Multi-Spectral Imaging and Data Fusion for Real-Time Bleeding Detection

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Introduction and Motivation: Enhancing Real-Time Incident Monitoring

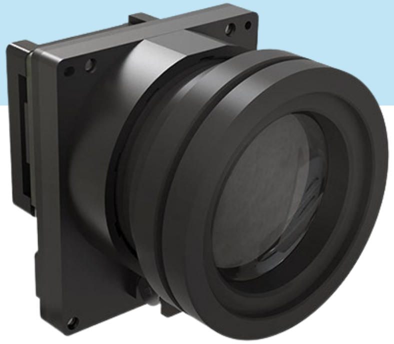
- Advancement of smart cities requires real-time incident monitoring.
- Real-time bleeding detection provides crucial insights for rescue teams in emergency situations.
- Addresses scenarios where victims may be unattended or incapacitated, enabling remote assessment of patient condition.

Key Advantage:

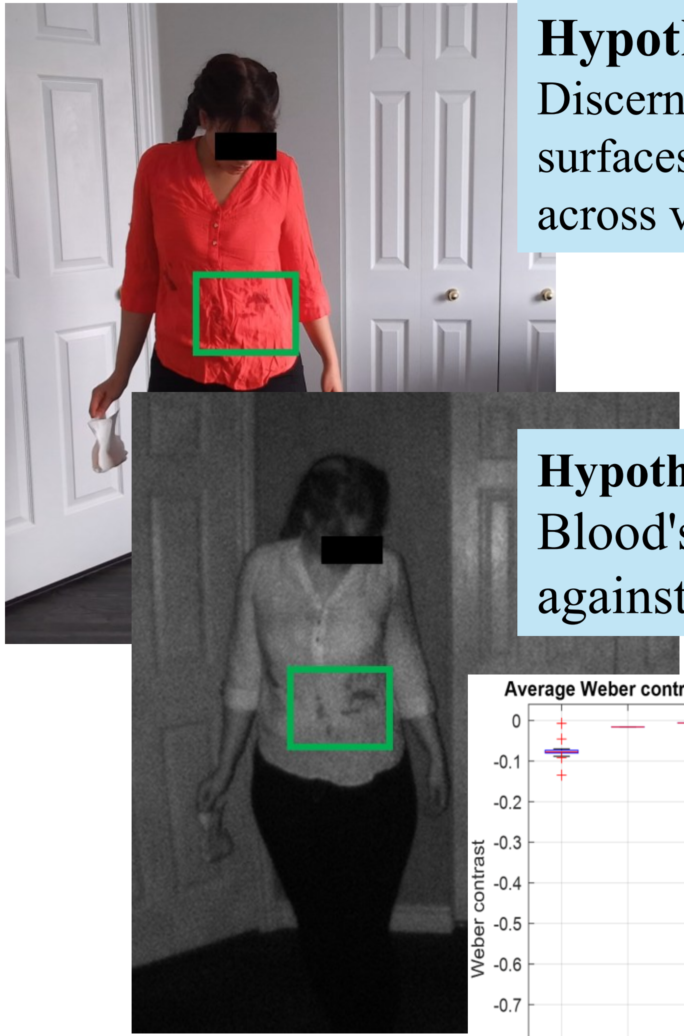
- Effective operation in **low-light conditions** and discrimination between blood and other fluids.
- Current literature has limited exploration of liquid spill detection using visual sensors, especially with **combined thermal and near-infrared imaging** for bleeding detection.

Multi-Spectral System Architecture

System utilizes **two Microcalibir** [1] thermal cameras and **two** RGB-D **Kinect Azure** [2] sensors
with active infrared (IR) cameras pulsing at 850 nm.

