Title: *Contactless Privacy-Preserving Ambient Intelligence for In-Home Care After Hospital Discharge*

Problem Statement

Readmission of patients after discharge from hospital is common and often costly [1]. In the United States, one-fifth of the discharged patients (nearly 2.6 million seniors), face an acute medical complication within 30 days that requires readmission or emergency department (ED) visits [2,3]. Our goal is to reduce this readmission rate, especially among older adults. In this project, we introduce an intervention approach based on the monitoring of Activities of Daily Living (ADL) trajectories using computer vision (CV) technology.

Core Research Idea

Video-recording provides a non-intrusive alternative to wearable sensors for ADL automated monitoring. Recent advances in CV have shown promise in human activity classification from videos [4,5,6,7]. If we apply these techniques to classify clinically relevant activities accurately, an inexpensive, passive, continuous layer of safety and monitoring can be developed for the aging population. While RGB cameras are standard for visual sensing, they can capture highly identifiable data and may raise privacy concerns. In our previous studies, we used depth sensors to address privacy concerns [8,9]. These sensors capture depth images with pixel values recording a calibrated distance between the objects and the sensor. Depth images do not capture appearance details and hence are often suitable for capturing course activities; however, they fall short when it comes to an understanding of the detailed activities of daily life. To understand the underlying information of movements and interactions with objects, in this study, we propose to use RGB videos but take several precautions and develop novel methods (explained below) to ensure privacy and transparency of the developed AI system. To the best of our knowledge, an automated, non-intrusive, privacy-compliant vision-based system trained on real video data for continuous senior activity detection and long-term health monitoring has not been developed before. We acknowledge that it is essential to co-develop this technology with privacy and security in mind, with the continued involvement of all stakeholders (patients, family, caregivers, etc.), legal experts, and policymakers. We will use several emerging privacy-preserving techniques developed recently (e.g., face blurring [10], body masking [11], differential privacy [12], & homomorphic encryption [13]). In this proposal, to reduce 30-day hospital readmission rates among older adults, we introduce an intervention approach based on the monitoring of ADL trajectories using CV technology. We implement our proposal in three steps: In the *1st step*, we develop a CV-based activity detection algorithm to describe and compare the ADL trajectories of the population with readmission or ED visits and the non-admitted counterpart. In *step 2*, we develop a predictive model that anticipates future readmission or ED visits based on the deterioration of ADL trajectories. *Step 3* will include a clinical intervention based on the prediction of our developed CV model.

Detailed Technical Approach

In *Step 1*, we will develop CV models to compare and differentiate the ADL trajectory between the patients with different outcomes. We hypothesize that patients with readmission or ED visit outcomes have a different ADL trajectory compared to non-admitted patients within 30 days of hospital discharge. In collaboration with Stanford Hospital, we will collect video data from homes of 20-40 participants, chosen from high-risk adults over 65 within 72 hours of discharge from the hospital. We exclude patients who are permanently non-ambulatory or discharged to skilled nursing facilities. The activities we are tracking include mobility (sitting, standing, walking), sleeping, eating/drinking, dressing/grooming, bathing/toileting, and left the room.

In *Step 2*, we will develop a predictive model to estimate potential readmission/ED visits. We hypothesize that ADL trajectory metrics measured with a CV system can accurately predict readmission/ED visit composite outcomes 24-48 hours before the occurrence. A 24-48 hours ahead prediction is needed to optimize resource deployment for intervention. We will collect video data from homes of 20-40 randomly selected participants within 72 hours of discharge. In *Step 3*, we will develop a CV-assisted intervention system to reduce readmission/ED visits. We hypothesize that a timely intervention system based on continuous vision-based monitoring can reduce composite readmission outcomes. The population of Step 2 will be used for this intervention. We will develop an alert system for the composite outcomes based on the prediction from step 2. The intervention methods include follow-up phone calls and home visits.

Human-Centered Design

Similar to other technologies, transformation into the clinical utility at scale must overcome challenges such as rigorous clinical validation, appropriate data privacy, and transparency while centering stakeholder perspectives and in-depth consideration of constraints and prospective impacts. In this study, in addition to the technical aspects of the work, we will study the complex interplay among the physical environment, health-critical human behaviors, and human centered aspects of artificial intelligence. Adverse experiences with AI technologies can taint future receptivity and hence have cascading long-term repercussions that pose barriers to the widespread adoption and success of these systems. To avoid such adversaries, our proposal contributes several methodological advances that are informed by and integrated with human centered research efforts around user acceptance and other socio-technical challenges.

Potential Impacts and Future Plans

Our research project has strong translational promise, directly building AI technologies to increase the quality of care and, ultimately, life. We foresee that this pilot analysis through PAC Stanford Hospital collaboration will motivate a more extensive study for an independent NIH R01 or an NSF proposal. We anticipate that the ultimate system will be useful for all hospitals.

