

# Abstract Track

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

**Anonymous Author(s)**

EMAIL@SAMPLE.COM *Address*

**Editors:** List of editors' names

### Abstract

We present a Machine Learning (ML) study case to illustrate the challenges of clinical translation for 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. Results of the ML heuristics showed the promising implementation, validation and application of thinner networks to classify 4CV with limited datasets. We conclude this work mentioning the need for (a) datasets to improve diversity of demographics, diseases, and (b) the need of further investigations of thinner models to be run and implemented in low-cost hardware to be clinically translated in the ICU in LMICs.

**Keywords:** Machine Learning, Artificial Intelligence, 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 (Vieillard-Baron et al., 2008; Campbell et al., 2018). Typically, the identi-

fication of cardiac abnormalities from 2D US views (Apical 4-Chamber (A4C), Parasternal Long-Axis and other six views) is achieved by specialist clinicians in echocardiography following the Focused Intensive Care Echo protocol (Hall et al., 2017). However, the application of point-of-care echocardiography of ICU patients in low- and middle-income countries (LMICs) 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 (Feigenbaum, 1996; Khamis et al., 2017; 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 (Becker et al., 2016; Hao et al., 2021; Tran et al., 2021). One promising approach to address such challenges is the application of Machine Learning (ML) and Artificial Intelligence (AI) methods 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/low risk of heart failure, detection of endocardial borders and automatic left ventricle assessment in 2D echocardiography videos (Tromp et al.,

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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).

The first and second challenges are important because of 2D US video data requires to appropriately be collected, validated and managed to apply AL and ML methods, and the third challenge 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 such challenges.

This work presents a scoping review for (a) AI-empowered echocardiography for ICU in LMICs and (b) classification US images with thinner neural networks. We present a ML case study to classify A4C US image considering three thinner neural networks trained with curated data from ICU patients in LMICs. We present training results from

SqueezeNet for different datasize, number of frames and clips batches. Further details for datasets, results of thinner networks are also added in the appendixes. We conclude with needs for clinical translation and add future work with validation of AI-based models.

## 2. Scoping review

### 2.1. AI-empowered echocardiography for ICU in LMICs

William and Marshall (2001) reviewed various AI-based applications in the ICU where real-time analysis of waveforms of electrocardiograms and electroencephalograms with 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. 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), and mentioned that the most studied diseases are sepsis, infection and kidney injury. Despite such advances, there is little 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

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AI. Kerdegari et al. (2021b,a); Nhat et al. (2021) presented a deep-learning pipelines to classify lung US pathologies for ICU patients in LMICs, stating the challenges of data imbalance, integration of technology and the limited IT infrastructure.

## 2.2. Classification of US images with thinner neural networks

Classifying echocardiograms has been successfully done in the previous years (Section A), however real-time deployment of AI-models suggest to require thinner networks. For instance, 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 real-time performance at inference time of 40 ms per image ( $\sim 20\text{Hz}$ ) Al-Dhabyani et al. (2019) applied AlexNet and transfer learning of four architectures (VGG16, Inception, ResNet, and NASNet) with and without augmentation techniques to perform tumor classification of breast US imaging. Authors stated that transfer learning with NASNet presented the best accuracy (99%) using BUSI+B datasets with DAGAN augmentation. Xie et al. (2020) proposed a dual-sampling convolutional neural network for US image breast cancer classification, being their network more efficient for such task 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 against DarkNet19, GoogleNet, MobileNetV2 and SqueezeNet, being ShrapML (8layers-6CNN and 2FC, making a network of 0.43 million parameters) 10x faster than MobileNetV2 and offering the highest accuracy.

## 3. Machine learning case study

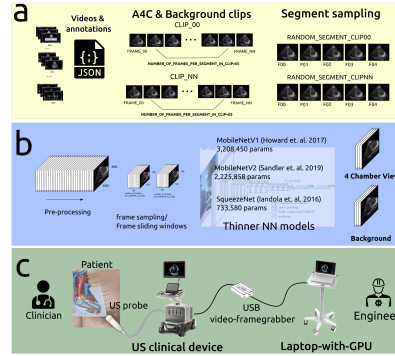


Figure 1: ML pipeline of real-time AI-empowered echocardiography for ICU in LMICs: (a) timestamp labelling of A4C frames and clips, (b) classification pipeline with thinner neural networks, and (c) low-cost clinical system with Epiq Q7, cardiac probe X5-1, USB video-frame grabber and 16GB GeForce RTX 3080 GPU Laptop.