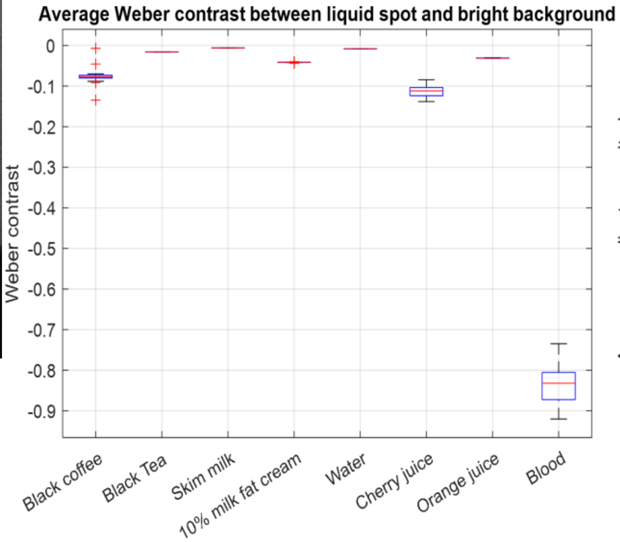


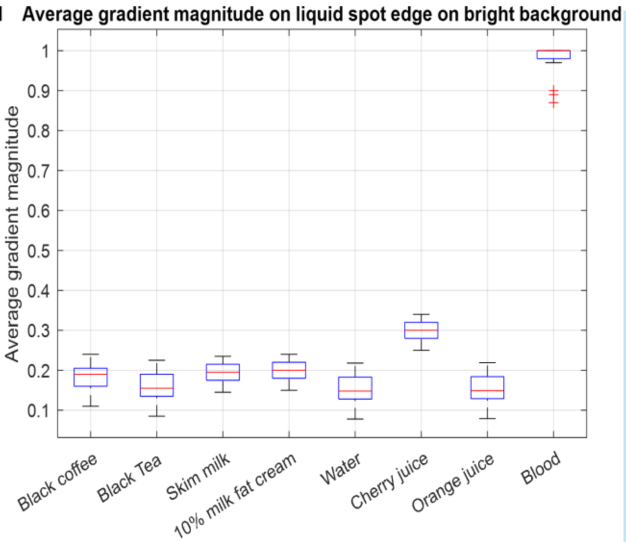
Core Hypotheses



Hypothesis 1 (Thermal):
Discernible temperature disparity between blood and surrounding surfaces (skin, clothing, objects, flooring) enables detection across various scenarios using thermal cameras.

Hypothesis 2 (IR):
Blood's unique response to IR emitted pulses (850 nm) acts as a key discriminatory factor against common liquids.





- Blood exhibits a notable absorption pattern of 850 nm pulses, appearing significantly lower in intensity (darker) in IR images.
- Other liquids remain nearly imperceptible at 850 nm wavelengths.

Deep Learning Methodology: Thermal Modality

Presence of Other Warm Objects to Help the Network Learn the Difference

Methodology:

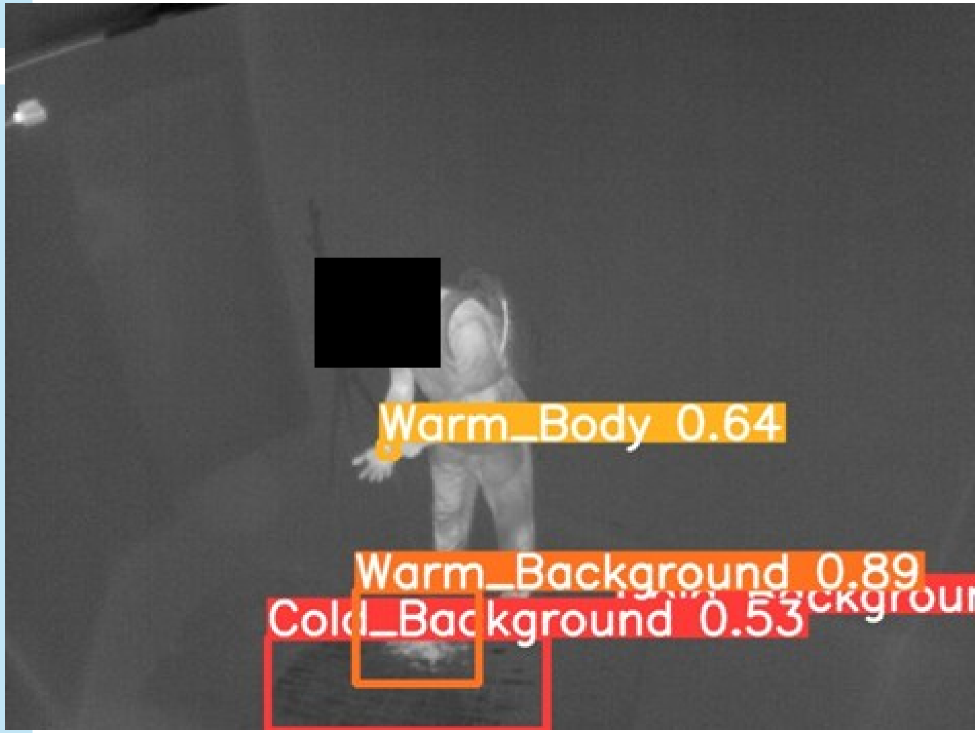
Detector: YOLO [4] (You Only Look Once) object detector.
Dataset: 40 bleeding simulation cases (80 sequences).
Simulated with warm water (~37°C) on diverse surfaces: cloth, wrist, floor, mattress (various materials).

Data Augmentation: Horizontal flip, cropping, shearing, rotation, brightness, blur, Gaussian noise.

Class Labels:

- Warm liquid on body
- Warm liquid on background
- Cold liquid on body
- Cold liquid on background
- Warm dripping liquid

Mitigation Classes: Face, Forehead (to reduce false positives).



Deep Learning Methodology: Near-Infrared Modality

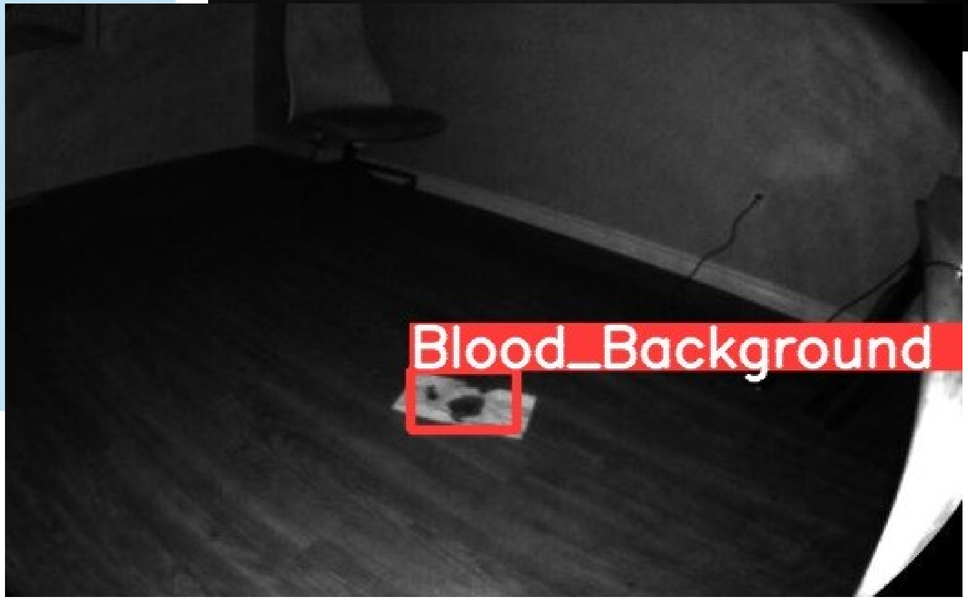
Methodology:

Detector: YOLO (You Only Look Once) object detector.
Dataset: Mixed real (187 images) and synthetic IR images.
Synthetic Generation: Registered thermal and IR images; liquid pixels in IR computationally darkened to mimic blood.

