ALFred: An Active Learning Framework for Real-world Semi-supervised Anomaly Detection with Adaptive Thresholds

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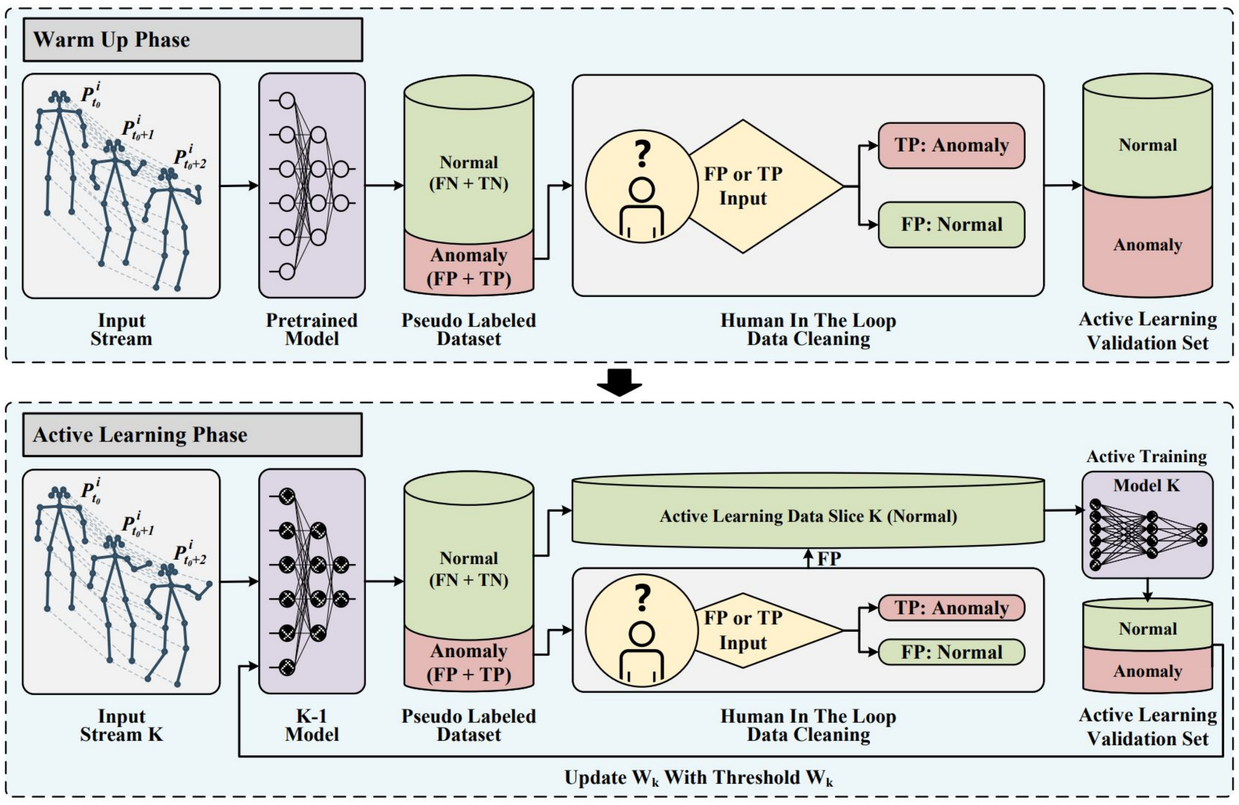
Introduction

- **Video Anomaly Detection (VAD) Challenges:**
  - **Dynamic nature of human actions.**
  - **Lack of decision threshold in deployment.**
  - **Lack of real world scenario evaluation.**
- **Focus:**
  - **Assessing VAD algorithms in real-life conditions using an active learning framework.**
- **Results:**
  - **ALFred achieves an EBI (Error Balance Index) of 68.91 for Q3 in real-world simulated scenarios.**

Framework Overview



Contributions

- **Introducing ALFred, an active learning framework, applicable to existing models, for real-world VAD with adaptive thresholds.**
- **Bringing human-in-the-loop functionality to introduce reliable training and validation sets for active learning.**
- **Comparing training results that showcase the benefits of ALFred in offline training.**
- **Conducting extensive experiments that showcase the benefits of ALFred in adapting to unseen data.**

Training Methodology & Metrics

- **Training Methodology:**
  - **Continual Learning:**
    No filtering is applied
  - **Pseudo-Continual Learning:**
    Only data pseudo-labeled as normal
  - **Active Learning:**
    Human annotators identify FP among the pseudo-labeled anomalies
  - **AL Light:**
    A variant of active learning that minimizes annotator workload
- **Metrics**
  - **Error Balance Index:**

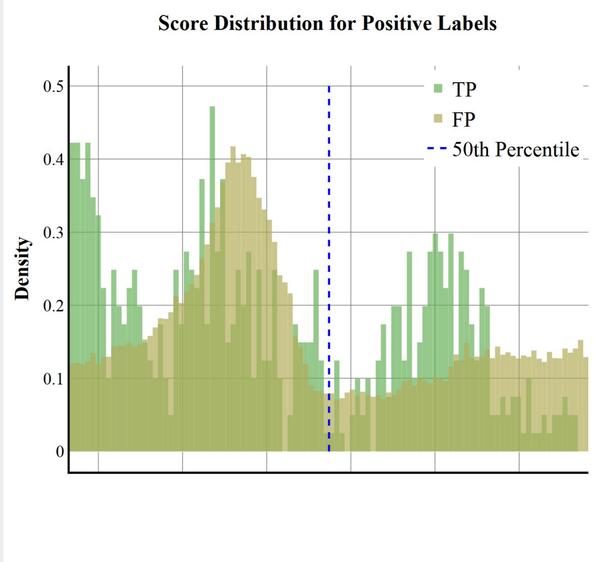
$$\text{EBI} = \frac{2 \times ((1 - FNR) \times (1 - FPR))}{(1 - FNR) + (1 - FPR)}$$

