Abstract Track

A Machine Learning Case Study for AI-empowered echocardiography of Intensive Care Unit Patients in low- and middle-income countries

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Abstract

We present a study case to illustrate the challenges of AI and ML methods to be integrated and translated into clinical practice in a real-time AI-empowered echocardiography system with data of ICU patients in LMICs. Such ML case study includes data preparation, curation and labelling from 2D Ultrasound videos of 31 ICU patients in LMICs and model selection, validation and deployment of three thinner neural networks to classify apical four-chamber view. We conclude that there is need of datasets to improve diversity of demographics, diseases and devices to deploy and validate ML models, and the need of further investigations of thinner models to run in low-cost hardware. The code and other resources to reproduce this work are available at `https://github.com/vital-ultrasound/echocardiography`.

Keywords: Machine Learning, Artificial Intelligence, Deep Learning, Echocardiography.

1. Introduction

Echocardiography is an important clinical procedure in Intensive Care Units (ICUs) because of the features of Ultrasound (US) image modality such as portability, low cost, non-ionising radiation and its real-time capabilities to visualise cardiac anatomy (Feigenbaum, 1996; Vieillard-Baron et al., 2008; Singh and Goyal, 2007; Campbell et al., 2018). Typically, the identification of cardiac abnormalities from 2D US views (Apical 4-Chamber View (A4C), Apical 3-Chamber View (A3C), Apical 2-Chamber View (A2C), Parastemal Long-Axis View (PLAX), etc) is achieved by specialist clinicians in echocardigraphy following the Focused Intensive Care Echo (FICE) protocol (Hall et al., 2017). However, the application of point-of-care echocardiography in the ICU faces two challenges: (1) intra-view variability of echocardiograms (physiological variations of patients and acquisition parameters) and inter-observer variability of expertise for sonographer and radiologist (Khamis et al., 2017; Feigenbaum, 1996; Field et al., 2011), and (2) limited number of specialist clinicians to perform US imaging analysis and to provide accurate diagnosis, and the limited equipment and hospitalisation requirements in low- and middle-income countries (LMICs) (Hao et al., 2021; Tran et al., 2021; Becker et al., 2016). One promising approach to address such challenges is with the application of Artificial Intelligence (AI) and Machine Learing (ML) to echocardiography (Asch et al., 2022). AI-empowered echocardiography has been successful for detection of different apical views, inter-observer variability of sonographer's expertise, implementation of one-stop AI models with multimodal imaging (US, MRI and clinical data), detection of high risk or low risk of heart failure, detection of endocardial borders and automatic left ventricle assessment in 2D echocardiography videos (Tromp et al., 2022; Zhang et al., 2022; Behnami et al., 2020; Ono et al., 2022).

In spite of the success in applying AI and ML methods to support echocardiography, there are still important challenges for these methods to be integrated as clinical system and translated to clinical practice:

1. inter-view similarity of echocardiograms (similar views of valve motion, wall motion, left ventricle, etc) and transducer position during acquisition when performing serial echoes (Zhang et al., 2018),

2. redundant information in the clinical echo system (icons, date, frame rate, etc) (Khamis et al., 2017) and variation of US images from different clinical US systems (Brindise et al., 2020), and
3. internal and external validation of AI-based models, data patient privacy to train commercial algorithms, and regulations of software as medical devices (Stewart et al., 2021).

Challenges (1) and (2) are important because of 2D US video data requires to appropriately be collected, validated and managed to apply AL and ML methods, and challenge (3) because AI-based medical devices require to be aligned to standards to then be ready for clinical translation. Hence, the adoption of good machine learning practices (data curation, open-source code implementation, model selection, training and tuning; model validation and inference) might help to address challenges in real-time AI-empowered echocardiography used as point-of-care in the ICU for patients in LMICs.

This work presents a scoping review of (a) AI-empowered echocardiography for ICU in LMICs, (b) Classification of echochardiograms and (b) Classification US images with thinner neural networks. We present a machine learning case study of US image classification using three thinner neural networks trained with four chamber views data from curated data from LMICs. As way to show the impact of thinner neural networks, we specifically present results from SqueezeNet for different datasize, number of frames and clips batches, training parameters. We then conclude and add future work.