Data Augmentation: Horizontal flip, cropping, shearing, rotation, brightness, blur, Gaussian noise.

Class Labels:

- Blood on skin
- Blood on background (clothes, floor)



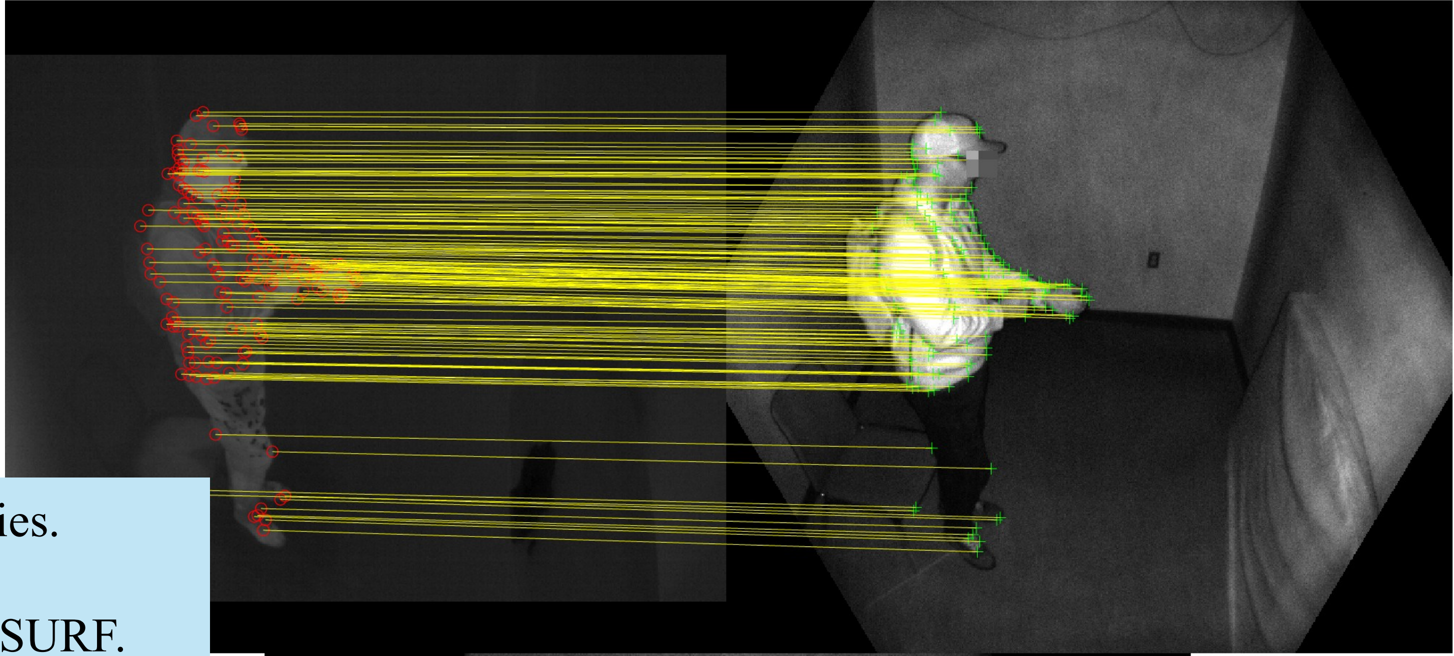
Annotation Strategy

Challenge:
Irregular, dynamic liquid shapes.

Optimization: Fewer, larger bounding boxes for entire liquid patches.

Benefit: Improved detection accuracy, aligns with thermal properties.

Multi-Modal Image Registration



Importance: Spatial correspondence between modalities.

Challenge: Nonlinear radiation distortion limits SIFT/SURF.

Solution: RIFT (Radiation-Variation Insensitive Feature Transform) [5].

