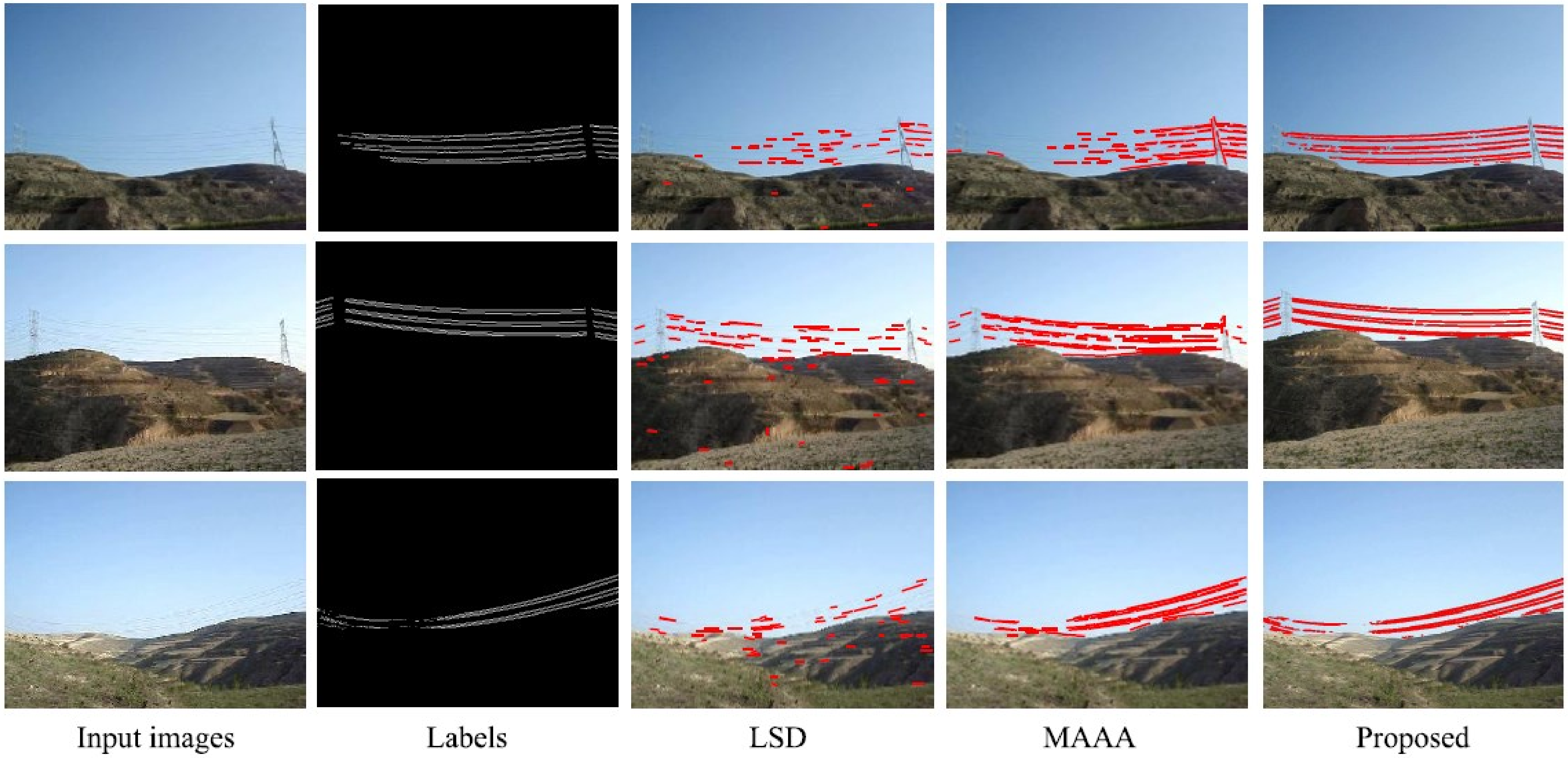


Image 8: Information fusion module in [LIY2019].

Powerline Segmentation



Results from the comparison of the attentional powerline detection with LSD and Multiple auxiliaries assisted airborne (MAAA) [LIY2019].