2. Scoping review

2.1. AI-empowered echocardiography for ICU in LMICs

Hanson III and Marshall (2001) reviewed various AI-based applications in the ICU where real-time analysis of waveforms of electrocardiograms and electroencephalograms using neural network were used to identify cardiac ischemia and diagnosis of myocardial ischemia. Ghorbani et al. (2020) reported how deep learning models predicts systematic phenotypes from echocardiogram images which are difficult for human interpreters. Cheema et al. (2021) reported five patients with covid-19 in the ICU to illustrate "how decision making affect in patient care" and how the use of AI-enabled tools provided real-time guidance to acquire desired cardiac 2D US views with the steering of user's transducer position and hand movement. Recently, Hong et al. (2022) reviewed 673 papers that apply ML methods to help making clinical decision in the ICU, of these studies the majority used supervised learning (91%) and few of them applied unsupervised learning and reinforcement learning methods. Similarly, Hong et al. (2022) identified 20 of the most frequent variables in ML pipelines for ICU patients, being the top five (age, sex, heart rate, respiratory rate, and pH). Hong et al. (2022) mentioned that typical outcomes in the ICU are mortality, survival, and long-term quality of life and the most studied diseases are sepsis, infection and kidney injury. Despite such advances, there is few research on AI-empowered echocardiography used by clinicians in the ICU, specifically in LMICs. For instance, Tran et al. (2021) reported challenges in resourced limited ICUs including: infrastructure, education, personnel, data pipelines, regulation and trust in AI. Also, Kerdegari et al. (2021b,a); Nhat et al. (2021) presented a deep-learning pipeline to classify lung US pathologies for ICU patients in LMIC, stating the challenges of data imbalance, integration of technology and the limited IT infrastructure.

2.2. Classification of echochardiograms

Khamis et al. (2017) considered 309 clinical echocardiograms of apical views which were visually classified and labelled by two experts into three classes: 103 A2C views, 103 A4C views and 103 ALX views to then applied spatio-temporal feature extraction (Cuboic Detector) and supervised learning dictionary (LC-KSVD) resulting in an overall recognition rate of 95%. Van Woudenberg et al. (2018) applied DenseNet and LSTM to extract temporal information on sequences of 16000 echo cine frames to classify 14 heart views with an average accuracy of 92.35%. Van Woudenberg et al. (2018) also presents timing diagrams to quantify frame arrival and real-time performance to operate at 30 frames per second, while providing feedback with a mean latency of 352.91 $\pm$ 38.27 ms when measured from the middle of the ten-frame sequence. Zhang et al. (2018) performed view classification with 277 echocardiograms to create a 23-class models (including A4C no occlusions, A4C occluded LA, A4C occluded LV, etc) using 13-layer CNN with 5-fold cross-validation for accuracy assessment and resulting in 84% for overall accuracy where challenges for partial obscured LVs for A2C, A3C and A4C. Similarly, Zhang et al. (2018) applied U-net to segment 5 views (A2C, A3C, A4C, PSAX, PLAX) and CNN model for 3 cardiac diseases with the use of A4C capturing most of the information for the diseases.