Team

The Partnership in AI-Assisted Care (PAC) is an interdisciplinary collaboration between the School of Medicine and the Computer Science (CS) Department, focusing on cutting edge computer vision and artificial intelligence technologies to solve some of the most critical problems in healthcare. This project will be led by Prof. Fei-Fei Li (co-director of PAC, Professor of CS) and Prof. Kevin Schulman (Professor of Medicine). Two of the key personnel in the project include Dr. Ehsan Adeli (Faculty at School of Medicine and affiliate at the CS Department), and Alan Luo (Ph.D. student). Besides, this project will benefit from the support and collaboration of Prof. Arnold Milstein (co-director of PAC) and Drs. Amit Kaushal (clinical assistant professor), Haya Rubin (clinical advisor), Matthew Mesias (research partner), Paul Tang (adjunct professor), and Vittavat Termglinchan (instructor).

Budget

The requested budget of $75,000 will be used for equipment such as sensors and compute units ($20,000), wireless network charges for transmitting data from patients' homes to our servers ($1,000), and 50% graduate student Research Assistant over three quarters ($54,000).

References

[1] Donzé, J., Aujesky, D., Williams, D. and Schnipper, JL, 2013. Potentially avoidable 30-day hospital readmissions in medical patients: derivation and validation of a prediction model. JAMA internal medicine, 173(8), pp.632-638.

[2] Jencks, S.F., Williams, M.V. and Coleman, E.A., 2009. Rehospitalizations among patients in the Medicare fee-for-service program. New England Journal of Medicine, 360(14), pp.1418-1428.

[3] Hughes, Lloyd D., and Miles D. Witham. "Causes and correlates of 30 day and 180 day readmission following discharge from a Medicine for the Elderly Rehabilitation unit." BMC geriatrics 18, no. 1 (2018): 1-10.

[4] Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).

[5] Simonyan, K. and Zisserman, A., 2014. Two-stream convolutional networks for action recognition in videos. In Advances in neural information processing systems (pp. 568-576).

[6] Ji, J., Krishna, R., **Fei-Fei, L.** and Niebles, J.C., 2020. Action Genome: Actions As Compositions of Spatio-Temporal Scene Graphs. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 10236-10247).

[7] Lu, M., Poston, K., Pfefferbaum, A., Sullivan, E.V., **Fei-Fei, L.,** Pohl, K.M., Niebles, J.C. and **Adeli, E.,** 2020. Vision-based Estimation of MDS-UPDRS Gait Scores for Assessing Parkinson's Disease Motor Severity. In Medical Image Computing and Computer Aided Intervention (MICCAI).

[8] **Luo, Z.,** Hsieh, J.T., Balachandar, N., Yeung, S., Pusiol, G., Luxenberg, J., Li, G., Li, L.J., Downing, N.L., Milstein, A. and **Fei-Fei, L.**, 2018. Computer vision-based descriptive analytics of seniors' daily activities for long-term health monitoring. Machine Learning for Healthcare (MLHC), 2.

[9] Xue, D., Sayana, A., Darke, E., Shen, K., Hsieh, J.T., **Luo, Z.,** Li, L.J., Downing, N.L., **Milstein, A.** and **Fei-Fei, L.,** 2018. Vision-based gait analysis for senior care. arXiv preprint arXiv:1812.00169.

[10] Wang, J., Amos, B., Das, A., Pillai, P., Sadeh, N. and Satyanarayanan, M., 2017, June. A scalable and privacy-aware IoT service for live video analytics. In Proceedings of the 8th ACM on Multimedia Systems Conference (pp. 38-49).

[11] Kocabas, M., Athanasiou, N. and Black, M.J., 2020. VIBE: Video inference for human body pose and shape estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 5253-5263).

[12] Xu, C., Ren, J., Zhang, D., Zhang, Y., Qin, Z. and Ren, K., 2019. GANobfuscator: Mitigating information leakage under GAN via differential privacy. IEEE Transactions on Information Forensics and Security, 14(9), pp.2358-2371.

[13] Acar, A., Aksu, H., Uluagac, A.S. and Conti, M., 2018. A survey on homomorphic encryption schemes: Theory and implementation. ACM Computing Surveys (CSUR), 51(4), pp.1-35.

[14] Jobin, A., Ienca, M. and Vayena, E., 2019. The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), pp.389-399.

[15] Zhou, J. and Chen, F. eds., 2018. Human and machine learning: Visible, explainable, trustworthy and transparent. Springer.

[16] Caliskan, A., Bryson, J.J. and Narayanan, A., 2017. Semantics derived automatically

from language corpora contain human-like biases. Science, 356(6334), pp.183-186. [17] Zou, J. and Schiebinger, L., 2018. Design AI so that it's fair. Nature, 559(7714), pp.324- 326.

[18] **Adeli, E.,** Zhao, Q., Pfefferbaum, A., Sullivan, E.V., **Fei-Fei, L.,** Niebles, J.C. and Pohl, K.M., 2019. Representation Learning with Statistical Independence to Mitigate Bias. arXiv preprint arXiv:1910.03676.

[19] Pimple, K.D., 2002. Six domains of research ethics. Science and engineering ethics, 8(2), pp.191-205.

[20] Dai, J., Wu, J., Saghafi, B., Konrad, J. and Ishwar, P., 2015. Towards privacy-preserving activity recognition using extremely low temporal and spatial resolution cameras. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 68-76).

[21] McMahan, B., Moore, E., Ramage, D., Hampson, S. and y Arcas, B.A., 2017, April. Communication-efficient learning of deep networks from decentralized data. In Artificial Intelligence and Statistics (pp. 1273-1282).