Beyond Data Scarcity: Quality Barriers to Trustworthy AI in Low-Resource Medical Imaging

Artificial Intelligence (AI) has the potential to democratize healthcare access in low- and middle-income countries (LMICs) however many AI systems deployed in these settings fail to deliver equitable outcomes, raising concerns about their reliability and fairness [1]. While these shortcomings are often attributed to limited dataset size, our ongoing work suggests that data quality is a more critical barrier.

Variation in imaging protocols and scanner effects significantly reduce model generalizability, with multi-site classification experiments showing existing data harmonization techniques fail to eliminate scanner biases [2]. For instance, chest X-ray AI systems demonstrate systematic bias against underrepresented populations, including female and black patients with lower socioeconomic status [3]. Inconsistent or low-quality annotations compromise reliability, while systematic dataset biases such as gender imbalance produce classifiers that perform unevenly between male and female patients in medical imaging tasks [4]. Without standardized frameworks like the METRIC system for medical data quality assessment [5], large portions of imaging data remain unusable for trustworthy AI in healthcare.

We propose the Practical, Actionable, Contextual, and Equitable (PACE) framework, a data quality system designed for low-resource settings. The PACE framework extends general systems like METRIC [5] by introducing lightweight protocols through standardized acquisition protocols and continuous quality monitoring frameworks. We anticipate the PACE framework will lead to more robust and equitable AI models, which we will demonstrate in a prospective clinical validation study. Shifting focus from data quantity to a structured quality framework like PACE is essential for building AI systems that are fair, reliable, and capable of reducing health disparities in LMICs

Keywords: Trustworthy AI, Medical Imaging, Data Quality, Fairness, Low-Resource Settings

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