Result: Affine transformation for pixel-to-pixel alignment.

b)

Rule-Based Alarm System: Fusing Thermal and IR Detections

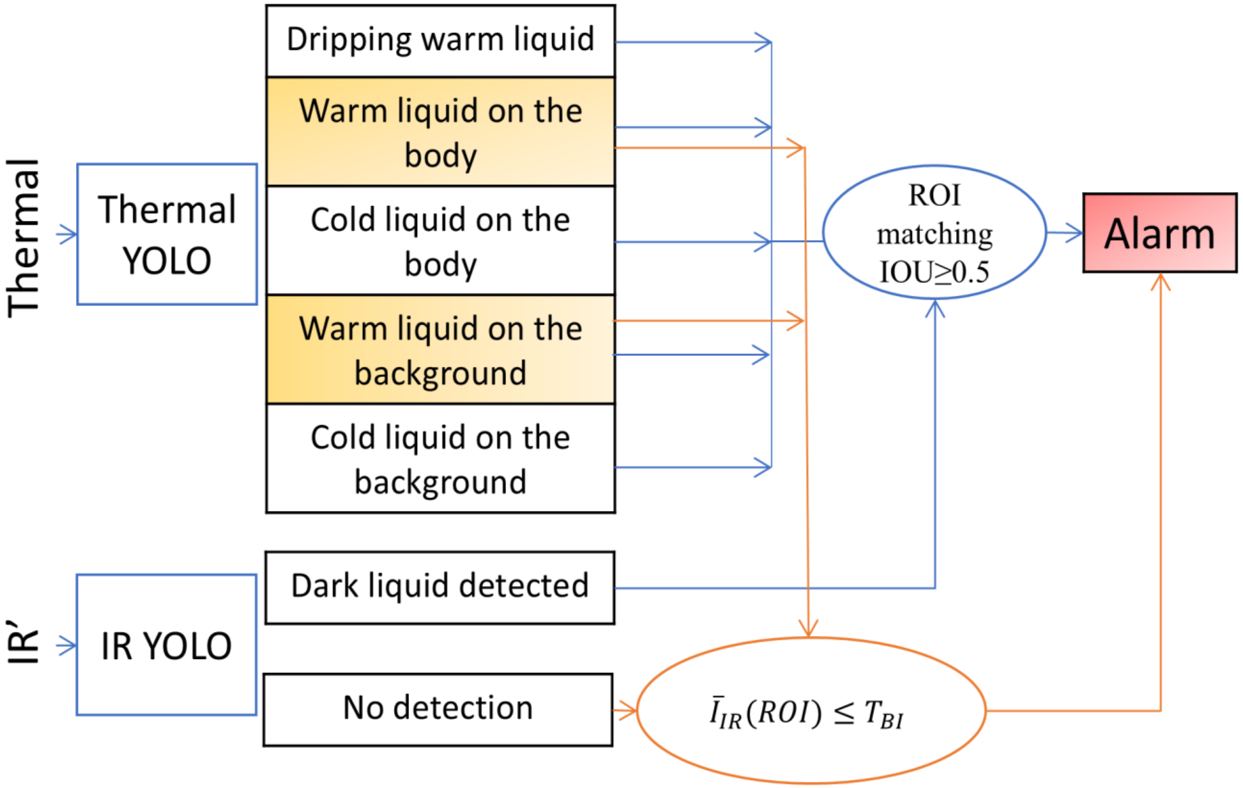
Decision Logic

Detection Matching: Intersection over Union (IoU ≥0.5) between thermal and IR bounding boxes.

Primary Alarm (Bleeding Confirmed): Dark area in IR AND Warm liquid in Thermal.
Rationale: Dark IR is most reliable for blood.

Notice/Warning (Liquid Detected):
Dark area in IR AND Cold/Unspecified liquid in Thermal.

