Abstract Track

Challenges in Real-time AI-empowered echocardiography for Intensive Care Units in low- and middle-income countries: A Machine Learning Case Study

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Editors: List of editors' names

Abstract

We present a machine learning case study on the current and future challenges of implementing a real-time AI-empowered echocardiography system for ICU in LMICs. We present reproducible heuristics from a small video dataset of 31 subjects in the ICU, data preparation, curation and labelling, model selection, validation and deployment. The code and other resources to reproduce this work are available at https://github.com/vital-ultrasound/echocardiography.

Keywords: deep learning; echocardiography; real-time artificial intelligence;

1. Introduction

Echocardiography is an important clinical procedure in Intensive Care Units (ICU) because of the advances of Ultrasound (US) such as portability, low cost, low radiation and its real-time capabilities to visualise and access cardiac anatomy (Feigenbaum, 1996; Vieillard-Baron et al., 2008; Singh and Goyal, 2007; Campbell et al., 2018). Despite that, there are various challenges in the current application of point-of-care echocardiography in the ICU:

- Intra-view variability of echocardiograms (physiological variations of subjects and acquisition parameters) and inter-observer variability of expertise for sonographer and radiologist (Khamis et al., 2017; Feigenbaum, 1996; Field et al., 2011).
- Inter-view similarity of echocardiograms (similar views of valve motion, wall motion, left ventricle, etc) when performing serial echoes and transducer position during acquisition (Zhang et al., 2018)
- Redundant information in the clinical echo system (icons, date, frame rate, etc) (Khamis et al., 2017) and variation of Ultrasound images from different clinical US systems (Brindise et al., 2020).
- 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).
- Limited number of expert clinicians to perform US imaging analysis and to provide accurate diagnosis, as well as equipment and hospitalisation requirements in low- and middle-income countries (LMICs) (Hao et al., 2021; Tran et al., 2021).

One promising approach to address such challenges is with the application of Artificial Intelligence 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 or automatic detection of endocardial border detection and left ventricle assessment in 2D echocardiography videos (Tromp et al., 2022; Zhang et al., 2022; Behnami et al., 2020; Ono et al., 2022). However, there is little to no studies on how real-time AI-empowered echocardiography might impact patient management in the ICU in LMICs. Particularly, how good machine learning practices (data curation, open-source code implementation, model selection, training and tuning; model validation and inference) are addressing challenges on real-time AI-empowered echocardiography used as point-of-care in the ICU.

This work presents (a) a scoping review of AI-empowered echocardiography for ICU in LMICs and (b) real-time AI-empowered echocardiography, (c) a machine learning case study of US image classification using deep learning of four chamber views from curated data from LMICs and (d) conclusions future work.

2. AI-empowered echocardiography for ICU in LMICs

Hanson III and Marshall (2001) reviewed various applications of AI 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. Hanson III and Marshall (2001) also reviewed various clinical scenarios where variables such as central venous pressure (CVP), left ventricular ejection fraction (EF), heart rate (HR), hemoglobin (HGB) and oxygen saturation (O2sat) were used with Bayesian networks to provide probabilistic cardiac output. Ghorbani et al. (2020) reported how deep learning models predicts systematic phenotypes which are difficult for human interpreters from echocardiogram images, the extraction of labels local structures and features (e.g. pacemaker lead, dilation of left atrium, hypertrophy for left ventricular) and labels from the physician-interpreted report (e.g, catheters, pacemaker, and defibrillator leads). 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 US with the steering of user's transducer position and hand movement. Recently, Hong et al. (2022) reviewed 673 papers that made use of machine learning 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. Similarly, Hong et al. (2022) identified 20 of the most frequent variables in ICU patients with the top five (age, sex, heart rate, respiratory rate, and pH) in machine learning pipelines. Hong et al. (2022) mentioned that typical outcomes in the ICU are mortality, survival, and long-term quality of life where the most studied diseases are sepsis, infection and kidney injury.

However, there is few research on AI-empowered echocardiography used by clinicians in the ICU specifically in LMICs where, for instance, Tran et al. (2021) reported challenges in resourced limited ICUs including: infrastructure, education and personnel, data pipelines, regulation and trust in AI. Also, Kerdegari et al. (2021b,a); Nhat et al. (2021) presented a deep-learning lung US pathology classifier for ICU patients in LMIC, stating the challenges of data imbalance, integration of technology and IT infrastructure.

3. Real-time AI-empowwered echocardiography

3.1. State of the art

Van Woudenberg et al. (2018) trained an DenseNet-LSTM with 2K clips of 4 chamber view in which the real-time system made use of 10 input frames and reported a latency of 352.91ms. Toussaint et al. (2018) proposed ResNet18-SP trained with 85k frames of Fetal US imaging, reporting real-time performance at inference time of 40 ms per image or $\sim$20Hz. Østvik et al. (2021) proposed Echo-PWC-Net trained with Synthetic/Simulated/Clinical, reporting real-time performance with 7 frames for the input. Recently, Wu et al. (2022) applied baselines of UNET with temporal context-aware encoder (TCE) and bidirectional spatiotemporal semantics fusion (BSSF) modules to Echo-Dynamic datasets (10030 video sequences with of 200 frames of 112x112 pixes) and CAMUS datasets (450 video with 20 frames of 778x594 pixels), reporting metrics of Dice score (DS), Hausdorff Distance (HD), and area under the curve (AUC). Similarly, Wu et al. (2022) presented speed analysis to ensure low latency and real-time performance for eight methods using calculations number FLOPS (G), number of parameters (M) and speed (ms/f).

