Advances at the intersection of engineering, physics, and medicine have shaped some of the most meaningful improvements in global health. In recognition of how these innovations influence the quality of care and the lives of patients, I have committed myself to developing the skills needed to contribute to this ongoing progress. Yet I have also observed the persistent gap between what is technically possible and what is clinically accessible, particularly in resource-limited settings. Through my research experiences in artificial intelligence application in medicine in areas such as medical imaging and multi-omic data integration, I have developed a commitment to creating solutions that are both scientifically rigorous, clinically effective, and broadly implementable. I aspire to be part of a generation of scientists and engineers who bridge the existing gaps, by developing technologies that address real-world healthcare challenges regardless of geography or socioeconomic barriers. **I am therefore applying to the Harvard-MIT Health Sciences and Technology (HST) PhD program in Medical Engineering and Medical Physics (MEMP) because of its unique emphasis on translational research and clinical integration**. I believe this program offers the best environment to continue to learn and contribute in translational research in healthcare, given its diverse faculty in patient-centered clinical research, and computational methods.

My current research interests lie at the intersection of artificial intelligence, biomedical data science, and computational medicine. I have so far worked on developing trustworthy and interpretable methods for analyzing clinical and biomedical data, ranging from medical images to multi-modal datasets that integrate demographic and biomarker information. My work explores three complementary directions:

(A) Foundational algorithmic methods for building reliable, trustworthy automated machine learning systems such as incorporating uncertainty quantification to flag low-confidence predictions.

(B) Representation learning across diverse biomedical data modalities including ultrasound, magnetic resonance images, and computed tomography for predictive and diagnostic modeling.

(C) Ultimately working towards accessible and reliable methods for clinical applications, particularly in low-resource healthcare settings.

The challenges I aim to address center on the reliability, interpretability, and equitable deployment of computational methods in clinical practice, particularly for medical imaging and multimodal data integration with quantitative approaches that integrate biophysical insight with data-driven modeling. Many current systems may struggle with generalization across diverse patient populations, lack mechanisms for uncertainty awareness and remain inaccessible in settings with limited computational or clinical resources. The HST MEMP program offers an exceptional environment for pursuing such research, with its integration of engineering, physics, and clinical immersion, and emphasis on translational research.

I am especially excited about the Medical Physics component of the program, with courses like *Imaging Biophysics and Clinical Applications*, and the opportunity pursue subjects such as *Data Acquisition and Image Reconstruction in MRI*, which will ensure my data-driven methods are rigorously grounded in the physical principles of signal generation and device constraints. In my view, the quantitative physics training coupled with the mandatory clinical context as indispensable for developing meaningful translational tools. Furthermore, the **Neuroimaging Training Program** offers hands-on training in advanced imaging techniques that both directly support my current research interest, as well as prepare me for future expansive work in developing physics-informed computational methods across diverse imaging platforms and clinical applications.

My overarching goal is to bridge the technical and translational dimensions of artificial intelligence in medicine, developing systems that are computationally efficient, clinically meaningful, and deployable in real-world environments. In the short term, I aim to advance my expertise in biomedical data science with emphasis on model generalization, interpretability, and equitable performance across populations. In the long term, I aspire to lead research that drives data-informed healthcare innovations, translating computational and artificial intelligence innovations into deployable healthcare tools that improve diagnostic accuracy and expand global access to quality care. Beyond research, I am equally committed to mentorship and capacity building, contributing to the development of institutions in underserved communities capable of achieving globally recognized scientific impact.

My research experience spans roles at the Responsible Artificial Intelligence Lab (RAIL-KNUST), and at the Kumasi Center for Collaborative Research in Tropical Medicine (KCCR) as a Research Assistant and Engineer, where I have worked in developing AI-driven solutions for real-world healthcare challenges. My work in these roles has been recognized at national and international venues, including the annual International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI). At KCCR, work I am particularly proud of is a project on a context-specific LLM application designed to assist expectant mothers with gestational diabetes in disease management, further discussed in the next section.

Technical Contributions and Algorithmic Challenges

1. Large Kernel Architectures and Subgroup Generalization One of my most technically instructive projects involved the development of an end-to-end framework for breast tumor segmentation and pathological complete response (pCR) assessment in dynamic contrast-enhanced MRI [1]. I implemented a two-stage training strategy for segmenting breast lesions by expanding the kernel sizes of a ConvNeXt-based UNet in an iterative manner, followed by a self-normalizing network for assessing pCR based on high-dimensional radiomic biomarker features obtained from the segmentations. The results provided an important lesson in data distribution shifts. Subgroup analysis revealed significant variability: balanced accuracy reached 75% among patients aged 51–60 but declined to 30% in those aged 71+, highlighting the shortcomings of standard deep learning models when faced with imbalanced demographic data. This experience shifted my focus toward robustness and subgroup generalizability, motivating my current interest in integrating demographic priors directly into the learning process.

