

# Abstract Track

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

Anonymous Author(s)

EMAIL@SAMPLE.COM *Address*

**Editors:** List of editors' names

### Abstract

This is the abstract for this article.

**Keywords:** List of keywords

### 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
- Limited number of expert clinicians to perform US imaging analysis and provide accurate diagnosis, and equipment and hospitalisation requirements in low- and middle-income countries (LMICs) (Hao et al., 2021).

One promising approach is the use of Artificial Intelligence, 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), detect high risk or low risk of

heart failure automatic endocardial border detection and left ventricular 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 the identification of four chamber view 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 starting 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 inter-

## Abstract Track

preters. 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-empowered 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. [Tous-saint et al. \(2018\)](#) reported ResNet18-SP trained with 85k frames of Fetal US imaging with real-time performance of  $\sim 20Hz$ . [Østvik et al. \(2021\)](#) proposed Echo-PWC-Net trained with Synthetic/Simulated/Clinical for real-time using 7 frames for the input.

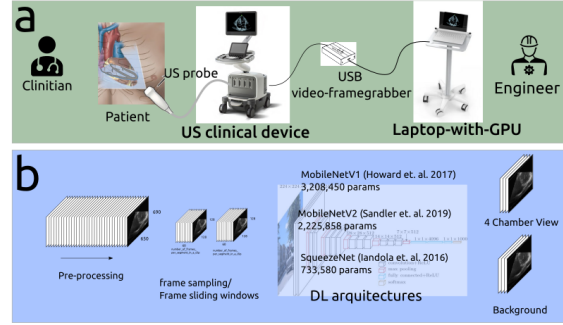


Figure 1: Real-time AI clinical system (a) clinical system, (b) deep learning pipeline.

#### 3.1. Classification of echocardiograms

[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  $352.91 \pm 38.27$  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. 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 vi-

# Abstract Track

sually 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 of standard views in freehand fetal US. Tous-saint et al. (2018) applied four feature extraction networks couple with batchnormalisation 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, NAS-Net) 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

86 patients of average age (?) ? male and ? female were collected by four clinicians of ? years of experience collected echocardiography datasets Figure 4. The collection was done with the clinical device GE Venue Go machine and GE convex probe C1-5-D.

#### 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.

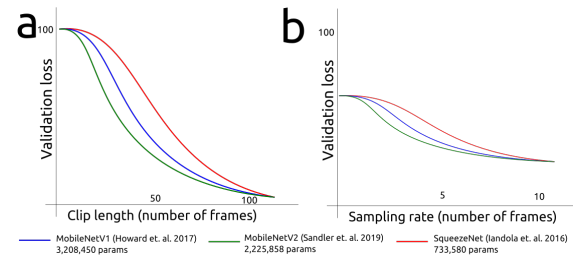


Figure 2: heuristics.

## 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.,

## Abstract Track

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).

## Acknowledgments

Acknowledgements go here.

## 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. Unsuper-
- vised 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. Guldán, 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](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,

## Abstract Track

- NTK Anh, PT Lieu, TTD Thuy, DB Thuy, NT Phong, NT Truong, PB Thanh, DTH Tam, Z Puthuchear, 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>.
- 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>.
- 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>.
- Brett A. Meyers, Melissa C. Brindise, R. Mark Payne, and Pavlos P. Vlachos. An integrated and automated tool for quantification of biomechanics in fetal and neonatal echocardiography. *medRxiv*, 2021. doi: 10.1101/2020.10.21.20217265. URL <https://www.medrxiv.org/content/early/2021/06/22/2020.10.21.20217265>.
- 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>.
- 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>.
- Nicolas Toussaint, Bishesh Khanal, Matthew Sinclair, Alberto Gomez, Emily Skelton, Jacqueline Matthew, and Julia A. Schnabel. Weakly supervised localisation for fetal ultrasound images. In Danail Stoyanov, Zeike Taylor, Gustavo Carneiro, Tanveer Syeda-Mahmood, Anne Martel, Lena Maier-Hein, João Manuel R.S. Tavares, Andrew Bradley, João Paulo Papa, Vasileios Belagiannis, Jacinto C. Nascimento, Zhi Lu, Sailesh Conjeti, Mehdi Moradi, Hayit Greenspan, and Anant Madabhushi, editors, *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.
- 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 Cozzzone, 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](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,



## Abstract Track

- 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. First Appendix**

This is the first appendix.

**Appendix B. Second Appendix**

This is the second appendix.

## Abstract Track

05-subjects      33-subjects

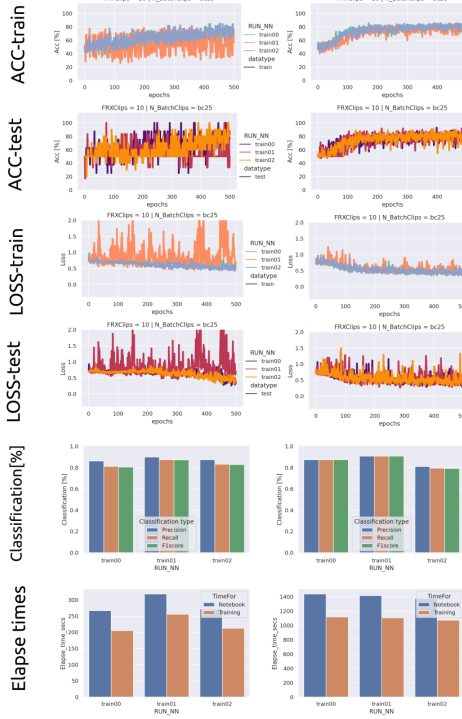


Figure 3: Heuristics for 5 and 33 subjects with 10 frames per clip and 25 batch size of clips using SqueezeNet ([Iandola et al., 2017](#)).

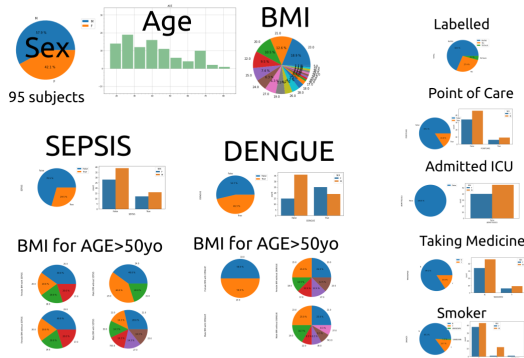


Figure 4: Patient demographics.