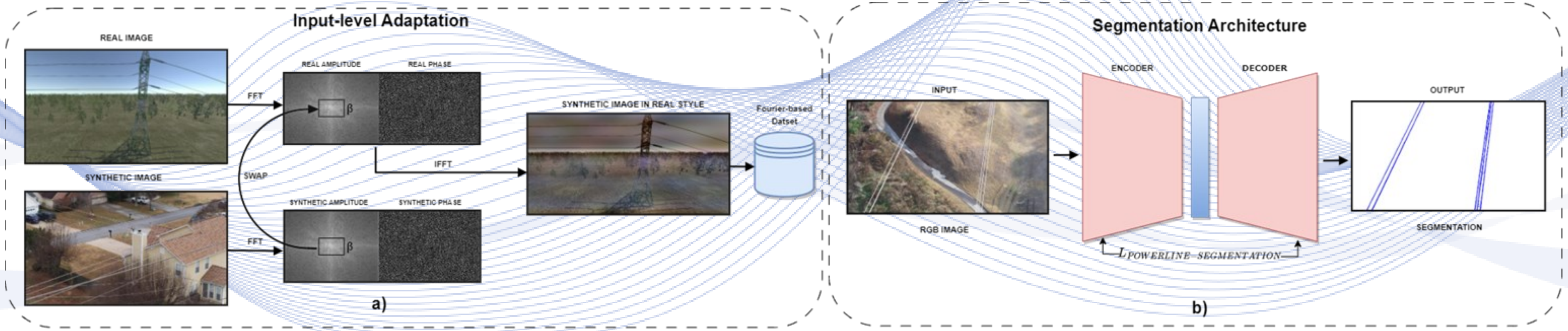
Powerline Segmentation

Domain Adaptation (**DA**) for powerline segmentation in aerial images [KAL2023] .

- **Synthetic Dataset**: RGB images with their corresponding segmentation maps captured in two Unity-created virtual environments.
- **Domain Adaptation**: bridge the domain discrepancy between the two datasets, a source (synthetic) dataset $\mathcal{D}_S =$

Powerline Segmentation

- Fourier-based image translation was employed by swapping the spectrum amplitude of a synthetic image with that of a random real image.
- Fourier **DA** utilized as a separate step and doesn't at all require any training to achieve domain alignment, instead relying on a simple Fourier Transform and its inverse.



The proposed framework for power line segmentation consists of two components: a) an input-level domain adaptation module that employs a Fourier-based image translation strategy, b) a high-performance semantic segmentation architecture trained with a power line segmentation loss.

Powerline Segmentation

- A comparison was conducted with existing SOTA method on TTPLA dataset where the proposed DA powerline segmentation method [KAL2023] outperforms the recently presented PLGAN [RAB2022] architecture by +3,82%

Method	Backbone Network	Image Resolution	TTPLA (Real dataset) Test set mIOU
PLGAN [RAB2022]	ResNet-6	512x512	53.30%
DA powerline segmentation [KAL2023]	ResNet-6	512x512	**57.12%**

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Pipeline Detection and Segmentation

Different sensors can be used for the pipeline detection.

- Visual sensors. The pipeline detection problem in computer vision is treated as a semantic segmentation problem [GUE2020].
- LIDAR-based detection is typically treated as a pipeline segmentation problem [GUE2020].
- Infrared thermal images has been used for automatic fault diagnosis on hot water pipelines [HAN2022].

For this presentation only computer vision and infrared thermal image are discussed.

Pipeline detection

Yolov4 Neural Network (single stage detector, twenty-four convolution layers and two fully connected layers) for pipeline detection [YAG2022].