2.3. Classification of US images with thinner neural networks

Baumgartner et al. (2017) proposed SonoNet which is a VGG-based architecture, having the same first 13 layers of VGG16, and SmallNet, loosely inspired by AlexNet, for real-time detection and bounding box localisation of standard views in freehand fetal US. Toussaint et al. (2018) applied four feature extraction networks couple with batchnormalization and soft proposal layer (VGG13-SP, VGG16-SP, ResNet18-SP, ResNet34-SP), resulting in 0.912 of average accuracy over six classes of fetal US views with ResNet18-SP. Al-Dhabyani et al. (2019) applied AlexNet and transfer learning of four architectures (VGG16, Inception, ResNet, and NASNet) without augmentation and with three augmentation techniques to perform tumor classification of breast ultrasound imaging. Authors stated that transfer learning with NASNet presented the best accuracy with 99% using BUSI+B datasets with DAGAN augmentation. Xie et al. (2020) proposed a dual-sampling convolutional neural network (DSCNN) for US image breast cancer classification, being DSCNN more efficient than AlexNet, VGG16, ResNet18, GoogleNet and EfficientNet. Recently, Snider et al. (2022) reported summaries of CNN heuristics to detect shrapnel in US images, including layer activators, 2D CNN layer architectures, model optimisers dense nodes, and the effect of image augmentation and dropout rate and epoch number. Similarly, Boice et al. (2022) proposed ShrapML, a CNN model to detect shrapnel in US imaging. Authors compared ShrapML (8layers–6CNN,2FC, 0.43 million of parameters) against DarkNet19, GoogleNet, MobileNetV2 and SqueezeNet, being ShrapML 10x faster than MobileNet2 and offering the highest accuracy.

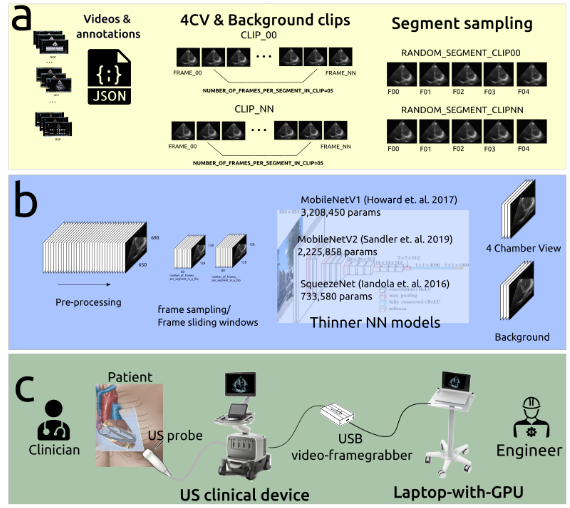

Figure 1: Machine learning pipeline for AI-empowered echocardiography for ICU in LMICs: (a) timestamp labelling of apical four chamber view frames and clips, (b) deep-learning pipeline with thinner Neural Networks (NNs), and (c) low-cost clinical system with Epiq Q7, cardiac probe X5-1, USB video-frame grabber and 16GB GeForce RTX 3080 GPU Laptop.

3. Machine learning case study

3.1. Dataset

Echocardiography videos of 31 patients in the ICU were considered for this work which were collected by four radiologists using the clinical US devices: GE Venue Go machine and GE convex probe C1-5-D. The 31 patients had the following demographics: Sex: % (Male): 58.1%; Age: mean, years (std): 38.70 (16.08); Weight: mean, Kg (std): 61.51 (15.06); Height: mean, m (std): 1.62 (0.07), and BMI: mean (std): 23.80 (4.30). See Appendix A for further details on the demographics of the dataset (distributions for sex, age, BMI, sepsis and dengue diseases), including the complete dataset of the total of 87 patients.

3.1.1. Ethics statement

This study was approved by the Oxford Tropical Research Ethics Committee (OxTREC) and the HTD Institutional Review Boards (Hospital of Tropical Diseases). All participants gave written informed consent to participate in the data collection before enrollment.

3.1.2. Data annotation, validation and management

Apical 4 Chamber view (A4C) is considered as an important view to compute heart failure measurements from 2D US echocardiography (Hall et al., 2017). For this work, timestamps in the video files for A4C were annotated by one research clinician of 10 years of experience using VGG Image Annotator (VIA). Then the same clinician and one researcher validated timestamps annotations where few filenames and timestamps were fixed. Figure 1(a) illustrates video and json files with their A4C and background clips to then be segmented.

3.2. Model selection and heuristics

Considering different datasets characteristic (number of frames, clips, pixel image, clinical equipment, etc) and the number of parameters of different networks, we selected three Neural Networks for our ML study: MobileNetV1 (Howard et al., 2017) with 3,208,450 parameters, MobileNetV2 (Sandler et al., 2018) with 2,225,858 parameters, and SqueezeNet (Iandola et al., 2017) with 733,580 parameters. We then performed heuristics for each model to understand the impact of their performance for different hyperparameters (dataset size, frames numbers and clip length).

