Abstract Track

Real-time AI-empowered echocardiography for Intensive Care Units in low- and middle-income countries

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Abstract

We review works on how real-time AI-empowered echocardiography might impact on implementing such systems in the ICU in LMICs. We present results from a small video dataset of 31 subjects, data preparation, curation and labelling, code implementation and model selection, validation and deployment. The code and other resources to reproduce this work are available at https://github.com/vital-ultrasound/echocardiography.

Keywords: echocardiography; 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 access cardiac anatomy (Feigenbaum, 1996; Vieillard-Baron et al., 2008; Singh and Goyal, 2007; Campbell et al., 2018). Despite that, there various challenges in the current clinical procedures in the ICU:

- Intra-view variability of echocardiograms (physiological variations of subjects and acquisition parameters) and sonographer expertise (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) 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), and
- 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 (LAMIC) (Hao et al., 2021).

One promising approach to address previous challenges is the use of Artificial Intelligence in echocardiography, AI-empowered echocardiography, that has been successful to detect different apical views, inter-observer variability of sonographer's expertise, multimodal imaging (us, mri and clinical data), high risk or low risk of heart failure or automatic 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 none studies on how real-time AI-empowered echocardiography might impact on implementing such systems in the ICU in LMICs. Particularly, how good machine learning practices (data curation, code implementation, model selection, training and tuning; model validation and inference) are followed to address real-time AI-empowered echocardiography in the ICU in LMICs.

2. AI-empowered echocardiography in the ICU

Cheema et al. (2021) presented five cases covid-19 intensive care unit (ICU) to illustrate "how decision making affect in patient care" and how the use of AI-enabled provided real-time guidance to acquire desired cardiac UL with the sterting of user's transducer position and hand movement. 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 myocardial ischemia. Hanson III and Marshall (2001) also reviewed various scenarios where AI is used in the ICU, such as Bayesian networks considering central venous pressure (CVP), left ventricular ejection fraction (EF), heart rate (HR), hemoglobin (HGB) and oxygen saturation (O2sat) resulting in a probabilistic cardiac output. Hanson III and Marshall (2001) also touched on data visualisation to demonstrate the hypothetical ICU for large number of patients (head injury, sepsis, acute respiratory distress syndrome, etc). Ghorbani et al. (2020) reported the first deep learning model to predict age, sex, weight and height from echocardiogram images and make use of such models to understand how models predicts systematic phenotypes which are difficult for human interpreters. Authors trained CCN models with 2.6 million echocardiogram images from 2850 patients with 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). Recently, Hong et al. (2022) reviewed 673 papers that made use of machine learning-enabled to help for clinical decision in the ICU, of these studies the majority used supervised learning (91%) few doing unsupervised learning and reinforcement learning. Similarly, Hong et al. (2022) identified 20 of the most frequent variables in machine learning-enabled in the ICU, 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 included typical patient outcomes, specific diseases, and stay of time evaluation.

3. Real-time AI-empowwered echocardiography

Wu et al. (2022) applied baselines of UNET with temporal context-aware encoder (TCE) and bidirectional spatiotemporal semantics fusion (BSSF) modules to EchoDynamic (10030 video sequences with of 200frames of 112x112 pixes) and CAMUS datasets (450 video of 20 frames of 778x594 pixels) with evaluation metrics of Dice score (DS), Hausdorff Distance (HD), and area under the curve (AUC). Wu et al. (2022) presented speed analysis, ensuring low latency and real-time performance, against eight methods using calculations number FLOPS (G), number of parameters (M) and speed (ms/f) which lowest one was 32 ms/f. 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) reported ResNet18-SP trained with 85k frames of Fetal US imaging with real-time performance of ∼20Hz. Østvik et al. (2021) proposed Echo-PWC-Net trained with Synthetic/Simulated/Clinical for real-time using 7 frames for the input.

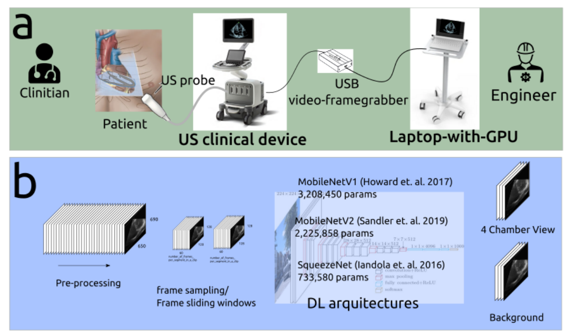

Figure 1: Real-time AI clinical system (a) clinical system, (b) deep learning pipeline.

3.1. Classification of echochardiograms

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) implemented a Tensorflow runner that performs contrast enhancement to then sent each frame to three identical CNNs running in separated threads to prevent lag during inference times. Then a shared buffer collects extracted features from CNNs to then awake the thread for the LSTM network from the previous ten frames to produce classification and quality prediction. 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 ± 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. 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. 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%.

3.2. Light neural networks to classify US images

Baumgartner et al. (2017) proposed SonoNet which is a VGG-based architecture, SonoNet64 used 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) being ResNet18-SP the best performing network with average accuracy over six classes of fetal US views (0.912). Authors mentions that detection and localisation of anatomical views were tested in real-time performance at inference time (40ms per image, or 20Hz). Al-Dhabyani et al. (2019) applied AlexNet and transfer learning based architectures (VGG16, Inception, ResNet, NASNet) without augmentation and with three augmentation techniques to perform tumor classification of breast ultrasound imaging. Authors stated that transfer learning NASNet presented the best performance with 99% with 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. Snider et al. (2022) reported summaries of CNN heuristics to detect shrapnel in US images. Authors presented summaries of model performance for layer activators, 2D CNN layer architectures, model optimisers dense nodes, and the effect of image augmentation and dropout rate and epoch number. 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.

