Bridging Patient Experience and Clinical Data: An LLM-Powered Chat Interface with Real-Time EEG Metrics

Zack Goldblum[1,2*], Haoer Shi[1,2], Victor Novakov[3], Brian Litt[1,2,4]

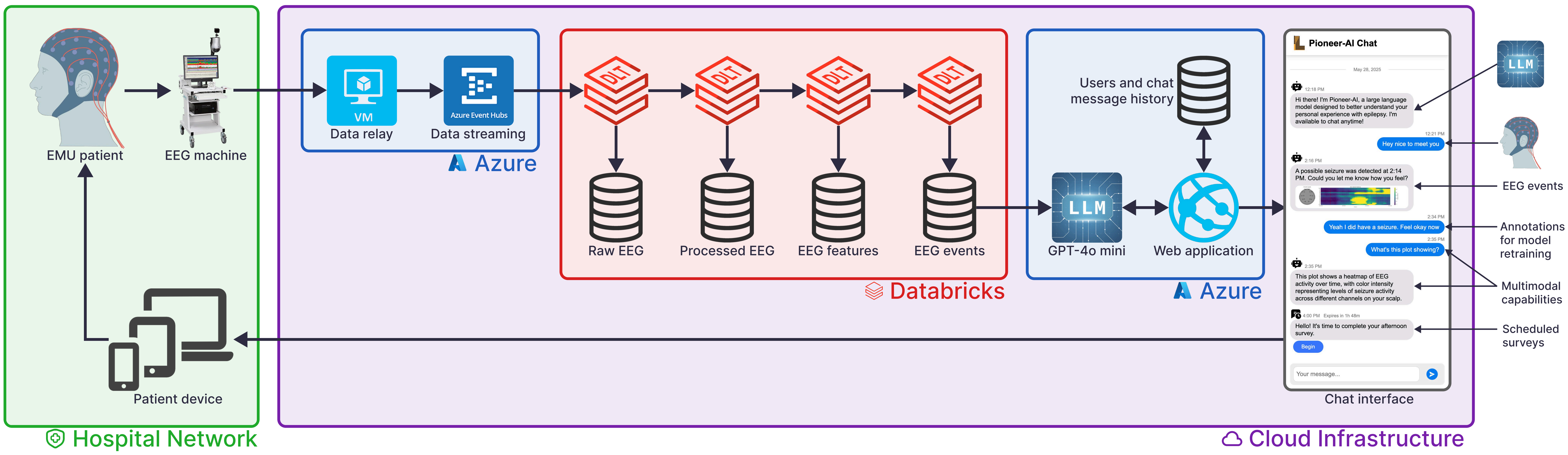
1 Center for Neuroengineering & Therapeutics, University of Pennsylvania
2 Department of Bioengineering, University of Pennsylvania
3 Department of Bioengineering, McGill University
4 Department of Neurology, University of Pennsylvania
* For correspondence, please email zackgold@seas.upenn.edu

CNT Center for Neuroengineering and Therapeutics | Litt Lab | Penn Engineering | Perelman School of Medicine, University of Pennsylvania

Background

- The integration of AI into healthcare has the potential to improve the delivery of care, especially for chronic conditions like epilepsy that require continuous monitoring and support[1].
- Contemporary research leveraging large language models (LLMs) predominantly focuses on enhancing diagnostic capabilities and supporting clinical decision-making.
- Direct patient-LLM communication in clinical environments has promising benefits for both patients and caregivers, yet remains largely unexplored[2].
- Challenges for this effort include ensuring the safety and constraint of LLM responses, managing protected health information (PHI), and integrating with hospital networks[3].
- **We have developed and deployed a system in the epilepsy monitoring unit (EMU) that utilizes an LLM to facilitate interactions between a patient and their real-time EEG data.**
- **We envision it conducting ecological momentary assessments and informing algorithms that learn and adapt over time.**

Methods



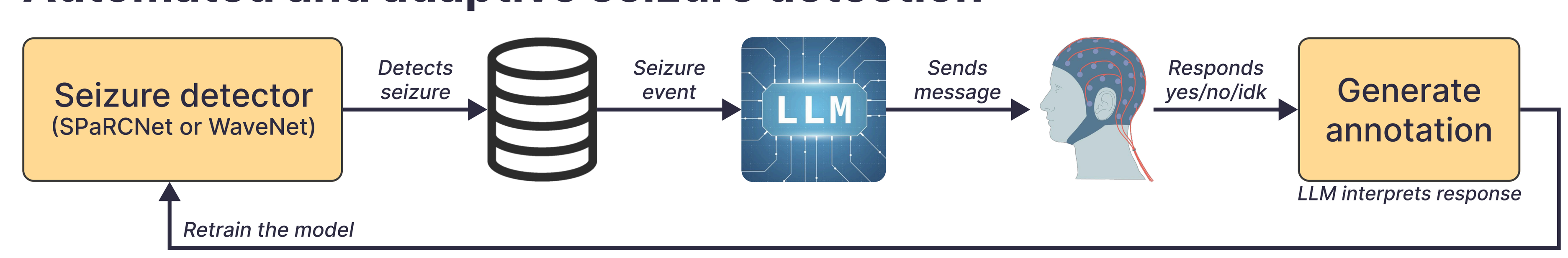
System architecture

1. Acquires the patient's real-time EEG data stream from the hospital network
2. Routes this data stream into the cloud for processing and analysis
3. Sends chat messages to the patient via the LLM based on EEG events
4. The LLM facilitates conversations, answers patient's questions, and more