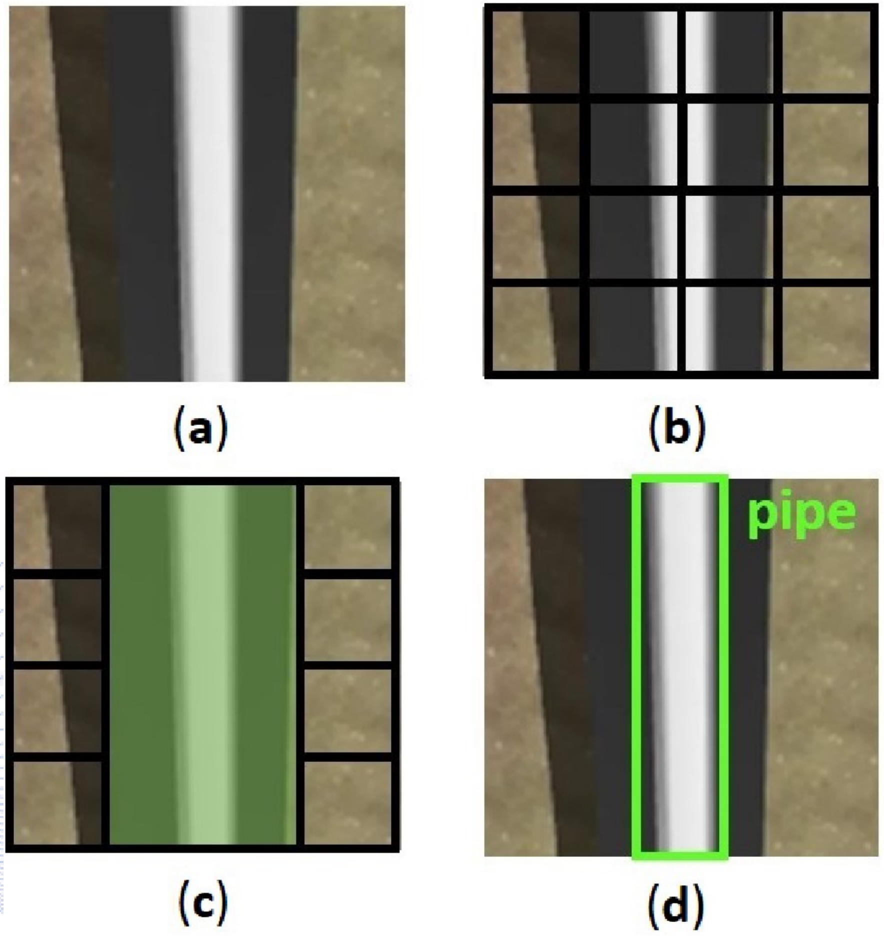
- **Input**: RGB image
- **Prediction**: Bounding Box that contains the pipe and a confidence score of the box. (x, y, h, w and confidence score)

Pipeline detection

In Yolov4:

- The input image is divided to an S × S grid
- Each grid cell predicts a number of bounding boxes along with their respective confidence.
- The grid cells which contain an object predicts additionally one set of conditional class probabilities Pr(Class|Object).
- A number of bounding boxes with their confidence and a class probability map are predicted and by multiplying them together the class-specific confidence score of the boxes is obtained.

Pipeline Detection



YOLO object detection: a) input image of pipe; b) image division to grid cells; c) merged boxes that contain the pipeline; d) generated bounding box [YAG2022].

Pipeline detection

The hyperparameters of the Yolo CNN used:

Optimizer	SGD (lr=0.01 learning rate)
Epochs	200
Batch size	16
Image size	
Weight decay	0.0004