Dark Background Scenario:
Warm liquid in Thermal BUT No IR detection (e.g., dark clothing).
If IR background intensity < *Threshold,* then *Warm liquid on dark background* → ***may require attention.***



Experimental Validation and Key Performance Insights

Implementation: C++ library, PyTorch/libTorch, real-time GPU (NVIDIA RTX 3090TI, 30 FPS).
Focus: Recognition rate (presence) over precise localization.

Modality	**Metric**	**Background**		**Body**	
		Warm	***Cold***	***Warm***	***Cold***
Thermal	RR	86%	89.18%	40.2%	44.4%
	FRR	6.5%	8.23%	12.9%	4.3%
IR	RR	80%		75%	
	FRR	0%		2.59%	
Multi-modal	RR	92%		68.3%	
	FRR	0%		0%	

Key Findings:

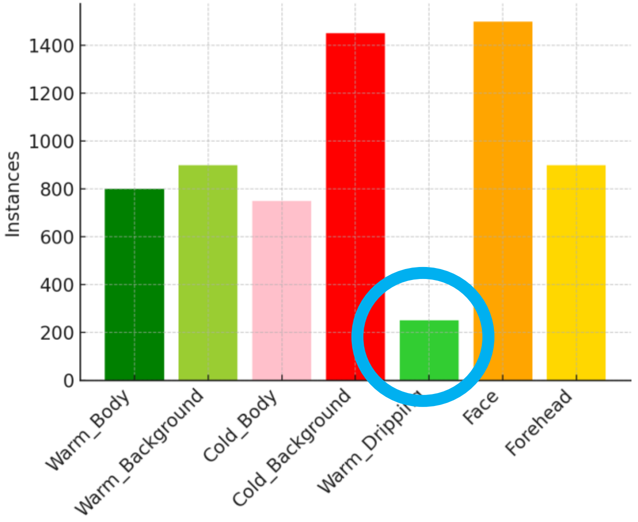
Surface Impact: Higher contrast, more effective on background surfaces.
Thermal Performance on Body: Challenging due to low temperature contrast with blood/skin.
False Positives (Thermal): 12.9% for warm liquid on body (heat trapped in joints).

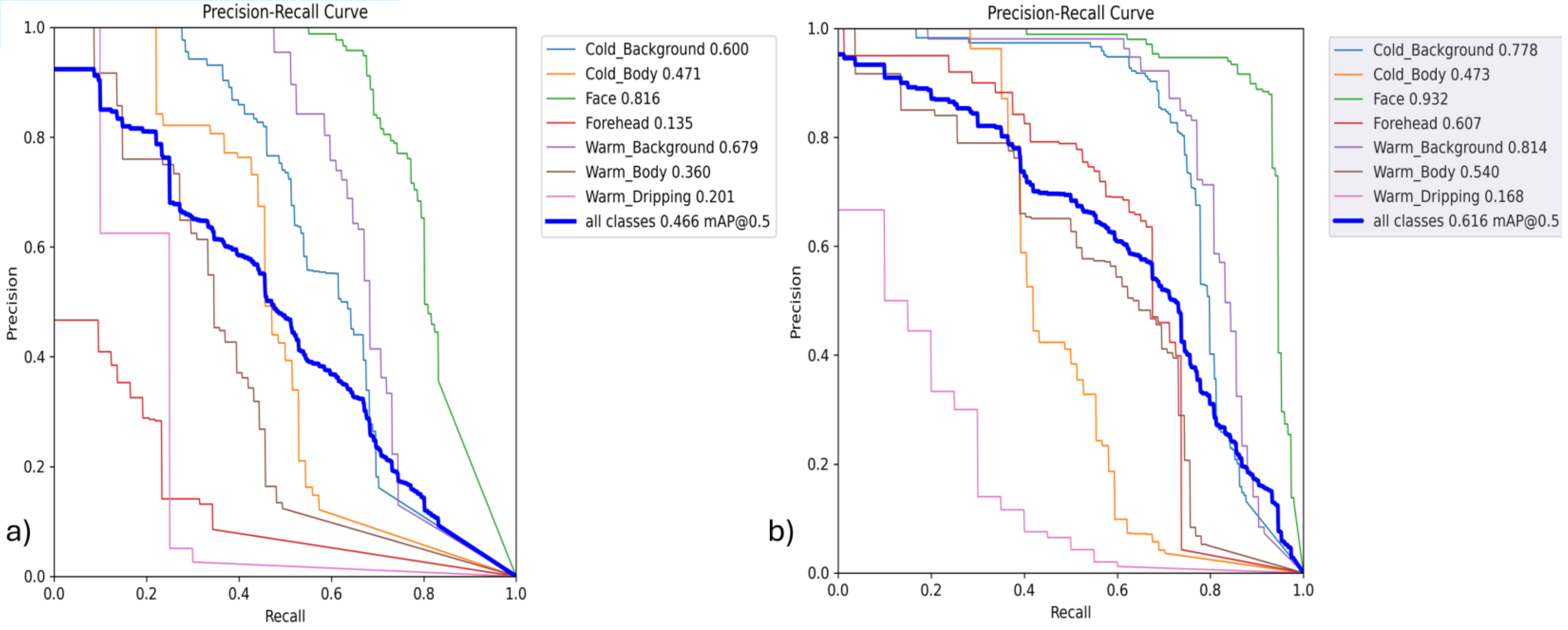
Experimental Validation and Key Performance Insights