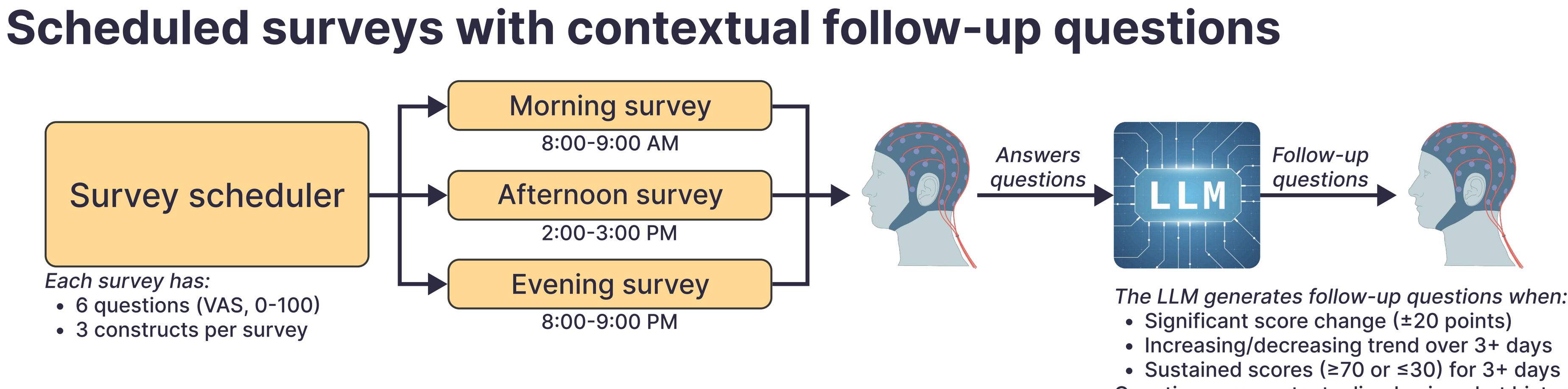
EEG Processing and Features	Features					
	YASA[4]	Alpha/delta ratio	Spike detector	Synchrony	SPaRCNet[5] (scalp)	WaveNet[6] (intracranial)
Downsample	100 Hz	No	No	No	200 Hz	128 Hz
Bandpass filter	0.4-30 Hz	0.5-100 Hz	0.5-100 Hz	0.5-100 Hz	1-40 Hz	0.5-100 Hz
Notch filter	60 Hz	60 Hz	60 Hz	60 Hz	60 Hz	60 Hz
Reject bad channels	Yes	Yes	Yes	Yes	Yes	Yes
Re-reference	CAR	CAR	CAR	CAR	Bipolar	Bipolar
Prewhiten	No	No	No	No	No	Yes
Window size	300 sec	60 sec	60 sec	60 sec	10 sec	1 sec
Window stride	300 sec	60 sec	60 sec	60 sec	2 sec	0.5 sec

* YASA performs sleep staging, SPaRCNet and WaveNet are seizure detectors

Automated and adaptive seizure detection



Scheduled surveys with contextual follow-up questions



Results & Conclusion

- **Lossless EEG data streaming** from the EMU to cloud infrastructure.
- **Real-time pipelines** for EEG processing, analysis, and event detection.
- **PHI-secure web application** accessible on patients' own devices.
- **LLM maintains clinical context** while automated safety filters block out-of-scope queries.
- **< 5 second latency** from EEG event detection to patient notification.
- **Multimodal capabilities** for LLM interaction with text and images.
- **Patient-generated annotations** (via LLM interpretation) continuously retrain the seizure-detection model.
- **LLM-driven survey system** delivers contextualized follow-up questions based on chat history and previous survey responses.
- **This system bridges objective physiological measurements and patient-reported experiences in epilepsy monitoring by integrating real-time EEG analytics with LLM-mediated patient communication.**

References

1. Boßelmann, C., Leu, C., & Lal, D. (2023). Are AI language models such as ChatGPT ready to improve the care of individuals with epilepsy? Epilepsia, 64(5), 1195–1199. https://doi.org/10.1111/epi.17570
2. Van Diessen, E., Van Amerongen, R. A., Zijlmans, M., & Otte, W. M. (2024). Potential merits and flaws of large language models in epilepsy care: A critical review. Epilepsia. https://doi.org/10.1111/epi.17907
3. Yang, R., Tan, T. R., Lu, W., Thirunavukarasu, A. J., Ting, D. S. W., & Liu, N. (2023). Large language models in health care: Development, applications, and challenges. Health Care Science, 2(4), 255–263. https://doi.org/10.1002/hcs2.61
4. Raphael Vallat, Matthew P Walker. (2021). An open-source, high-performance tool for automated sleep staging eLife 10:e70092. https://doi.org/10.7554/eLife.70092
5. SPaRCNet: Jing J, et al. (2023). Development of Expert-Level Classification of Seizures and Rhythmic and Periodic Patterns During EEG Interpretation. Neurology. 100(17):e1750-e1762. doi: 10.1212/WNL.0000000000207127
6. Thuwajit, Punnawish, et al. (2021). EEGWaveNet: Multi-Scale CNN-Based Spatiotemporal Feature Extraction for EEG Seizure Detection. IEEE Transactions on Industrial Informatics. doi: 10.1109/TII.2021.3133307