Comparison for models in different training from HuVAD

Model	Training Methodology	C0 FNR %	C0 FPR %	C1 FNR %	C1 FPR %	C2 FNR %	C2 FPR %
STG-NF	Continual Learning	**34.23**	33.00	27.42	56.32	**22.91**	59.36
	Pseudo-Continual Learning	48.46	**21.34**	33.55	**28.59**	35.27	**32.40**
	Active Learning	42.36	21.54	**23.21**	51.04	32.29	37.47
	AL Light	44.52	21.39	31.05	39.41	29.77	39.28
TSGAD	Continual Learning	27.80	51.29	62.64	17.08	**16.09**	49.39
	Pseudo-Continual Learning	26.00	**42.06**	**29.28**	38.62	37.67	44.19
	Active Learning	**13.26**	53.26	54.63	**10.93**	51.83	**22.25**
	AL Light	19.07	46.78	48.34	12.60	46.12	26.68
SPARTA	Continual Learning	**27.49**	47.59	**21.60**	54.89	23.23	47.16
	Pseudo-Continual Learning	29.63	46.58	23.59	53.08	23.81	**46.14**
	Active Learning	28.98	**45.66**	25.67	51.12	**21.93**	48.09
	AL Light	28.32	46.67	23.97	**50.00**	22.37	47.78

Model	Training Methodology	C3 FNR %	C3 FPR %	C4 FNR %	C4 FPR %	C5 FNR %	C5 FPR %
STG-NF	Continual Learning	45.11	16.83	40.44	85.33	**24.61**	76.12
	Pseudo-Continual Learning	**37.42**	**12.46**	42.02	**40.72**	32.14	**61.39**
	Active Learning	40.96	13.47	**41.02**	80.16	35.37	77.14
	AL Light	42.69	13.61	41.70	80.68	38.94	68.39
TSGAD	Continual Learning	40.44	35.11	61.23	**39.69**	43.31	34.97
	Pseudo-Continual Learning	**21.75**	53.51	42.12	56.32	**19.85**	57.99
	Active Learning	47.38	30.65	41.38	51.26	30.43	**25.52**
	AL Light	47.90	**29.93**	**40.70**	51.15	29.34	28.02
SPARTA	Continual Learning	26.73	15.54	**30.44**	62.15	**16.18**	63.85
	Pseudo-Continual Learning	26.36	15.48	32.37	61.60	17.81	62.59
	Active Learning	**26.29**	**14.53**	31.15	59.05	17.55	**59.99**
	AL Light	27.74	15.27	31.02	**58.94**	17.06	61.89

Score distribution & EBI distribution



Research Questions and Future Directions

- **Challenges:**
  - **Current pose-based anomaly detection performance still leaves room for improvement.**
  - **Need to assess timing, efficiency, and hardware requirements for real-world use.**
  - **Long-term, real-world monitoring is required to evaluate adaptability and identify failure modes.**
- **Future:**
  - **Employ meta-learning and reward-based adaptation to generalize across unseen environments.**
  - **Conduct structured, continuous deployment studies to measure robustness, efficiency, and real-world viability.**

Previous Work

[1] Pazho, Armin Danesh, et al. "Ancilia: Scalable intelligent video surveillance for the artificial intelligence of things." IEEE Internet of Things Journal 10.17 (2023): 14940-14951.

[2] Shanle Yao, Ghazal Alinezhad Noghre, Armin Danesh Pazho, and Hamed Tabkhi. Evaluating the effectiveness of video anomaly detection in the wild: Online learning and inference for real-world deployment. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, pages 4832–4841, June 2024.

[3] Ghazal Alinezhad Noghre, Armin Danesh Pazho, and Hamed Tabkhi. An exploratory study on human-centric video anomaly detection through variational autoencoders and trajectory prediction. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 995–1004, 2024.

[4] Ghazal Alinezhad Noghre, Shanle Yao, Armin Danesh Pazho, Babak Rahimi Ardabili, Vinit Katariya, and Hamed Tabkhi. Pheva: A privacy-preserving human-centric video anomaly detection dataset. arXiv preprint arXiv:2408.14329, 2024.

[5] Ghazal Alinezhad Noghre, Armin Danesh Pazho, and Hamed Tabkhi. Human-centric video anomaly detection through spatio-temporal pose tokenization and transformer, 2025. URL https://arxiv.org/abs/2408.15185.

[6] Yao, Shanle, et al. "From Lab to Field: Real-World Evaluation of an Ai-Driven Smart Video Solution to Enhance Community Safety." Armin and Alinezhad~ Noghre, Ghazal and Neff, Christopher and Bourque, Lauren and Tabkhi, Hamed, From Lab to Field: Real-World Evaluation of an Ai-Driven Smart Video Solution to Enhance Community Safety.