My Pathway in AI Research

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Background

Many years later, I can still remember the terms "adenocarcinoma" and "radical prostatectomy," which were the diagnosis and therapy an experienced urologist said to my grandpa after three weeks of anxious waiting, but no one knew how long my grandpa still needed to wait to receive the treatment. In sorrow, I was shocked by the amount of diagnosis and treatment planning time still required under medical professionals' extensive experience. As a middle school student then, I learned that researchers in the United States had begun to apply artificial intelligence (AI) to improve the efficiency of traditional healthcare processes.

This pivotal moment stayed with me, igniting a spark that would shape my future aspirations. Years later, when I was granted the opportunity to pursue my undergraduate education in the United States, I recognized it as a chance to transform that early realization into tangible action. As a computer science student, I am motivated to use the computational method to make positive impact on people's lives. To achieve my goal, I started my research in machine learning for health as an undergraduate.

Research in Machine Learning for Health

My research, which began in October 2022 at Emory University's AI Precision Lab under Dr. Rakesh Shiradkar's supervision, was my first step in realizing my dream of applying machine learning for health. My work addressed a critical challenge in medical AI: training deep learning models to learn prostate gland and tumor segmentation based on magnetic resonance imaging (MRI) scans from multi-institutional data while safeguarding patient privacy. This challenge is particularly acute in cancer diagnosis, where variations in MRI across institutions can lead to inconsistencies in diagnosis and treatment planning. To tackle this challenge, I employed federated learning, an innovative approach in AI that allows models to learn across multiple decentralized edge devices holding local data samples without exchanging them, where each "edge device" represented a distinct medical institution.

I led a group of three undergraduate students to implement the federated learning framework on the Rhino federated computing platform. It was tested on a simulation setting where I used Prostate-158 and PI-CAI datasets to simulate MRI images and ground-truth segmentation from two different institutes. The results were promising: compared to traditional centralized learning, we observed significant improvements in both prostate gland and tumor segmentation accuracy, as measured by the Sørensen–Dice coefficient and Jaccard index. These advancements could potentially allow more medical institutes to share and utilize deep learning models to improve diagnosis consistency and efficiency, addressing the issues that affected my grandpa and countless other patients. The impact of this work was recognized by the medical imaging community, leading to its acceptance as an oral presentation at the Society of Imaging Informatics in Medicine 2024 Annual Meeting and a poster presentation at the 2024 International Society for Magnetic Resonance in Medicine Annual Meeting & Exhibition.

Having investigated the capabilities of AI in enhancing the accuracy of prostate cancer diagnosis, I also target a more ambitious goal: exploring the potential of AI in combating the disease. Since January 2023, I have been mentored by Dr. Cassie Mitchell in the Pathology Dynamics Lab in the Coulter Department of Biomedical Engineering at Georgia Institute of Technology to learn how large language models can repurpose existing drugs for cancer treatment. I collaborated with other graduate and undergraduate students to manually annotate 3000+ PubMed abstracts with 20 unique biomedical labels to build a reliable, publicly available biomedical entity linking datasets for drug repurposing. I also experimented with the state-of-the-art large language model's capabilities on our curated dataset to examine its efficiency.

Motivated to gain more in-depth research experience in machine learning for cancer treatment, I was selected as 1 of the 20 outstanding undergraduates in the United States for the prestigious NIH/NCI-funded Summer Undergraduate Program for Educating Radiation Scientists (SUPERS@PENN) fellowship in 2023. It was an interdisciplinary summer research program on radiation oncology hosted by the Department of Radiation Oncology in the Perelman School of Medicine at the University of Pennsylvania. Mentored by Dr. Rafe McBeth, I have been involved in deep-learning research for radiation oncology. Generating a radiation dose map is essential for delivering radiotherapy for cancer treatment, but it is time-consuming due to the unique anatomical structure of each patient. To accelerate this procedure, I developed a transformer-based model, Swin UNETR++, that demonstrates state-of-the-art performance in predicting the radiation dose plan for head and neck cancer based on patients' CT scans, organs-at-risk contours, and planning target volume contours. My final presentation received an honorable mention in the summer program. More importantly, this work culminated in the publication of my first-authorship paper, "Swin UNETR++: Advancing Transformer-Based Dense Dose Prediction Towards Fully Automated Radiation Oncology Treatments," accepted by the Machine Learning for Health 2023 Symposium.

