Abstract Track

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

Anonymous Author(s) EMAIL@SAMPLE.COM *Address*

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. 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, 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 ∼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 hyperparameters (datasize, augmentations and clip length) as shown in Figure 2. See Appendix B for further details on each model.

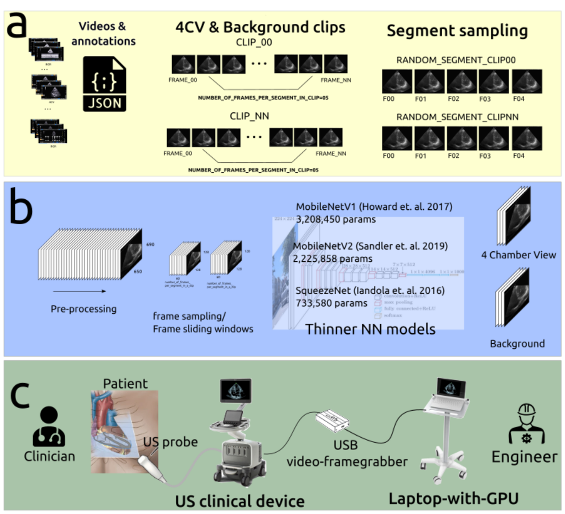

Figure 1: Proposed low-cost clinical system for real-time AI-empowered echocardiography: (a) timestamp labelling of four chamber view clips and frames, (b) deep-learning pipeline with thinner NNs, and (c) clinical system: Epiq Q7, cardiac probe X5-1, USB video-frame grabber and 16GB GeForce RTX 3080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

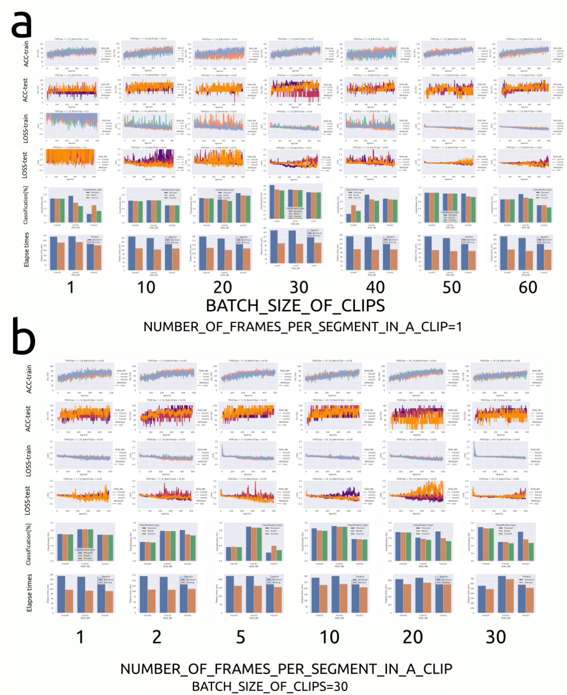

Figure 2: Heuristics for SqueezeNet (Iandola et al., 2017) with dataset of 5 subjects: (a) varying batch size and constant number of frames per segment equal to 1, and (b) varying number of frames per clip and constant batch size of clips equal to 10.

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.

References

Walid Al-Dhabyani, Mohammed Gomaa, Hussien Khaled, and Aly Fahmy. Deep learning approaches for data augmentation and classification of breast masses using ultrasound images. *International Journal of Advanced Computer Science and Applications*, 10(5), 2019. doi: 10.14569/IJACSA.2019.0100579. URL http://dx.doi.org/10.14569/IJACSA.2019.0100579.

Christian F. Baumgartner, Konstantinos Kamnitsas, Jacqueline Matthew, Tara P. Fletcher, Sandra Smith, Lisa M. Koch, Bernhard Kainz, and Daniel Rueckert. Sononet: Real-time detection and localisation of fetal standard scan planes in freehand ultrasound. *IEEE Transactions on Medical Imaging*, 36(11):2204–2215, 2017. doi: 10.1109/TMI.2017.2712367.

Delaram Behnami, Christina Luong, Hooman Vaseli, Hany Girgis, Amir Abdi, Dale Hawley, Ken Gin, Robert Rohling, Purang Abolmaesumi, and Teresa Tsang. Automatic cine-based detection of patients at high risk of heart failure with reduced ejection fraction in echocardiograms. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, 8(5):502–508, 2020. doi: 10.1080/21681163.2019.1650398. URL https://doi.org/10.1080/21681163.2019.1650398.