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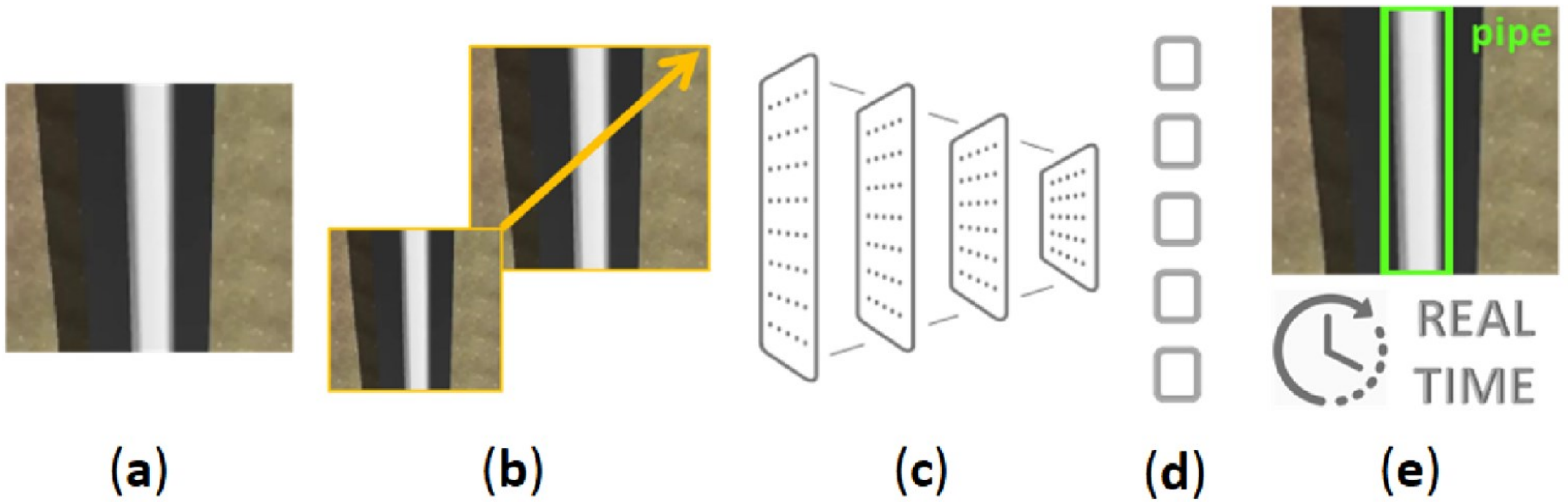
Pipeline detection



a) input image of pipe, b) resizing of the input image and ground truth, c) convolution and fully connected layers, d) pooling process, e) flattened output matrix, f) real time object detection [YAG2022].

Pipeline segmentation

Automatic fault diagnosis method for hot water pipes on infrared images [HAN2022] .

- Infrared images were used because the distribution of surface temperature of the insulation is a good indicator that the layer is damaged.
- The algorithm comprises of two parts: image segmentation and fault diagnosis.

Goal of image segmentation part is to decrease as much as possible the influence of the background.

Pipeline segmentation

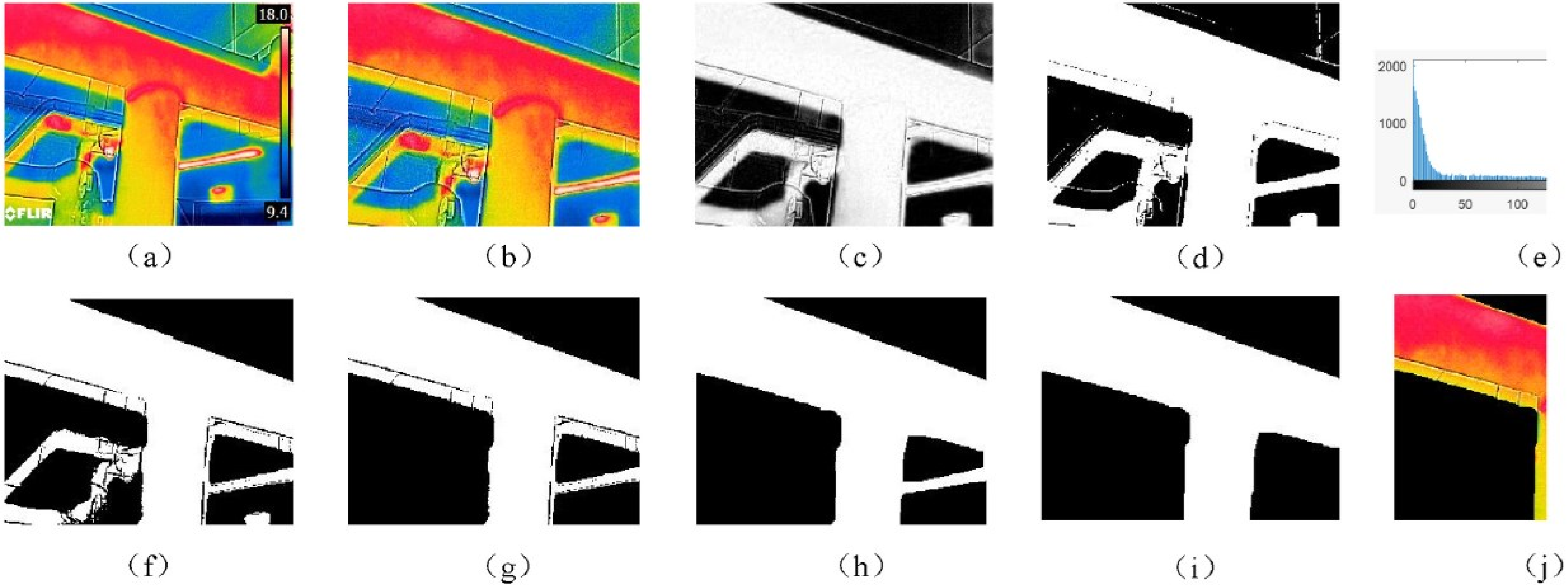
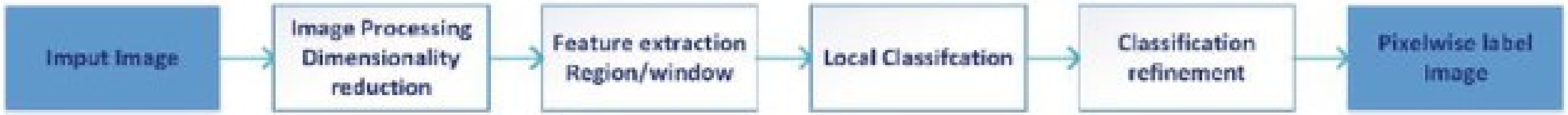