2. State-of-the-Art Segmentation in Low-Resource Contexts Recently, I supervised a team that achieved 1st Place in the Brain Tumor Segmentation Challenge (BraTS-SSA) at the 28th International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI 2025) [2]. We developed a segmentation-aware data augmentation pipeline combined with a deep ensembling approach. Segmentation-aware data augmentation involved performing very rigorous elastic deformation transforms that are masked only within the tumor regions, creating augmented samples that are anatomically plausible. We further combined diverse architectural paradigms: convolutional, transformer-inspired (ConvNeXt), and Mamba-based architectures, using probabilistic ensemble aggregation to produce final predictions that outperformed any single model approach.

3. Domain-Specific LLM Adaptation with Retrieval-Augmented Generation Another technically challenging project involved adapting large language models for domain-specific question-answering for gestational diabetes management, which I undertook at KCCR. This required solving several interconnected problems: experimenting with vector-based and graph-based retrieval-augmented generation (RAG) to ground responses in verified clinical information; fine-tuning and prompt engineering for reliable, evidence-based guidance across English and local languages; and designing a system architecture for deployment via WhatsApp to maximize accessibility. Working with domain experts, we iteratively refined the system based on clinical feedback and piloted it in a controlled environment. What made this project most rewarding was witnessing the direct clinical utility, and its potential to help standardize patient education, freeing up consultation time for more complex cases.

In Service to Community, I have had the honor of contributing in roles that allow me to give back and learn from those around me. Most recently, I have been involved in the Sprint AI Training Program for Medical Imaging Knowledge Translation (SPARK Academy) [1]. It is an initiative dedicated to advancing research capacity in medical imaging and deep learning especially in Africa, where I help coordinate the program and develop instructional materials for up and coming researchers and clinicians. A noteworthy outcome of this was supervising the Ghanaian team to winning first place in the Brain Tumor Segmentation Challenge (BraTS-SSA) at MICCAI 2025, marking the first time an African team has achieved this distinction [2]. My community engagements also include facilitating *SheCodes*, a girl-child empowerment program in STEM, where I teach students from the high-school to university levels in Python programming, microcontrollers, machine learning, and data science. In the open-source community, I have contributed to the TorchIO library for medical image processing, extended the nnU-Net framework to support additional use cases such as uncertainty modeling, and I am currently developing a Python library that simplifies access to medical image segmentation datasets for learning and benchmarking purposes [2]. In all these efforts, my goal is consistent: to help build communities and tools that make advanced computational methods and research more accessible, equitable, and impactful.

These experiences collectively inform my decision to pursue graduate study with the HST MEMP Program, demonstrating my preparedness through both independent research efforts [1] and effective teamwork and leadership evident in collaborative projects [2] and my coordination role at the SPARK AI Training Program. I am especially inspired by the works of **Dr. Polina Golland** whom I had the pleasure of meeting at MICCAI'25 for her works in computer vision applications in medicine; **Dr. Marzyeh Ghassemi** for her works in designing fair and private deep learning algorithms for healthcare which aligns with my interests in trustworthy methods; **Dr. Laura Lewis** and **Dr. Lauren O'Donnell** for their works in brain imaging analysis (dynamics, tractography) which aligns with my interest in neuroimaging and analysis; and **Dr. Peter Szolovits** for his pioneering works in biomedical informatics at the Clinical Decision Makign Group. I look forward to the opportunity of contributing my experience and perspective to the HST community, and learning from its culture of collaboration, where clinicians and scientists work together to transform research into tangible improvements in healthcare.

References

[1] **Toufiq Musah**. Large kernel mednext for breast tumor segmentation and self-normalizing network for pcr classification in magnetic resonance images. In *Artificial Intelligence and Imaging for Diagnostic and Treatment Challenges in Breast Care*, pages 72–80. Springer Nature Switzerland, 2026.

[2] Claudia Takyi Ankomah, Livingstone Eli Ayivor, Ireneaus Nyame, Leslie Wambo, Patrick Yeboah Bonsu, Aondona Moses Iorumbur, Raymond Confidence, and **Toufiq Musah**. How we won brats-ssa 2025: Brain tumor segmentation in the sub-saharan african population using segmentation-aware data augmentation and model ensembling. *arXiv preprint arXiv:2510.03568*, 2025.

[1] https://event.fourwaves.com/spark/pages
[2] https://github.com/toufiqmusah/MedSegMNIST