Emily N. Boice, Sofia I. Hernandez-Torres, and Eric J. Snider. Comparison of ultrasound image classifier deep learning algorithms for shrapnel detection. *Journal of Imaging*, 8 (5), 2022. ISSN 2313-433X. doi: 10.3390/jimaging8050140. URL https://www.mdpi.com/2313-433X/8/5/140.

Melissa C. Brindise, Brett A. Meyers, Shelby Kutty, and Pavlos P. Vlachos. Unsupervised segmentation of b-mode echocardiograms, 2020.

Steven J. Campbell, Rabih Bechara, and Shaheen Islam. Point-of-care ultrasound in the intensive care unit. *Clinics in Chest Medicine*, 39(1):79–97, 2018. ISSN 0272-5231. doi: https://doi.org/10.1016/j.ccm.2017.11.005. URL https://www.sciencedirect.com/science/article/pii/S0272523117301168. Interventional Pulmonology: An Update.

Baljash S. Cheema, James Walter, Akhil Narang, and James D. Thomas. Artificial intelligence–enabled pocus in the covid-19 icu: A new spin on cardiac ultrasound. *JACC: Case Reports*, 3(2):258–263, 2021. ISSN 2666-0849. doi: https://doi.org/10.1016/j.jaccas.2020.12.013. URL https://www.sciencedirect.com/science/article/pii/S2666084920314637.

Harvey Feigenbaum. Evolution of echocardiography. *Circulation*, 93(7):1321–1327, 1996. doi: 10.1161/01.CIR.93.7.1321. URL https://www.ahajournals.org/doi/abs/10.1161/01.CIR.93.7.1321.

Larry C. Field, George J. Guldan, and Alan C. Finley. Echocardiography in the intensive care unit. *Seminars in Cardiothoracic and Vascular Anesthesia*, 15(1-2):25–39, 2011. doi: 10.1177/1089253211411734. URL https://doi.org/10.1177/1089253211411734. PMID: 21719547.

Amirata Ghorbani, David Ouyang, Abubakar Abid, Bryan He, Jonathan H. Chen, Robert A. Harrington, David H. Liang, Euan A. Ashley, and James Y. Zou. Deep learning interpretation of echocardiograms. *npj Digital Medicine*, 3(1):10, Jan 2020. ISSN 2398-6352. doi: 10.1038/s41746-019-0216-8. URL https://doi.org/10.1038/s41746-019-0216-8.

C. William Hanson III and Bryan E. Marshall. Artificial intelligence applications in the intensive care unit. *Critical Care Medicine*, 29(2), 2001. ISSN 0090-3493. URL https://journals.lww.com/ccmjournal/Fulltext/2001/02000/Artificial_intelligence_applications_in_the.38.aspx.

NV Hao, LM Yen, R Davies-Foote, TN Trung, NVT Duoc, VTN Trang, PTH Nhat, DH Duc, NTK Anh, PT Lieu, TTD Thuy, DB Thuy, NT Phong, NT Truong, PB Thanh, DTH Tam, Z Puthucheary, and CL Thwaites. The management of tetanus in adults in an intensive care unit in southern vietnam [version 2; peer review: 3 approved]. *Wellcome Open Research*, 6(107), 2021. doi: 10.12688/wellcomeopenres.16731.2.

Na Hong, Chun Liu, Jianwei Gao, Lin Han, Fengxiang Chang, Mengchun Gong, and Longxiang Su. State of the art of machine learning–enabled clinical decision support in intensive care units: Literature review. *JMIR Med Inform*, 10(3):e28781, Mar 2022. ISSN 2291-9694. doi: 10.2196/28781. URL https://medinform.jmir.org/2022/3/e28781.

Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *CoRR*, abs/1704.04861, 2017. URL http://arxiv.org/abs/1704.04861.

Forrest N. Iandola, Song Han, Matthew W. Moskewicz, Khalid Ashraf, William J. Dally, and Kurt Keutzer. Squeezenet: Alexnet-level accuracy with 50x fewer parameters and <0.5MB model size, 2017. URL https://openreview.net/forum?id=S1xh5sYgx.

Hamideh Kerdegari, Phung Tran Huy Nhat, Angela McBride, Reza Razavi, Nguyen Van Hao, Louise Thwaites, Sophie Yacoub, and Alberto Gomez. Automatic detection of b-lines in lung ultrasound videos from severe dengue patients. In *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, pages 989–993, 2021a. doi: 10.1109/ISBI48211.2021.9434006.