Image segmentation results: (a) initial image, (b) cropped image, (c) grayscale image (d) Otsu's technique segmentation, (e) histogram of the red component image, (f) the segmentation result (the right peak method), (g) the largest connected component of (f), (h) output of closing, (i) output of opening (binary image of the pipe), and (j) the final segmented infrared image of the pipe. [HAN2022]

Pipeline segmentation

Classic semantic segmentation [GUE2020].

- Two step process: image processing for feature extraction, feature level classification.
- In dataset learned classes must be specified before training.



Classic semantic segmentation architecture [GUE2020].

Pipeline segmentation

Deep learning approach of the segmentation problem [GUE2020].

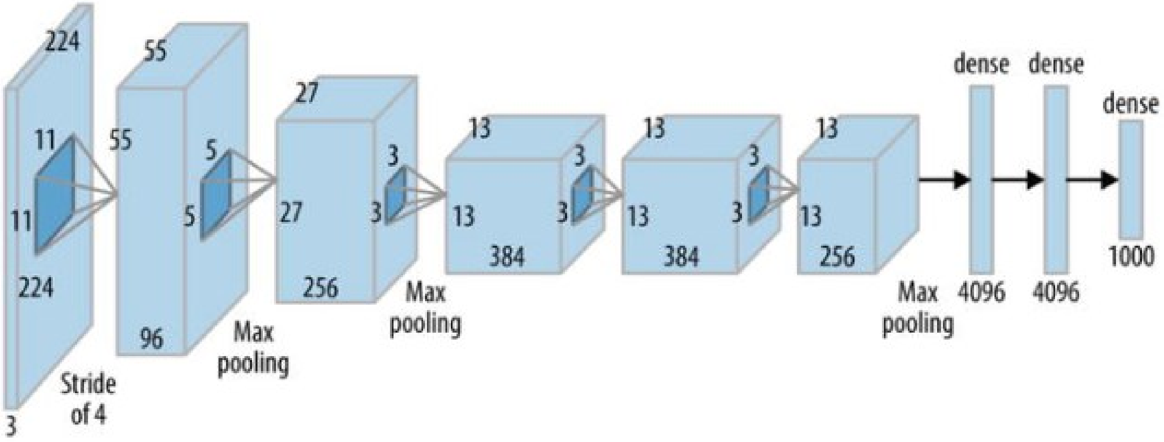
- At the scale of inference, image level probabilistic detection and pixel level classification can be produced.
- Provides localization using centroids and/or bounding boxes.
- Pixel level labelling can be achieved by using fully convolutional network (FCN).