Key Findings:

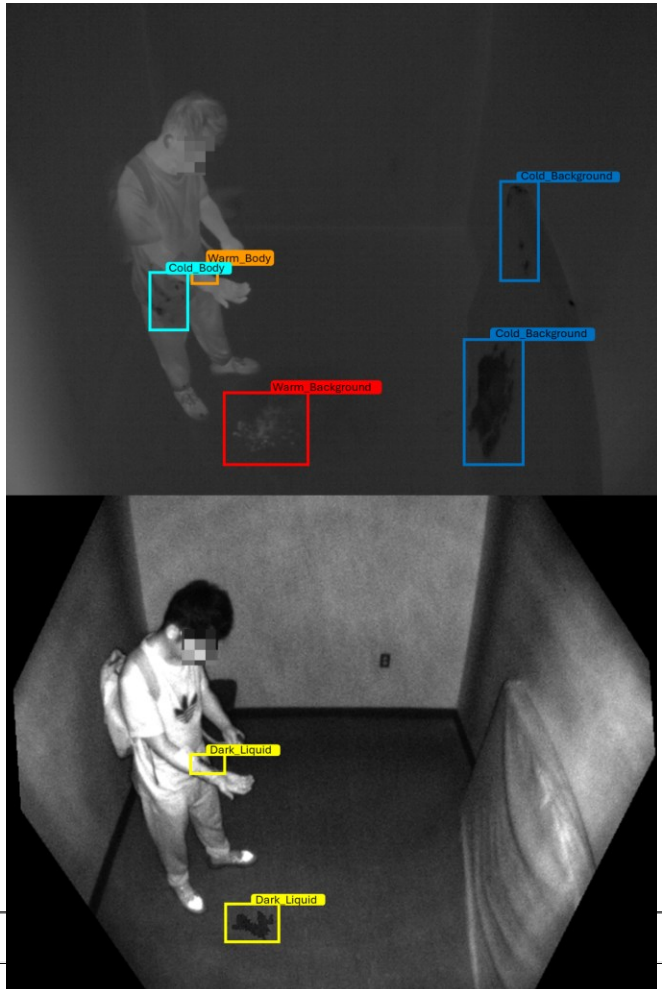
Annotation Benefit: Optimized strategy significantly improves mAP across classes.

