Automated Liquid-Line Detection in Handheld Syringe Videos

A Comparison of Edge-Based, Segmentation-Based, and Learning-Based Methods

author: Jorūnė Babarskaitė, email: jbabarskaite@student.tudelft.nl

TU Delft Delft University of Technology

1. Problem Definition

Why this matters

- Medication preparation in paediatric and neonatal care is high-risk
- Syringes are manually prepared in small, critical volumes
- Errors may still occur despite nurses double-checking

Why this is hard for computer vision

- Existing liquid-level methods are not designed for handheld syringes
- Syringe images present unique, unexplored challenges:
  - reflections
  - printed scale markings
  - hand occlusion
  - viewpoint variation (fixed with preprocessing by assuming OBB input)

2. Research Question & Methodology

Which computer vision approaches for liquid-line detection, when adapted to syringe images, achieve the best detection accuracy, and what are their key limitations in this medical setting?

Literature
Review existing liquid-line detection methods

→ **Categories**
Group approaches into categories
1. Edge-based
2. Segmentation-based
3. Learning-based

→ **Baseline Selection**
Select representative methods from each family

→ **Adaptation**
Adapt the methods to handle syringe images

→ **Evaluation**
Perform quantitative and qualitative analysis

3. Prior Work

Method Family	Works	Limitation
Edge-based	Eppel & Kachman [1]	Assumes known vessel boundary
Segmentation-based	Narasimhan et al. [2]	Requires colored liquid for label generation
Learning-based	Wu et al. [3]	Coarse fill states, not line position

Figure 1: Example of transparent vessels used in prior work: smooth transparent vessels without printed syringe-scale markings [1].

No prior method handles: opaque rubber stopper, transparent liquid, handheld camera, scarce data.

4. Selected Baselines

Method Name	Core idea	Training
Edge Scan	HSV mask → Sobel gradient → best horizontal edge	None
Blob-Prompted SAM 2	Find dark blob → bounding box prompt → SAM 2	None
YOLO-Prompted SAM 2	YOLO rubber stopper detector → SAM 2 prompt	YOLO only
ResNet Regression	ResNet18/50 → direct y-coordinate regression	Full

