

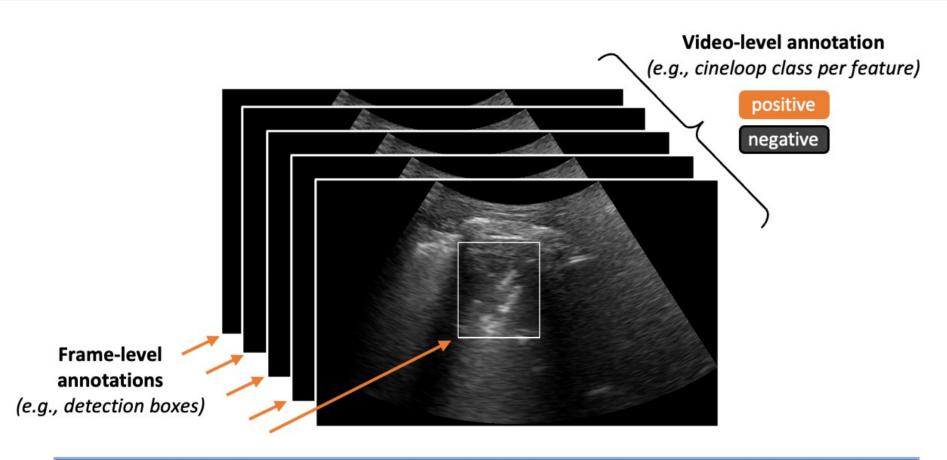
Weakly Semi-supervised Detector-based Video GH+ Classification with Temporal Context for Lung Ultrasound Labs



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Introduction



Method	Interpretability	Frame annotation burden		
Direct video classification	Poor	None		
Frame-based detection	Good	Significant		
Ours	Good	Minimal		

Technical challenge:

- Medical imaging tasks often require simultaneous frame detection and video classification.
 - **Example:** Lung ultrasound detection of consolidation and pleural effusion
- Standard detection models require frame-byframe annotations for training, which are costly.
- Direct video classifiers do not provide localization, which limits clinical interpretability.

Contributions:

- Address tradeoff between annotation burden and interpretability
- Provide simultaneous detection and classification on medical videos while requiring very limited frame-level supervision
- Introduce a mechanism to aggregate feature representation from spatial to temporal
- Demonstrate real-world effectiveness on a multicenter clinical lung ultrasound dataset

Methods						
Proposed framework: 1. Frame detection (weakly semi-	Frame-level detection (spatial)	Video-level tracking (temporal)	Tracklet-based cropping	Tracklet classifier $ \begin{array}{c} \hline \\ \hline $		
 supervised)¹: Stage 1, "Burn-in": supervised initialization Stage 2, Mutual learning: use frame- and video-labeled data for teacher-student training Aggregate predictions along tracklets: 	Frame-level detector	me Tracklet	ring Cropping Resizing	Subsampled output		
 Group predicted boxes into tracklets representing temporally connected regions Extract tracklet clips from the original video 3. Tracklet classification: 	Input: ultrasound video	Missing detections interpolated		tracklet $n \times x_{resize}^2$ $n \to n \to$		
 Second-stage network ("trackletNet") for tracklet classification using: enriched dataset of challenging examples from incorrect detector predictions weak semi-supervision using both 	Grange: Detections (predict bounding box) White: Ground truth	EV / Frames in a tracklet	Adjust predicted bounding boxes to squares (x_{resize}^2)	Subsampled tracklet from other tracklets Frame-level predictions		

frame and video annotations

- 4. Video classification:
 - Based on highest tracklet confidence

Output: video-level classification and framelevel detections

Figure 1. Detection and video classification framework. The method aggregates boxes from a 2D frame detector into tracklets, which are classified using a second-stage (CNN+LSTM) network. Both the frame detector and tracklet classifier are trained via weak semi-supervision using frame- and video-level labels.