Hamideh Kerdegari, Nhat Tran Huy Phung, Angela McBride, Luigi Pisani, Hao Van Nguyen, Thuy Bich Duong, Reza Razavi, Louise Thwaites, Sophie Yacoub, Alberto Gomez, and VITAL Consortium. B-line detection and localization in lung ultrasound videos using spatiotemporal attention. *Applied Sciences*, 11 (24), 2021b. ISSN 2076-3417. doi: 10.3390/app112411697. URL https://www.mdpi.com/2076-3417/11/24/11697.

Hanan Khamis, Grigoriy Zurakhov, Vered Azar, Adi Raz, Zvi Friedman, and Dan Adam. Automatic apical view classification of echocardiograms using a discriminative learning dictionary. *Medical Image Analysis*, 36:15–21, 2017. ISSN 1361-8415. doi: https://doi.org/10.1016/j.media.2016.10.007. URL https://www.sciencedirect.com/science/article/pii/S1361841516301876.

Phung Tran Huy Nhat, Hamideh Kerdegari, Angela McBride, Luigi Pisani, Nguyen Van Hao, Le Dinh Van Khoa, Shujie Deng, Le Ngoc Minh Thu, Duong Bich Thuy, VITAL Consortium, Marcus J. Schultz, Reza Razavi, Andrew P. King, Louise Thwaites, Sophie Yacoub, and Alberto Gomez. Lung ultrasound pathology classification for icu patient management in lmic. White paper, September 2021.

Shunzaburo Ono, Masaaki Komatsu, Akira Sakai, Hideki Arima, Mie Ochida, Rina Aoyama, Suguru Yasutomi, Ken Asada, Syuzo Kaneko, Tetsuo Sasano, and Ryuji Hamamoto. Automated endocardial border detection and left ventricular functional assessment in echocardiography using deep learning. *Biomedicines*, 10(5), 2022. ISSN 2227-9059. doi: 10.3390/biomedicines10051082. URL https://www.mdpi.com/2227-9059/10/5/1082.

Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

Siddharth Singh and Abha Goyal. The origin of echocardiography: a tribute to inge edler. *Texas Heart Institute journal*, 34(4):431–438, 2007. ISSN 0730-2347. URL https://pubmed.ncbi.nlm.nih.gov/18172524.

Eric J. Snider, Sofia I. Hernandez-Torres, and Emily N. Boice. An image classification deep-learning algorithm for shrapnel detection from ultrasound images. *Scientific Reports*, 12(1): 8427, May 2022. ISSN 2045-2322. doi: 10.1038/s41598-022-12367-2. URL https://doi.org/10.1038/s41598-022-12367-2.

Jonathon E Stewart, Adrian Goudie, Ashes Mukherjee, and Girish Dwivedi. Artificial intelligence-enhanced echocardiography in the emergency department. *Emergency Medicine Australasia*, 33(6):1117–1120, 2021. doi: https://doi.org/10.1111/1742-6723.13847. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1742-6723.13847.

Nicolas Toussaint, Bishesh Khanal, Matthew Sinclair, Alberto Gomez, Emily Skelton, Jacqueline Matthew, and Julia A. Schnabel. Weakly supervised localisation for fetal ultrasound images. In *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support*, pages 192–200, Cham, 2018. Springer International Publishing. ISBN 978-3-030-00889-5.

Huy Nhat Phung Tran, Nguyen Van Hao, Luigi Pisani, Hamideh Kerdegari, Duong Bich Thuy, Le Ngoc Minh Thu, Truong Thi Phuong Thao, Le Thi Mai Thao, Ha Thi Hai Duong, MarcusJ. Schultz, Reza Razavi, Andrew P. King, Louise Thwaites, Sophie Yacoub, and Alberto Gomez. Role of ai-enabled ultrasound imaging in a resource limited intensive care unit. White paper, September 2021.

Jasper Tromp, Paul J. Seekings, Chung-Lieh Hung, Mathias Bøtcher Iversen, Matthew James Frost, Wouter Ouwerkerk, Zhubo Jiang, Frank Eisenhaber, Rick S. M. Goh, Heng Zhao, Weimin Huang, Lieng-Hsi Ling, David Sim, Patrick Cozzone, A. Mark Richards, Hwee Kuan Lee, Scott D. Solomon, Carolyn S. P. Lam, and Justin A. Ezekowitz. Automated interpretation of systolic and diastolic function on the echocardiogram: a multicohort study. *The Lancet Digital Health*, 4(1):e46–e54, Jan 2022. ISSN 2589-7500. doi: 10.1016/S2589-7500(21)00235-1. URL https://doi.org/10.1016/S2589-7500(21)00235-1.