Pipeline segmentation

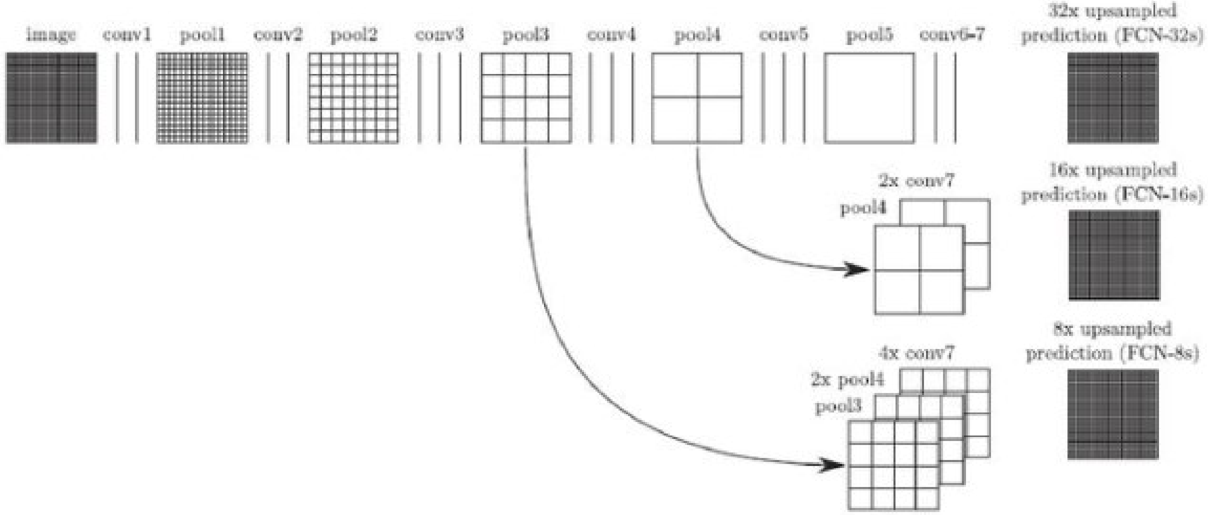
FCN16 model with AlexNet for pipeline segmentation [GUE2020].

- The AlexNet functioned as the semantic segmentation model.
- In this model deep features are extracted through convolutional and max pooling layers.
- High level information is lost during the propagation of the data through the layers. Hence a fusion of the data from multiple layers is needed by upsampling through deconvolution data from deep layers.

Pipeline segmentation



AlexNet architecture [GUE2020].

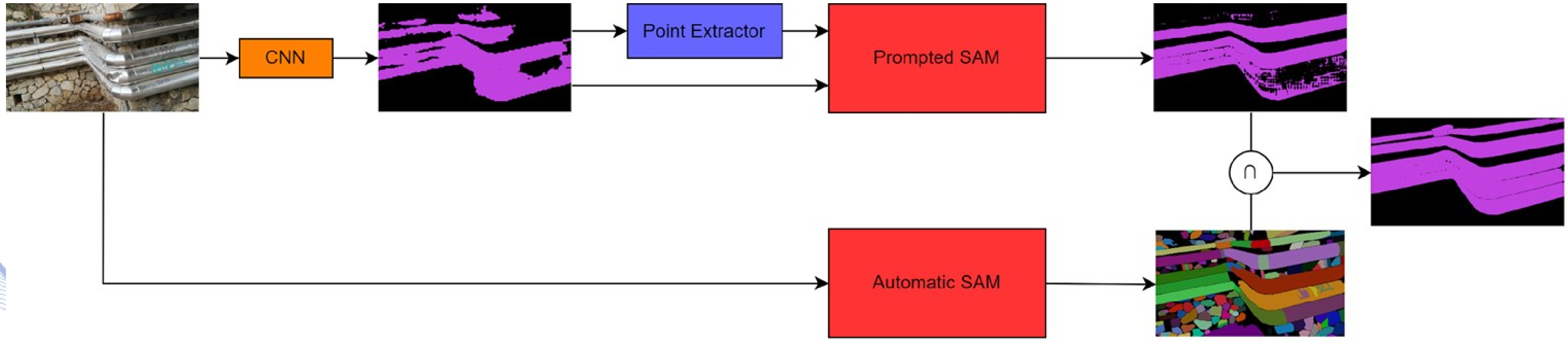


FCN32, FCN16 and FCN8 architectures to use data from deep layers and fuse deep features and spatial information [GUE2020].