3.3. Classification of 2D echocardiograms with thinner neural networks

MobileNetV1, MobileNetV2 and SqueezeNet were trained with data of 5 and 31 subjects (Appendix B) in which SqueezeNet showed constant training metrics. Hence, we present heuristics different datasize, batch size of clips, and numbe of frames per segment in a clip for SqueezeNet (Figure 2).

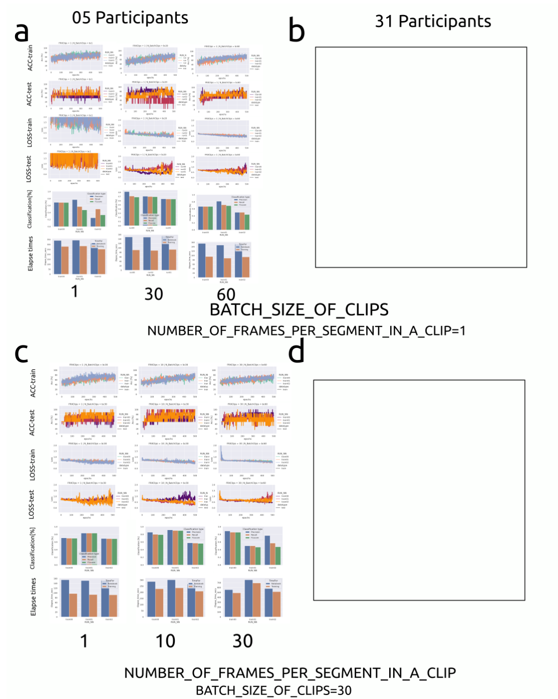

Figure 2: Heuristics for SqueezeNet (Iandola et al., 2017) with dataset of 5 and 31 subjects: (a, b) varying batch size with constant number of frames per segment equal to 1, and (c, d) varying number of frames per clip and constant batch size of clips equal to 10.

4. Conclusions and Future Work

We presented a machine learning case study that includes data selection, validation and management, model selection, validation. For future work, we will investigate real-time inference and deployment of thinner classification and segmentation models, leading to clinical translation of automatic assessment of ventricular size and function, and evaluation of regional wall motion abnormalities.

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Appendix A. Datasets

Figure 3 illustrates demographics for sex, age, BMI, sepsis and denque for the complete dataset and the 31 subjects considered for this work.

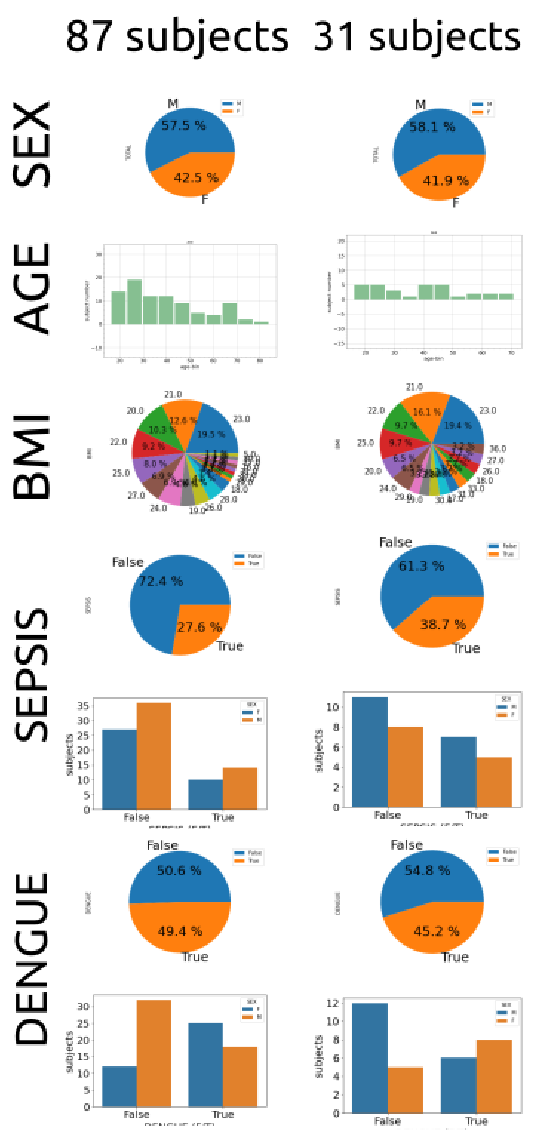

Figure 3: Patient demographics for sex, age, BMI, sepsis and dengue disease. Total number of patient is 87 of which data from 31 were curated, annotated and validated.