Experiments

Data:

- **Multi-center dataset** of 7,712 ultrasound videos from 420 patients at 8 sites (60 to 180 frames per video).
- Training, validation, and testing datasets separated by subject:

	Consolidation	Pleural effusion		
Training	99 frame-labeled videos, 6,677 video-labeled videos	80 frame-labeled videos, 9,836 video-labeled videos		
Validation	337 videos	273 videos		
Testing	599 videos	233 videos		

Experiments:

- Base classification model: CNN + LSTM
- Base detector-based classification model: STN²
- Reduce ROI: bypass detection step → directly use whole image to train and evaluate trackletNet (Table 1, row 3)

Table 1. Frame detection and video classification results for consolidation and pleural effusion.

Approach	Frame	Video/tracklet	# of FLL	# of VLL	Detection	Classification
	detector	classifier	videos	videos	(Test AP_{50})	(Test AUC)
Direct	N.A.	EfficientNet+LSTM	0	6677 / 9836	N.A.	0.748 / 0.809
video	N.A.	MobileNet+LSTM	0	6677 / 9836	N.A.	0.870 / 0.910
classifier	N.A.	CNN+LSTM(video)	0	6677 / 9836	N.A.	0.909 / 0.894
Detector-	STN	Uninorms	99*/80*	6677 / 9836	N.A.	0.886 / 0.916
based	WSS Yolo+TR	MaxConf	99/80	6677 / 9836	0.345 / 0.334	0.880 / 0.893
video	WSS Yolo+TR+FLT	CNN+LSTM(tracklet)	99/80	6677 / 9836	0.381 / 0.365	0.936 / 0.938
classifier	WSS Yolo+TR	MaxConf	14**	6677	0.318	0.905
	WSS Yolo+TR+FLT	CNN+LSTM(tracklet)	14**	6677	0.369	0.927

Table 2. Ablation experiments for consolidation frame detection and video classification.

Frame detector	Video/tracklet classifier	# of FLL	# of VLL	Detection	Classification
		videos	videos	(Test AP_{50})	(Test AUC)
FS Yolo	Max conf	99	0	0.257	0.845
WSS Yolo	Max conf	99	6677	0.329	0.882
WSS Yolo + TR	Max conf	99	6677	0.345	0.880
WSS Yolo + TR	CNN+LSTM (Single frame)	99	6677	0.345	0.905
WSS Yolo + TR	CNN+Dense (Subsampled tracklet)	99	6677	0.345	0.921
WSS Yolo + TR	CNN+LSTM (Subsampled tracklet)	99	6677	0.345	0.936
WSS Yolo + TR + FLT	CNN+LSTM (Single frame)	99	6677	0.371	0.905
WSS Yolo + TR + FLT	CNN+Dense (Subsampled tracklet)	99	6677	0.366	0.921
WSS Yolo + TR + FLT	CNN+LSTM (Subsampled tracklet)	99	6677	0.381	0.936

- Simple rule-based aggregation: bypass tracklet classifier → classify video based on max detection confidence (Table 2, rows 2 and 3)
- Remove tracker: bypass tracking step → directly use frame detection confidences for video classification
- Remove temporal aggregation by trackletNet: classify tracklet based on single (central) frame (Table 2, row 4)

WSS: weakly semi-supervised; FS: fully-supervised; TR: tracking; FLT: filtering detection results based on tracklet predictions; FLL: frame-level labeled; VLL: video-level labeled;
*: frame-level bounding box label was used to create the frame-level class label; **: experiments performed on consolidation dataset only



Figure 2. Examples of videos correctly classified by trackletNet but not by frame detector. White: ground-truth; Orange: detector confidences; Green: tracklet confidences.

¹Jiahong Ouyang, Li Chen, Gary Y Li, Naveen Balaraju, Shubham Patil, Courosh Mehanian, Sourabh Kulhare, Rachel Millin, Kenton W Gregory, et al. Weakly semi-supervised detection in lung ultrasound videos. In *International Conference on Information Processing in Medical Imaging*, pages 195–207. Springer, 2023. ²Subhankar Roy, Willi Menapace, Sebastiaan Oei, Ben Lui- jten, Enrico Fini, Cristiano Saltori, Iris Huijben, Nishith Chennakeshava, Federico Mento, Alessandro Sentelli, et al. Deep learning for classification and localization of covid-19 markers in point-of-care lung ultrasound. IEEE transactions on medical imaging, 39(8):2676–2687, 2020.