3.2. Classification of echochardiograms

Khamis et al. (2017) considered 309 clinical echocardiogram 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 16K 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.

3.3. Thinner neural networks to classify US images

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 which offered the highest accuracy.

4. Machine learning case study

4.1. Dataset

Echocardiography videos of 31 patients in the ICU were considered for this work which were collected by four radiologists using the clinical 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, including the complete dataset of 87 patients.

4.1.1. 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 before enrollment.

4.1.2. Data annotation, validation and management

Being 4 chamber view (4CV) the main view to compute Heart Failure Measurement, timestamps of 4CV video files from 31 subjects were annotated by one research clinician of 10 years of experience using VGG Image Annotator (VIA).

Then the same clinician and one researcher validated annotations in a round of two iterations where few filenames timestamps were fixed. Figure 1(a) illustrates video frames and clip management.

4.2. Model selection and heuristics

Considering the complexity of state-of-the-art networks and thinner neural networks, we selected four thinner Neural Networks for our ML study: MobileNetV1 (Howard et al., 2017) 3,208,450; MobileNetV2 (Sandler et al., 2018) 2,225,858; SqueezeNet (Iandola et al., 2017) 733,580 and ShrapML (Boice et al., 2022) 430,000 (networks and parameters, respectively). We then performed heuristics for each model to understand their performance for different hyper-parameters (datasize, augmentations and clip length) as shown in Figure 2. See Appendix B for further details on each model.

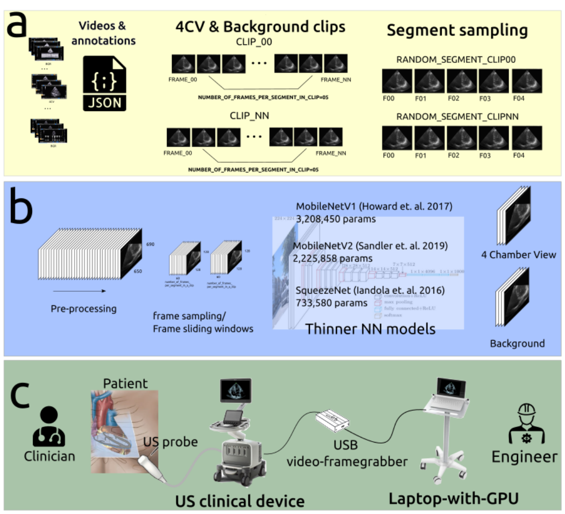

Figure 1: Proposed low-cost clinical system for real-time AI-empowered echocardiography: (a) timestamp labelling of four chamber view clips and frames, (b) deep-learning pipeline with thinner NNs, and (c) clinical system: Epiq Q7, cardiac probe X5-1, USB video-frame grabber and 16GB GeForce RTX 3080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

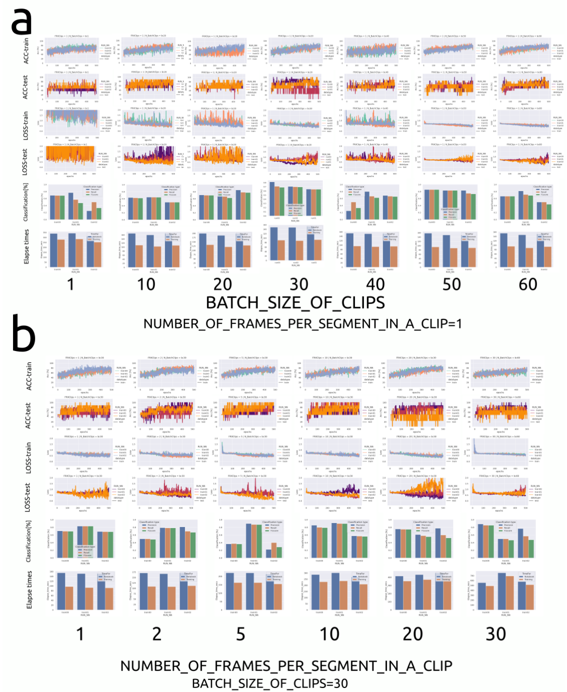

Figure 2: Heuristics for SqueezeNet (Iandola et al., 2017) with dataset of 5 subjects: (a) varying batch size and constant number of frames per segment equal to 1, and (b) varying number of frames per clip and constant batch size of clips equal to 10.

5. Conclusions and Future Work

We presented a machine learning case study, including data selection, validation and management, model selection, validation and in a low-cost clinical system. Future work, we will investigate thinner segmentation models, model deployment and clinical validation in the ICU.

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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.