Pipeline segmentation

- Cooperation of a CNN segmentation model [PAP2021] and Segment Anything Model [KIR2023].
- The CNN model produces masks of the pipes.
- A prompted SAM goal is used to refine the segmentation masks produced by CNN model.
- SAM also runs on automatic mode to produce masks for all objects.
- The final segmentation mask is produced by fusing the two intermediate outputs.

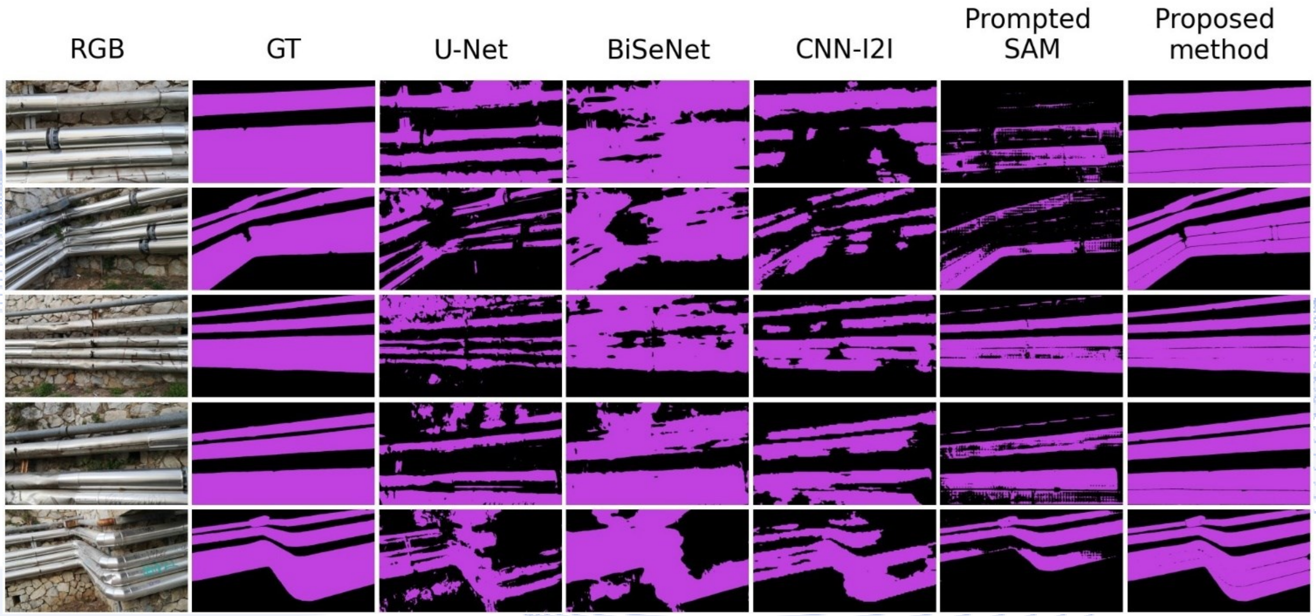
Pipeline segmentation



CNN	CNN for semantic segmentation	Point Extractor	Point Extraction Module	Prompted SAM	Prompted SAM model	Automatic SAM	Automatic mask generation SAM	∩	Mask Matching

Pipeline segmentation

- The performance of the model was evaluated using the Intersection-over-Union (IoU) metric.



	IoU (%)			
	non-pipe	**pipe**	**mIoU**	**mPA(%)**
U-Net [7]	52.0	46.1	49.0	66.0
BiSeNet [8]	54.2	65.4	59.8	75.4
I2I-CNN [9]	68.5	63.7	66.1	79.7
prompted SAM	78.9	79.3	79.1	88.3
Proposed System	**89.0**	**90.9**	**89.9**	**94.8**

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Pipeline segmentation

Pipe image segmentation.

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Q & A

Thank you very much for your attention!

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