### 3.1. Dataset

Echocardiography videos of 31 anonymised patients in the ICU were considered for this work which were collected by four radiologists using the clinical US devices: GE Venue Go machine with GE convex probe C1-5-

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D. The 31 patients had the following demographics: Sex: % (Male): 58.1%; Age: 38.70 (16.08) years; Weight: 61.51 (15.06) Kg; Height: 1.62 (0.07) m, and BMI: 23.80 (4.30). Values represent mean(std). See Appendix B for further details on the demographics of the dataset, including the complete dataset of 87 patients.

### 3.1.1. ETHICS STATEMENT

This study was approved by the anonymised entity one and anonymised entity two. 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). Hence, 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)).

### 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 this work: 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 num-

bers and clip length). MobileNetV1, MobileNetV2 and SqueezeNet were trained with data of 5 and 31 subjects (Appendix C) in which SqueezeNet showed constant training metrics. Hence, Figure 2 presents the impact of different datasize, batch size of clips, and number of frames per segment in a clip for SqueezeNet.

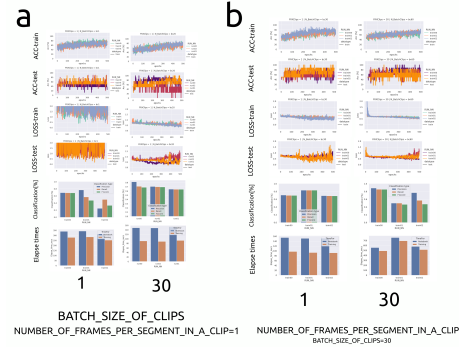


Figure 2: Heuristics for SqueezeNet with dataset of 5 subjects: (a) varying batch size with constant number of frames per segment equal to 1, and (b) varying number of frames per clip with constant batch size of clips equal to 10.

### 4. Conclusions and Future Work

We presented a ML case study that includes data selection, validation and management, model selection and validation. Our results show the promising use of thinner neural networks to address scarcity of datasets and model deployment in low-cost hardware. Future work will include real-time inference and deployment of thinner classification and segmentation models, leading to clinical translation of cardiac outputs of ICU patients in LMICs. The code, data and other resources to reproduce this work will be available upon acceptance of this work.

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## Appendix A. Classification of echocardiograms

[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 (Cuboid 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.