Nathan Van Woudenberg, Zhibin Liao, Amir H. Abdi, Hani Girgis, Christina Luong, Hooman Vaseli, Delaram Behnami, Haotian Zhang, Kenneth Gin, Robert Rohling, Teresa Tsang, and Purang Abolmaesumi. Quantitative echocardiography: Real-time quality estimation and view classification implemented on a mobile android device. In Danail Stoyanov, Zeike Taylor, Stephen Aylward, João Manuel R.S. Tavares, Yiming Xiao, Amber Simpson, Anne Martel, Lena Maier-Hein, Shuo Li, Hassan Rivaz, Ingerid Reinertsen, Matthieu Chabanas, and Keyvan Farahani, editors, *Simulation, Image Processing, and Ultrasound Systems for Assisted Diagnosis and Navigation*, pages 74–81, Cham, 2018. Springer International Publishing. ISBN 978-3-030-01045-4.

Antoine Vieillard-Baron, Michel Slama, Bernard Cholley, Gérard Janvier, and Philippe Vignon. Echocardiography in the intensive care unit: from evolution to revolution? *Intensive Care Medicine*, 34(2):243–249, Feb 2008. ISSN 1432-1238. doi: 10.1007/s00134-007-0923-5. URL https://doi.org/10.1007/s00134-007-0923-5.

Huisi Wu, Jiasheng Liu, Fangyan Xiao, Zhenkun Wen, Lan Cheng, and Jing Qin. Semi-supervised segmentation of echocardiography videos via noise-resilient spatiotemporal semantic calibration and fusion. *Medical Image Analysis*, 78:102397, 2022. ISSN 1361-8415. doi: https://doi.org/10.1016/j.media.2022.102397. URL https://www.sciencedirect.com/science/article/pii/S1361841522000494.

Jiang Xie, Xiangshuai Song, Wu Zhang, Qi Dong, Yan Wang, Fenghua Li, and Caifeng Wan. A novel approach with dual-sampling convolutional neural network for ultrasound image classification of breast tumors. *Physics in Medicine and Biology*, 65(24):245001, dec 2020. doi: 10.1088/1361-6560/abc5c7. URL https://doi.org/10.1088/1361-6560/abc5c7.

Jeffrey Zhang, Sravani Gajjala, Pulkit Agrawal, Geoffrey H. Tison, Laura A. Hallock, Lauren Beussink-Nelson, Mats H. Lassen, Eugene Fan, Mandar A. Aras, ChaRandle Jordan, Kirsten E. Fleischmann, Michelle Melisko, Atif Qasim, Sanjiv J. Shah, Ruzena Bajcsy, and Rahul C. Deo. Fully automated echocardiogram interpretation in clinical practice. *Circulation*, 138(16):1623–1635, 2018. doi: 10.1161/CIRCULATIONAHA.118.034338.

URL https://www.ahajournals.org/doi/abs/10.1161/CIRCULATIONAHA.118.034338.

Zisang Zhang, Ye Zhu, Manwei Liu, Ziming Zhang, Yang Zhao, Xin Yang, Mingxing Xie, and Li Zhang. Artificial intelligence-enhanced echocardiography for systolic function assessment. *Journal of Clinical Medicine*, 11(10), 2022. ISSN 2077-0383. doi: 10.3390/jcm11102893. URL https://www.mdpi.com/2077-0383/11/10/2893.

Andreas Østvik, Ivar Mjåland Salte, Erik Smistad, Thuy Mi Nguyen, Daniela Melichova, Harald Brunvand, Kristina Haugaa, Thor Edvardsen, Bjørnar Grenne, and Lasse Lovstakken. Myocardial function imaging in echocardiography using deep learning. *IEEE Transactions on Medical Imaging*, 40(5):1340–1351, 2021. doi: 10.1109/TMI.2021.3054566.

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.