However, as I delved deeper into this work, I confronted a critical challenge in AI-driven healthcare: the "black box" nature of deep learning models. This lack of interpretability raises concerns about AI predictions' trustworthiness and clinical applicability, especially in high-stakes fields like radiation oncology. Driven by this realization, I posed a crucial question: how confident are deep learning models in predicting radiation dose maps? To address this reliability concern, I proposed a deep evidential learning framework to estimate epistemic and aleatoric uncertainties in dose map prediction. This approach provides clinicians with valuable information about the reliability of AI-generated dose plans in clinical settings. This work was recently accepted by the Computers in Biology and Medicine journal, further validating its importance in advancing the field of medical AI.

These experiences in dose prediction and uncertainty quantification provided me with valuable insights into the complexities of radiotherapy planning. However, I realized that accurate dose prediction, while crucial, is just the first step in a comprehensive radiotherapy workflow. Returning to the SUPERS@PENN program in the summer of 2024, I began to tackle the next critical challenge: creating deliverable treatment plans. I proposed using conditional diffusion models to generate Volumetric Modulated Arc Therapy (VMAT) plans for breast cancer patients, winning the Dr. Stephen W. Tuttle Research Award for outstanding research and the best final presentation. While the AI-generated plans showed promising results in simulation, I recognized a crucial gap: the need to incorporate ongoing feedback from medical professionals. The dynamic nature of clinical practice, with evolving treatment standards and patient-specific needs, necessitates a more adaptive approach. This realization led me to propose an iterative reinforcement learning from human feedback framework for radiotherapy planning in my AAAI UC research statement.

Research in Robot Learning

I've always been driven to explore how AI can help people from various angles. This passion led me to join the Robot Learning and Reasoning Lab at Georgia Tech. Under Dr. Danfei Xu's supervision, I embarked on a new journey to understand and answer some interesting questions in robot imitation learning with deep generative modeling. Specifically, I am working on my undergraduate research thesis, Enhancing Imitation Learning for 6 DoF Pick-and-Place Tasks under Spatial Occlusion with Conditional Diffusion Models.

Barriers in AI Research

As a first-generation student from a low-income family studying abroad in the U.S., finding AI research opportunities is challenging. Many summer undergraduate research programs, including those at my home institution, are REU-based and NSF-funded, which typically require U.S. citizenship. Out of hundreds of summer programs, only a handful accept international undergraduates, with even fewer focused on computer science. While some international students gain experience through unpaid visiting positions during summer, my family's financial situation prevents me from pursuing these volunteer opportunities. However, I refused to let these obstacles deter me from pursuing my passion for AI research. As a first-generation student, I adopted a proactive strategy to overcome these challenges. I sought advice from the career office and graduate students. I began to take senior-level classes since my second year to build core knowledge and stay competitive for research positions. To optimize costs, I secured volunteer research positions with my PI at my home institution during the academic year while applying to those few summer research programs that can accept international students and offer stipends. This two-pronged approach allowed me to gain valuable experience year-round while managing financial constraints.

My Anticipated Benefits from AAAI UC

As a first-generation student, connecting with others is my primary source of guidance and horizon-broadening. The AAAI UC offers a unique platform for these crucial interactions. I hope to get advice from my mentors on how to proceed with my proposed project and anticipate valuable conversations with successful individuals, including peers, AI experts, faculty, and graduate students, which will significantly shape my path toward a Ph.D. in computer science. Through these exchanges, I also expect to gain diverse perspectives on AI graduate studies, early career advice, and insights into the graduate school application process. This networking opportunity is especially vital for me, as it will provide the guidance and information I need to navigate my academic and professional journey in AI research.

My Contributions to AAAI UC

On the academic side, my research experience in machine learning for health and robot learning allows me to contribute unique perspectives to the AAAI UC. I can offer insights into addressing real-world challenges in healthcare AI and robotics, highlighting their intersections, such as my proposed reinforcement learning for radiotherapy automation. By sharing my experiences across these domains, I aim to foster interdisciplinary discussions and demonstrate the versatility of AI applications. On the personal growth side, I want to share strategies for overcoming barriers in pursuing AI research as a first-generation student from a low-income family, potentially inspiring and motivating fellow undergraduates facing similar challenges.