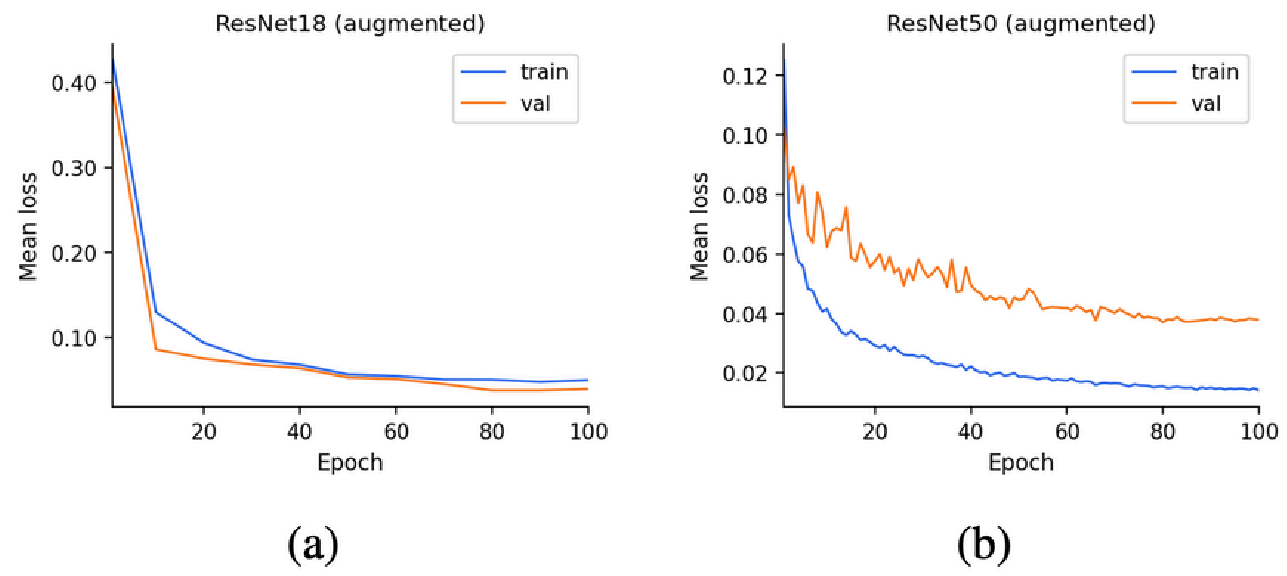

Figure 2: Training curves for (a) ResNet18 and (b) ResNet50. ResNet18 converges with train and val loss reaching similar values, while ResNet50 shows a persistent gap despite identical training configuration.

5. Results

$$Y_{\text{norm}} = \frac{|\bar{y}_P - \bar{y}_A|}{h_{\text{barrel}}}$$

$\bar{y}_P$ – predicted y-coordinate midpoint
$\bar{y}_A$ – annotated y-coordinate midpoint
h_{barrel} – syringe barrel height in pixels (derived from OBB)

Method	Detection rate	Y_{norm} mean	Y_{norm} median
Edge Scan	100%	1.31%	**0.33%**
Blob-Prompted SAM 2	100%	1.83%	0.41%
YOLO-Prompted SAM 2	91%	**1.03%**	0.69%
ResNet18	100%	8.96%	3.26%
ResNet50	100%	7.53%	3.42%

Median – typical per-frame performance
Mean – possibly skewed by outlier failures

- **Edge Scan** 0.33% median – well below graduation marking spacing (2–5%)
- **Blob-Prompted SAM 2** almost matches **Edge Scan** with zero training data (0.08% gap)
- **YOLO-Prompted SAM 2** – lowest mean (1.03%), but skips 9% of frames; mean is low by skipping anomalous data
- **ResNet** median almost 10× worse – likely learned session position priors instead of stopper appearance

Our experiments show calibrated classical and zero-shot methods both significantly outperform regression.

6. Failure Cases

Failure mode 1: Colored stopper

- HSV mask targets dark achromatic pixels
- Teal stopper excluded from mask → detector falls back to graduation mark
- YOLO abstains (best); Edge Scan + Blob-Prompted SAM 2 fall back to the wrong dark edge

Failure mode 2: Inverted crop

- Nurse holds syringe upside-down → OBB crop flipped
- Gradient selects wrong stopper face → systematic offset ≈ stopper height
- Affects all methods equally

Failures are systematic and predictable – fixable by orientation detection and dynamic color thresholding!

7. Conclusion & Future Work

Answer to the research question:

Domain-aligned classical methods and zero-shot foundation models significantly outperform regression at limited data scale.

- **Edge Scan:** best precision, fully interpretable
- **Blob-Prompted SAM 2:** near-identical precision to Edge Scan, requires zero training
- **ResNet:** fails under domain shift – data diversity is the bottleneck, not model capacity

Future work:

- Needle-tip detection → eliminate orientation ambiguity
- Dynamic color thresholding → handle non-standard rubber stoppers
- Temporal rolling median → smooth single-frame outliers

In medical settings, data will likely always be limited – calibrate, don't train.

References

[1] Sagi Eppel and Tal Kachman. Computer vision-based recognition of liquid surfaces and phase boundaries in transparent vessels, with emphasis on chemistry applications. 04 2014.

[2] Gautham Narayan Narasimhan, Kai Zhang, Ben Eisner, Xingyu Lin, and David Held. Self-supervised transparent liquid segmentation for robotic pouring, 2022.

[3] You Wu, Hengzhou Ye, Yaqing Yang, Zhaodong Wang, and Shuiwang Li. Liquid content detection in transparent containers: A benchmark. *Sensors (Basel, Switzerland)*, 23, 2023.

Source code & full results

github.com/joruniuke/Liquid-Line-Detection-in-Syringes