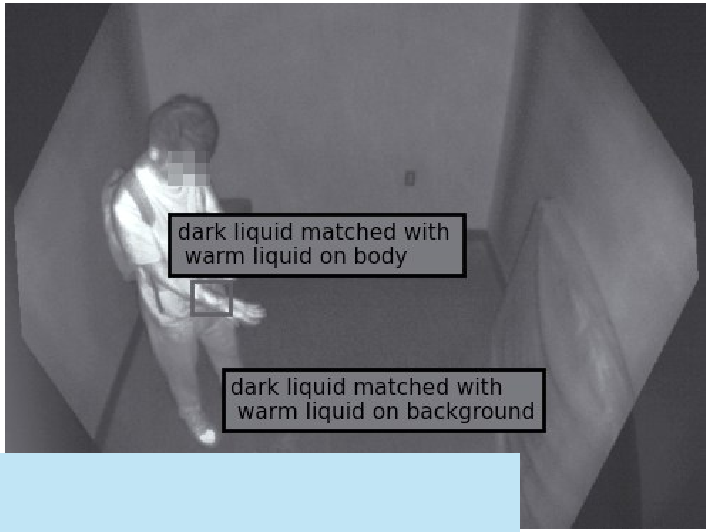
Dripping Liquid: Most challenging due to small sample size and appearance.





Multi-Modal Synergy and Comprehensive Performance





Key Findings (Continued):

Multi-Modal Enhancement: Significantly improves performance by eliminating false detections via cross-checking.

Surface Type & Temperature Impact (Referring to previous table):

- 100% accuracy for warm liquid on soft background (mattress).
- Reduced accuracy on solid backgrounds.
- Higher rates on textiles vs. skin (due to absorption/contrast).

	On Background				On Subject			
	Warm		Cold		Warm		Cold	
Liquid temperature relative to the surface beneath the liquid	Soft (Mattress)	Solid (Flooring)	Soft (Mattress)	Solid (Flooring)	Textile	Skin	Textile	Skin
Recognition Rate (%) with confidence threshold = 0.4	100%	75.00%	90.54%	0% *(No test sample)*	54.16%	50%	51.85%	0% *(No test sample)*

Conclusion

Summary:

- **Real-time bleeding detection system**: Long-wave (thermal) + Near-infrared imaging. **Validated blood's unique 850 nm IR spectral signature (lower intensity).**
- **Employed complementary deep object detectors (Thermal & IR).**
- **Optimized annotation strategy**: improved detection.
- **Robust detection**: Precise multi-modal matching and association.
- **Multi-modal data fusion**: Leverages thermal signature & dark IR appearance.
- **Rule-based alarm system**: Real-time responsiveness.
- **Significant Step**: Accurate, reliable bleeding detection for medical/emergency applications.

Key Future Work:

Dripping Liquid: Improve detection (sample size, feature learning).
False Positives: Collect diverse data (address body joint misclassifications).
Model Consolidation: Explore single YOLOv5 model for thermal + IR input (acceleration).

References

[1] Teledyne DALSA, “MicroCalibir compact uncooled LWIRcores.” https://www.teledynedalsa.com.

[2] Microsoft, “Azure Kinect DK.”,https://www.microsoft.com/en-us/d/azure-kinect-dk/8pp5vxmd9nhq?activetab=pivot:overviewtab.

[3] DeJong, S. A., Lu, Z., Cassidy, B. M., O’Brien, W. L.,Morgan, S. L., and Myrick, M. L. “Detection Limits forBlood on Four Fabric Types Using Infrared Diffuse Reflec-tion Spectroscopy in Mid- and Near-Infrared Spectral Win-dows,” Analytical Chemistry, 2015, 87(17):8740-7. DOI:10.1021/acs.analchem.5b01825

[4] Jocher, G., Ultralyctics, Yolov5, url:https://github.com/ultralytics/yolov5.

[5] Li, J., Hu, Q., and Ai, M. “RIFT: Multi-Modal Image Match-ing Based on Radiation-Variation Insensitive Feature Trans-form,” in IEEE Transactions on Image Processing, vol. 29,pp. 3296-3310, 2020, doi: 10.1109/TIP.2019.2959244.

Thank you!

Questions?

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