Appendix B. Heuristics of model selection

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

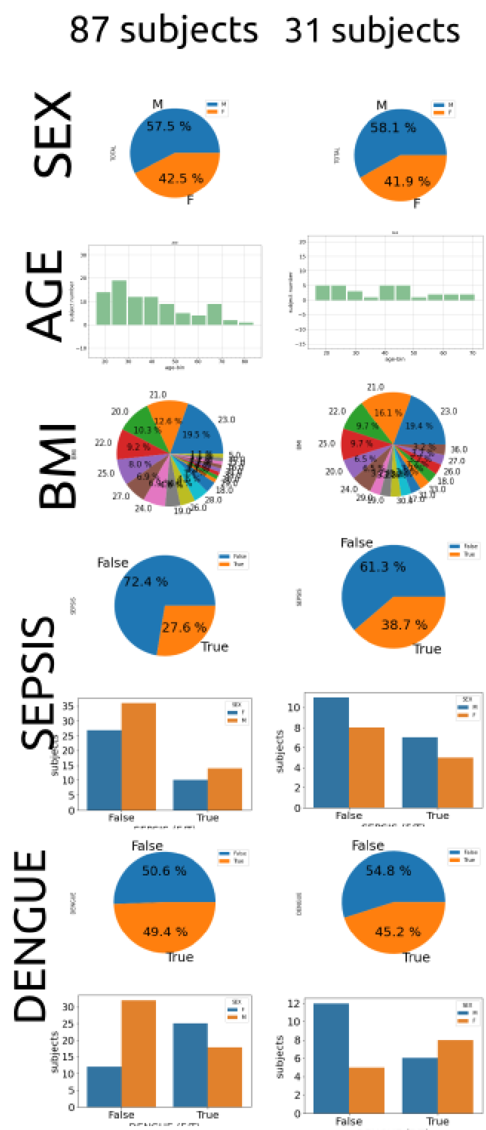

Figure 3: Patient demographics.

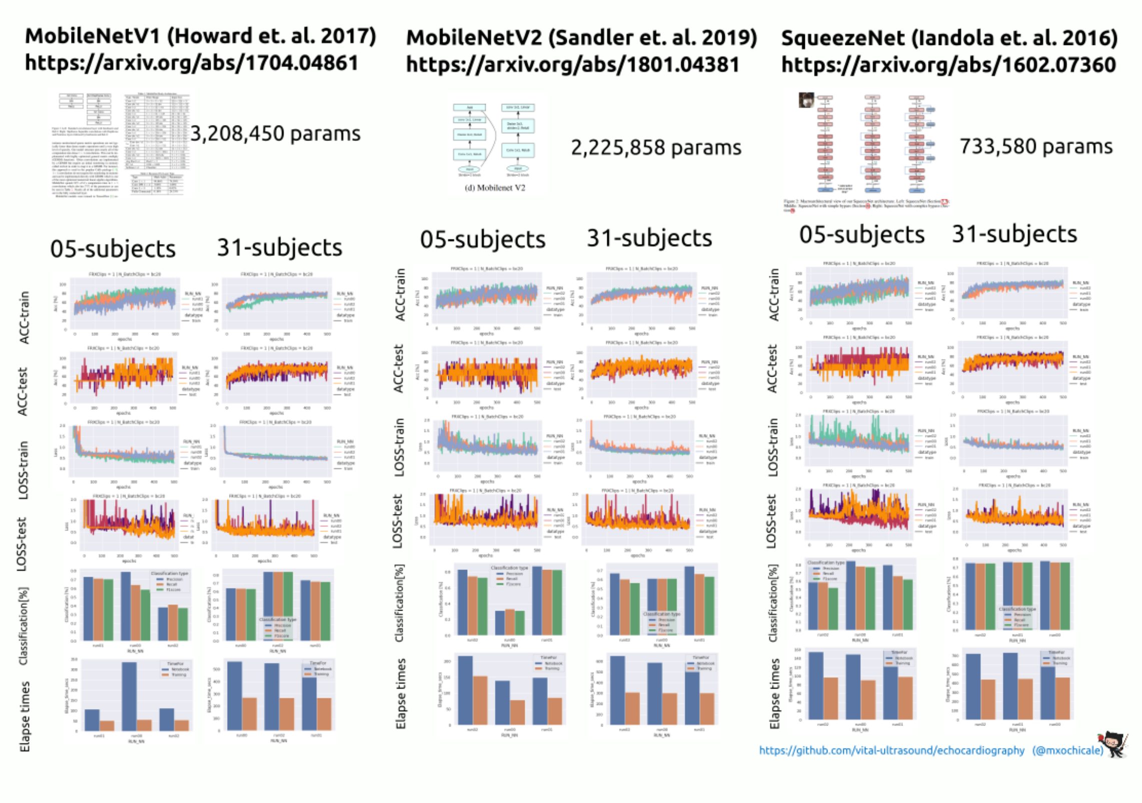

Figure 4: Heuristics for 5 and 31 subjects with 1 frames per clip and 20 batch size of clips for MobileNetV1 (Howard et al., 2017), MobileNetV2 (Sandler et al., 2018), and SqueezeNet (Iandola et al., 2017) 733,580

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