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## Appendix B. Datasets

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

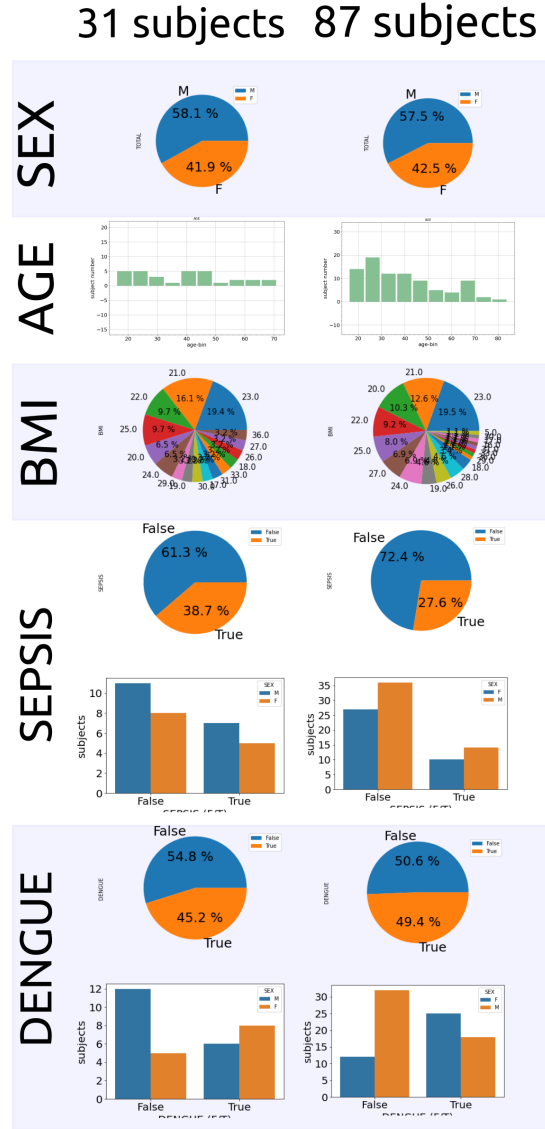


Figure 3: Patient demographics for sex, age, BMI, sepsis and dengue disease. The total number of patient is 87 of which data from 31 were curated, annotated and validated.

**Appendix C. Heuristics of model  
selection**

Figure 4 illustrates heuristics for accuracy, train, classification and elapse times of 5 and 31 subjects.

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**MobileNetV1 (Howard et. al. 2017)**  
<https://arxiv.org/abs/1704.04861>



**3,208,450 params**

**MobileNetV2 (Sandler et. al. 2019)**  
<https://arxiv.org/abs/1801.04381>



**2,225,858 params**

**SqueezeNet (Iandola et. al. 2016)**  
<https://arxiv.org/abs/1602.07360>



**733,580 params**

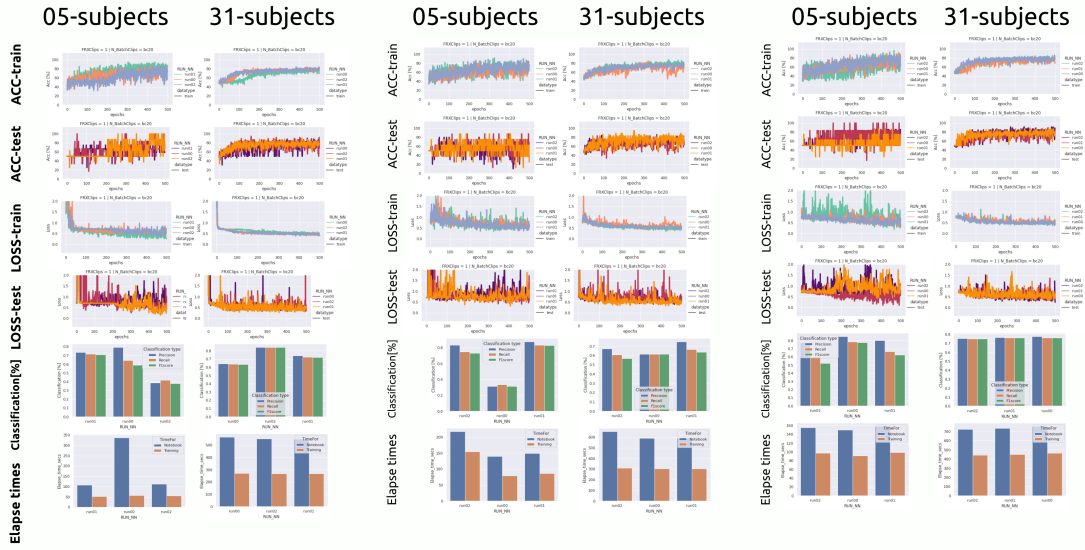


Figure 4: Heuristics for 5 and 31 subjects with 1 frames per clip and 20 batch size of clips for MobileNetV1 (Howard et al., 2017) with 3,208,450 parameters, MobileNetV2 (Sandler et al., 2018) with 2,225,858 parameters, and SqueezeNet (Iandola et al., 2017) with 733,580 parameters. Models were trained three times (run01, run02 and run03) to illustrate the impact of the training on randomised datasets which were splitted 70% for train, 15% for test and 15% for validation. **Note:** It is recommended to zoom in the figures to see further details (figure DPI is 300).

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