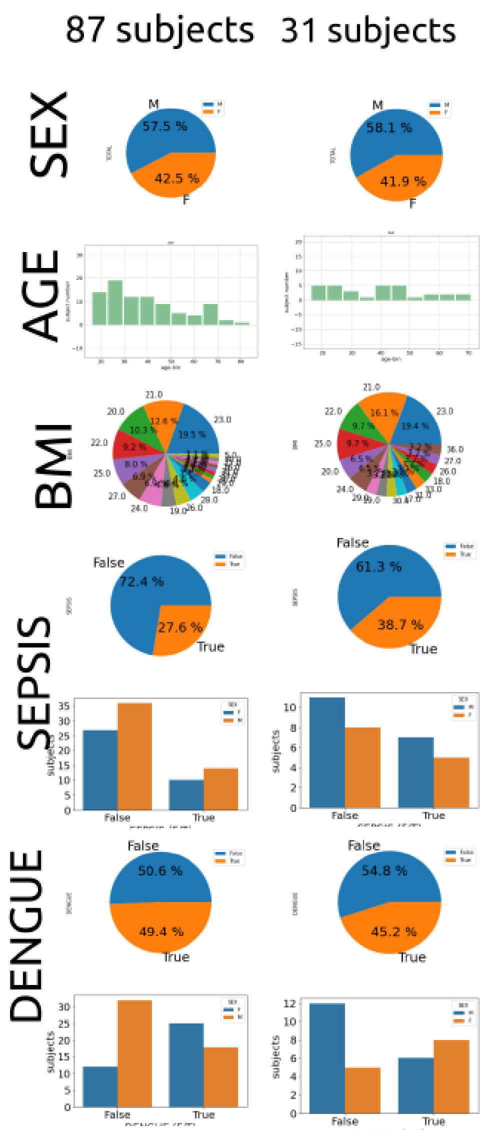

Figure 3: Patient demographics.

Appendix B. Heuristics of model selection

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

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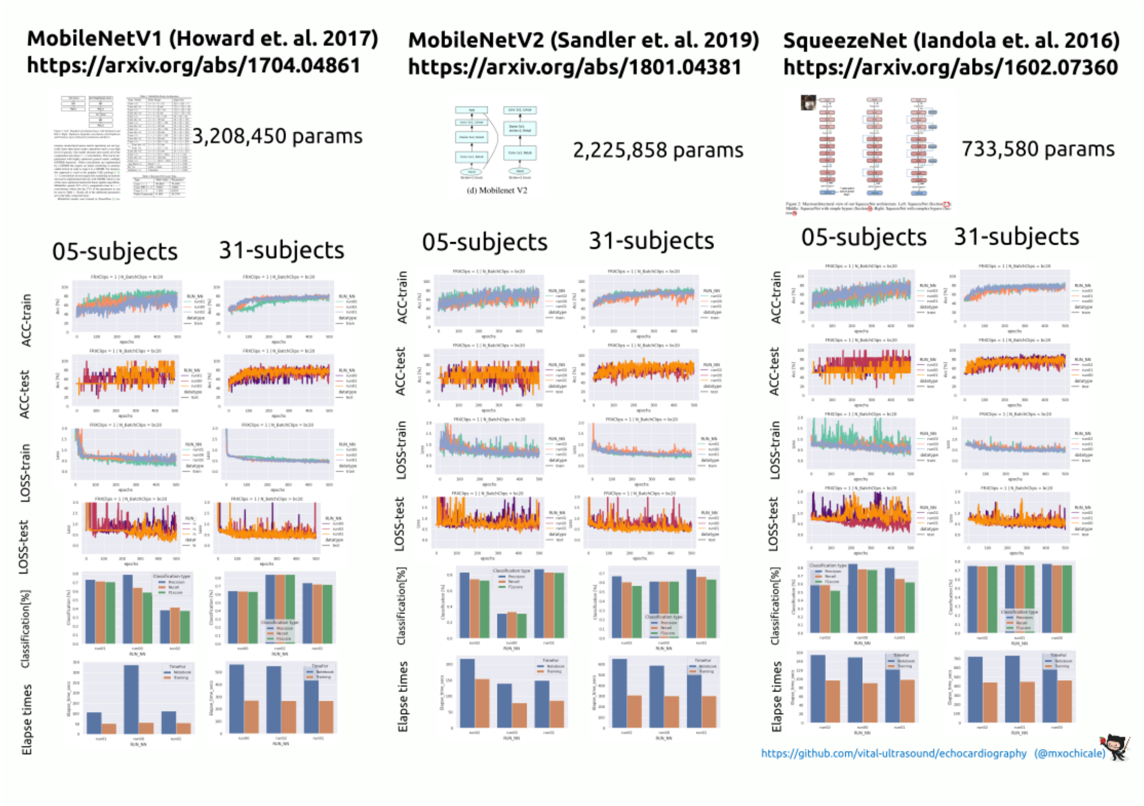

Figure 4: Heuristics for 5 and 31 subjects with 1 frames per clip and 20 batch size of clips for MobileNetV1 (Howard et al., 2017), MobileNetV2 (Sandler et al., 2018), and SqueezeNet (Iandola et al., 2017) 733,580

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