Table 1: Neural Networks

Networks	Parameters	Source
MobileNetV1	3,208,450	
MobileNetV2	2,225,858	
Iandola et al. (2017)	733,580	

3.3. Datasets

Echocardiography videos of 31 subjects in the ICU were considered for this which were collected by four clinicians of ? years of experience collected using clinical device GE Venue Go machine and GE convex probe C1-5-D. The 31 subjects has the following characteristics: 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); BMI: mean (std): 23.80 (4.30); Sepsis % (with): 61.3%; Dengue % (with): 54.8%, and Tetanus % (with): 87.1%. See Figure 4 with further details on the demographics of the dataset, including the complete dataset of 87 subjects.

3.3.1. Ethics statement

This study was approved by ? and the ethics committee ? All participants gave written informed consent to participate before enrollment.

4. Heuristics

Figure 2 shows validation loss curves against three models (MobileNetV1, MobileNetV2, SqueezeNet). See Figure 3 for further results on SqueezeNet Training performance.

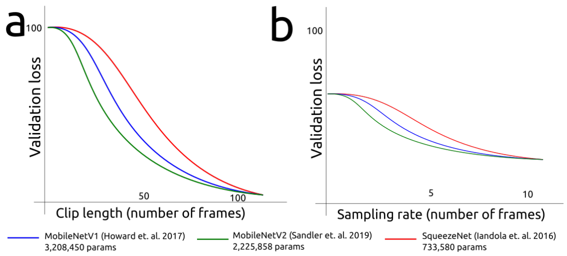

Figure 2: heuristics.

5. Conclusions and Future Work

2D velocity vector fields of flow blow can help to detect abnormal flow patterns as done in fetal and neonatal echocardiography (Meyers et al., 2021). Create synthetic Ultrasound images for GE Vivid E9, Hitachi Prosound U7, Philips iE 33 Vision, Siemens SC2000, and Toshiba Artida ultrasound systems (Brindise et al., 2020).

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Appendix A. First Appendix

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Appendix B. Second Appendix

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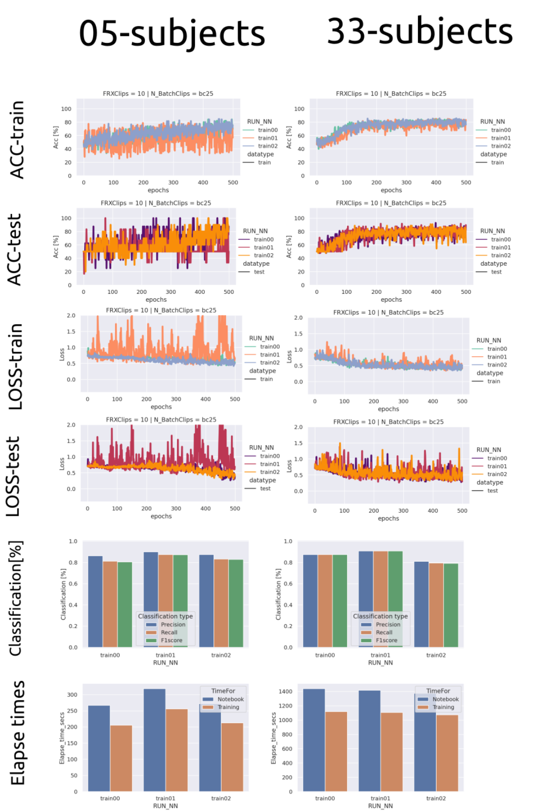

Figure 3: Heuristics for 5 and 33 subjects with 10 frames per clip and 25 batch size of clips using SqueezeNet (Iandola et al., 2017).

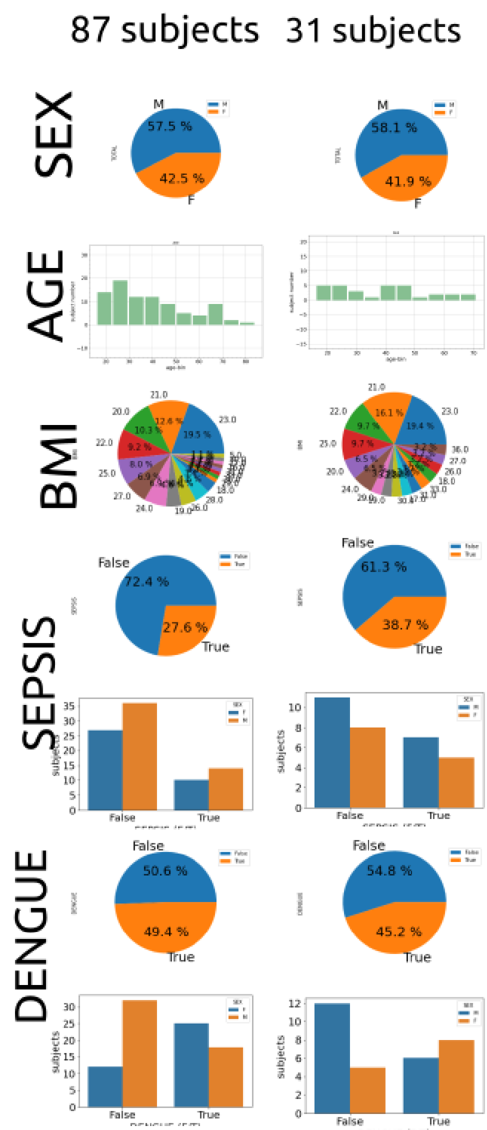

Figure 4: Patient demographics.