I stepped into healthcare AI four years ago during my graduate coursework at the University of California, Irvine. Since then, I have developed a strong passion for medical image analysis research, having seen through multiple projects how automated interpretation of biomedical images using deep learning and computer vision can improve disease diagnosis and treatment. Therefore, I aim to pursue a PhD in Computing Science to develop AI-driven multimodal medical imaging systems that address three central challenges in the field such as **fairness, explainability, and edge deployment** with the goal of improving clinical outcomes.

UCI Experience: My interest in image analysis began during my master's at UCI, particularly through my Machine Learning and Data Mining course. There I fine-tuned deep learning models ranging from traditional Neural Networks, and CNNs to VGG-19 and ResNet-50 on MNIST, Fashion-MNIST, and CIFAR-10. Through this course, I built a strong foundation in basic concepts of computer vision and deep learning. Subsequently, in my AI in Biology and Medicine course, I deepened medical image analysis skills by implementing an end-to-end pipeline for chest X-ray based pneumonia detection, where I combined advanced image preprocessing techniques with state-of-the-art algorithms such as InceptionV3 and DenseNet-121. Collectively, through these experiences, I not only earned a travel grant to attend the A^2 Symposium on Healthcare AI at Johns Hopkins Medicine but realized my passion for a PhD in Computing Science with an emphasis on medical image analysis.

Fairness: As a lecturer at XXX, Pakistan, I mentored student teams developing physician-in-the-loop AI systems for fetal ultrasound analysis to localize anatomical structures and detect brain anomalies. I guided the team to implement Faster R-CNN (ResNet backbones) for anatomical localization on fetal-phantom data (85% accuracy). Additionally, when classification performance stalled, I proposed a literature-driven shift to include a Vision Transformer alongside CNN based models improving anomaly classification accuracy from 89% to 98%. Subsequently, I suggested conducting multimodal analysis by fine-tuning a BLIP (Bootstrapping Language Image Pre-training) because of its generative component to generate captions indicating gestational age and anomaly type of ultrasound. Specifically, I trained team to implement BLIP algorithm achieving an 82% BLEU (Bilingual Evaluation Understudy) score. This project reinforced my belief in physician-in-the-loop systems as decision-support tools for clinicians. Additionally, it also highlighted the practical challenges associated with dataset bias caused by the imbalanced distributions of sensitive attributes, such as ethnicity, age or gender that are sometimes unintentionally correlated with disease classes in the training data. This combination of technical progress and understanding of potential and challenges of the field through in-depth literature review is idea preparation for PhD focused on fair multimodal medical image analysis.

Edge Deployment. At the "Co-creating with GPT-5" Hackathon (AI/ML API & lablab.ai, USA), I developed an AI navigation assistant for people with visual impairments. This system runs on people's smartphone or tablet and uses the image taken by these devices. Then it utilizes an algorithm which is a combination of YOLOv12 which performs real-time object detection, MiDaS for calculating monocular depth estimation of detected objects. Finally, it leverages GPT-5 (via zero-shot prompting) to convert scene understanding into step-by-step path guidance in natural language. I also added a fall-detection module by extracting video frames from video captured by same smart device and applying an object detection algorithm from Roboflow (mAP@50 99.3%, precision 98.6%, recall 99.5%. During this project, I became aware of a key challenge in multimodal AI which is that many state-of-the-art multimodal algorithms are too computationally heavy for deployment on mobile devices. This motivated me to explore literature on edge deep learning for computer vision, particularly methods that enable energy-efficient, low-latency, and privacy-preserving inference. As a result, my interest has sharpened toward designing edge-deployable multimodal algorithms for healthcare so that real-time decision support can run directly on a physician's smartphone or tablet. Hence, this is one of the research paths which I want to pursue during my PhD.

Explainable healthcare AI: During remote research assistantship at University of Oklahoma, USA, I used data of Swiss medical students (886 students, 20 characteristics) to investigate whether student at the risk of severe self-reported physical health issues can be predicted using socio-geo-demographics, study details and mental health indicators. I first carried out in-depth data pre-processing and then built predictive modeling pipelines using algorithms including Extreme gradient Boosting (XGBoost), and logistic regression. To address class imbalance, I implemented the Synthetic Minority Over-sampling Technique (SMOTE) and tuned hyperparameters with grid-search cross-validation, improving accuracy by 2% then previously published work using same date set. During this project, I confronted the "black-box" nature of conventional data-mining models by implementing SHAP feature-importance plots to enhance transparency, leading to a first authored paper. Through this work, I learned about both the necessity and potential of explainable AI to help clinicians understand the reason behind specific AI algorithms and explored explainable AI techniques for images including Deep SHAP, and Grad-CAM. This experience positions me well to conduct research on interpretable AI systems and how these can be used to augment doctors' clinical decision making based on medical image tasks.

Looking Ahead: In my future research, I aim to work on fair, explainable and edge deployable multimodal medical image analysis algorithms to aid disease diagnosis and treatment. I am drawn to School of Computing Science of XX University for its strength in computer vision and graphics, advanced research facilities, and faculty expertise in medical imaging and deep learning. I'm especially interested in the work of Medical Image Analysis Lab, specifically the paper on BiasPruner, a novel continual learning (CL) framework that mitigates bias through debiased subnetworks, in sequential medical image classification. I am interested in extending this work by developing robust methods to mitigate intersecting sources of bias in the absence of full bias information. I am also excited by the lab's work on evaluating the clinical utility and explainability of AI for glioma brain MRI, and I intend to build more powerful, clinician-centered explainable-AI techniques grounded in real clinical workflows. Finally, I am interested in exploring challenges associated with edge deployment of deep learning algorithms such as determining optimal sparsity level and avoiding potential loss of accuracy.

With a solid foundation in healthcare AI, deep learning, and computer vision, I'm well prepared for this opportunity. After completing my PhD, I aim to join a computer science university in my home country to train next generation of computer scientists and medical imaging researchers.

[1] E. T. R. Babar and M. Mujeeb U. Rahman. A smart, low-cost, wearable technology for remote patient monitoring. IEEE Sensors Journal. 21, 19 (Oct. 2021), 21947–21955. DOI:https://doi.org/10.1109/jsen.2021.3101146