

Deep Learning Models for Automatic Differential Recognition of Lung Diseases in Lung Ultrasound Data

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Abstract

Lung diseases such as tuberculosis, bacterial pneumonia and COVID-19 are a major global health burden. Early and accurate diagnosis is critical to improve survival rates. X-ray and computed tomography remain the gold standards for pulmonary screening, but cost, infrastructure, and radiation exposure keep them out of reach in many low- and middle-income countries (LMICs). Recently, lung ultrasound (LUS) has emerged as a low-cost, portable, radiation-free alternative suitable for resource-constrained settings, but its reliability depends on operator expertise and varies between observers, challenges worsened by radiologist shortages. Deep learning shows promise for automating LUS interpretation, but many models are computationally intensive, offer limited interpretability, and give less emphasis to precise localization of diagnostic artifacts. Reliance on geographically homogeneous datasets and limited integration into mobile workflows further restrict their use in LMICs. This thesis closes the gap through four contributions: (i) a curated dataset of 1,062 images collected by three senior radiologists at Mulago and Kiruddu National Referral Hospitals under ethical approval, with 613 images annotated for B-lines and subject-level partitioning; (ii) ParSE-CNN, a lightweight parallel convolutional network with Squeeze-and-Excitation attention that classifies images as COVID-19, other lung pathology, or healthy; (iii) YOLOv5-PBB, a YOLOv5 extension with polygonal bounding boxes that localize B-lines more precisely and interpretably than rectangular boxes; and (iv) a mobile LUS screening pipeline integrating each model independently, with ParSE-CNN for real-time classification and YOLOv5-PBB for artifact localization. ParSE-CNN achieved 94.68% accuracy with only 5.18 million parameters. YOLOv5-PBB reached precision 0.931, recall 0.918, and mAP 0.936 in a 14 MB model. Deployed average inference times were 0.006 s for classification and 33.1 ms for localization. Together, these models, a contextually relevant dataset, and a practical deployment pipeline bridge algorithmic innovation and point-of-care application. They underscore the potential of AI-assisted LUS to improve diagnostic access, enable timely clinical decisions, and strengthen healthcare delivery in resource-limited settings.