Appendix B. Heuristics of model selection

Figure 4 illustratres heristics for accuraty, train, classification and elapse times of 5 and 31 subjects.

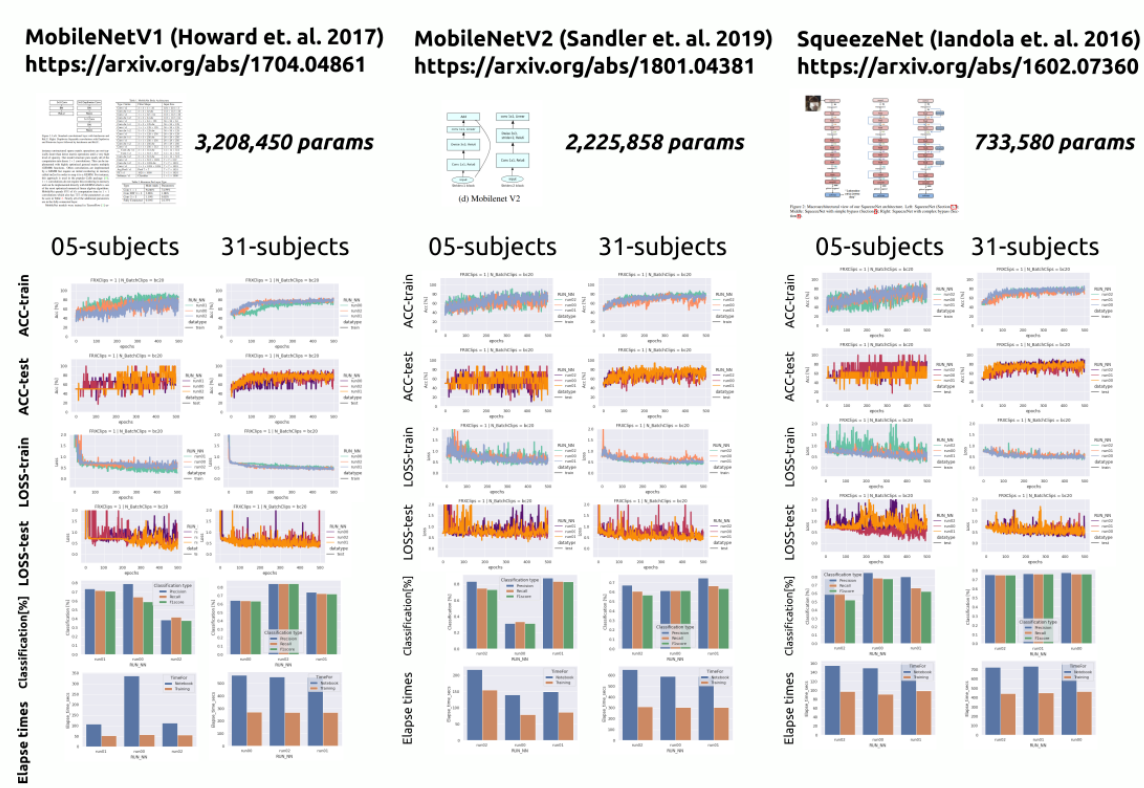

Figure 4: Heuristics for 5 and 31 subjects with 1 frames per clip and 20 batch size of clips for MobileNetV1 (Howard et al., 2017) with 3,208,450 parameters, MobileNetV2 (Sandler et al., 2018) with 2,225,858 parameters, and SqueezeNet (Iandola et al., 2017) with 733,580 parameters.