

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

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July 18, 2022

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1 Introduction

In the last decades the use of echocardiography is an important clinical approach in Intensive Care Units (ICU) because of the adtages of US devices 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 the previous advances, there various challenges in the current practices of clinical ultrasound:

- Intra-view variability of echochardiograms (physiological variations of subjects and adquisition parameters) and sonographer expertise, [Khamis et al., 2017, Feigenbaum, 1996, Field et al., 2011].
- Inter-view similarity of echochardiograms (similar views of valve motion, wall motion, left ventricle, etc) and transducer position during adquisition, [Zhang et al., 2018], redudant information in the clinical echo system (icons, date, frame rate, etc). [Khamis et al., 2017]
- Limited number of expert clinitians to perform US imaging analysis and provice accurate diagnosis, and equipment and hospitalisation requirements in low- and middle-income countries (LMICs) [Hao et al., 2021].

1.1 AI-empowered echocardiography

[Hanson III and Marshall, 2001] reviwed various applications of AI in the ICU where real-time analysys of waveforms of electrocardiograms and electroencephalograms using neuoral network were used to idenfy cardiac ischemia and diagnosis myocardial ischemia. [Hanson III and Marshall, 2001] also reviewed various scnerations 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 probablitistic cardiac output. [Hanson III and Marshall, 2001] also touched on datavisualiaistion to demonstrate the hypothetical ICU for large number of patients (head injury, sepsis, acute respiratory distress syndrome, etc).

Ghorbani et al. in 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 difficul for human interpreters [Ghorbani et al., 2020]. Authors trained CCN models with 2.6 million echocardiogram images from 2850 patients with the extraction of labels local strucutre 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 desicion 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.

Tromp et al. classified a dataset of 1145 2D echocardiography videos as apical 4 chamber (A4C) view, apical 2 chamber (A2C) view, parasternal long axis (PLAX) view, or 2D other views and focused versions of the main views [Tromp et al., 2022]. Authors used CNN of four layers, dense network and softmax output layer, trained with categorical cross-entropy loss function, then a second classifier of an unsupervised deep learning clustering CNN, trained with mean square error and Kullback-Leibler loss functions [Tromp et al., 2022].

[Zhang et al., 2022] reviewed AI’s applications in left ventricular systolic function (LVEF) and global longitudinal strain (GLS), pointing out its dependant to the sonographers’s expertise (inter-observer variability) and post-processing and variability in different US devices. [Zhang et al., 2022] pointed the challenges of AI-enhanced echocardiography for interpretability of results and its sensitivity to sample shortage, to which authors mention about the potentials of multimodal imaging (us, mri and clinical data) to improve detection rate of diseases.

[Behnami et al., 2020] applied DenseNet-like network for feature learning and RNN unit with bidirectional Gated Recurrent Units to alleviate loss of information from the earlier frames of echos to automatically detect high risk or low risk of heart failure with reduced ejection fraction with an overall accuracy of 83.15%, precision of 82.6% and recall of 81.1%. [Behnami et al., 2020] mentioned that EF is highly user-dependant to which they propose to collect more data,

[Liu et al., 2021] proposed pyramid local attention neural network (PLANet) to improve segmentation performance of automatic methods in 2D echocardiography. PLANet was evaluated with CAMUS and sub-EchoNet-Dynamic datasets, showing a better performance against geometric and clinical metrics.

[Ulloa Cerna et al., 2021] made use of DNN to learn spatiotemporal features from echocardiography video data to enhance clinical prediction of 1 yr all-cause mortality where video echo data linked to EHR data that included hand-crafted echocardiography-derived measurements (EDMs), additional clinical variables and individual outcomes. The DNN model presents "superior prediction performance" over four cardiologist and two benchmark clinical models: the pooled cohort equations (PCE) and Seattle Heart Failure (SHF) risk score [Ulloa Cerna et al., 2021]. [Ulloa Cerna et al., 2021] used "full, raw (annotation-free) echocardiographic videos to make predictions by learning from more than 812,278 clinically acquired echocardiography videos of the heart (50 million images)."

[Jafari et al., 2021] pointed out the challenges of obtaining high quality for less experience operators and the high variability of echo quality and cardiovascular structures across different patients to which authors proposed "Bayesian deep learning approach for fully automatic LVEF estimation based on segmentation of the left ventricle (LV) in parasternal short-axis papillary muscles (PSAX-PM) level". [Jafari et al., 2021] made use of 2,680 patients with PSAX-PM echo cine acquired by a variety of ultrasound devices, namely iE33, Vivid i/7/9/95, Sonosite, and Sequoia (only 554 echo cines were considered as ground truth with LV mask delineated by an experienced level III echocardiographer).

Author(s), year	Datasets (clips)	Input frames	Flops	Model; Params	Latency	Hyper-parameters	Code
[Wu et al., 2022]	EchoDynamic (10Kc) CAMUS (.5Kc)	3	56.359	TCE-BSSF;74.798	32 (ms/f)	lr=10e-4;epochs=100; CR=5-fold	-
[Van Woudenberg et al., 2018]	AP4(2Kc)	10	-	DenseNet-LSTM;	352.91ms	-	-
[Østvik et al., 2021]	Synthetic/Simulated/Clinical	7	-	Echo-PWC-Net	-	-	-

Ono et al. applied differen models where Unet++ demonstrated good performance for automatic endocardial border detection and left ventrical assesment in 2D echocardiographu videos [Ono et al., 2022]. The datasets to train networks was made of 2798 images from 118 videos of which 22 videos with 465 frames were for 4CV [Ono et al., 2022]. Ono et al. also touched on the challenges of providing explainable AI for US imaging.

1.2 Real-time AI-empowered echocardiography

In terms of real-time analysys of 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]. Wu et al. 2022, ensuring low latency and real-time performance, presented speed analysis againts eight methods using calculations number FLOPS (G), number of parameters (M) and speed (ms/f) which lowest one was 32 ms/f [Wu et al., 2022].

2 Methods for AI-empowered echocardiopgraphy

2.1 Image Quality Assessment

[Labs et al., 2021] considers chamber clarity, depth gain, on-axis attributes, apical fore-shoredness.

2.2 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. performed view classification with 277 echochardiograms 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 assement and resulting in 84% for overall accuracy where challenges for partial obscured LVs for a2c, a3c and a4c [Zhang et al., 2018]. 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. 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 (Cubic Detector) and supervised learning dictionary (LC-KSVD) resulting in an overall recognition rate of 95% [Khamis et al., 2017].

2.2.1 Classification of other US images

[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.

2.3 Clustering techniques

Zhang et al. mentioned that 23 view classes from 7168 individually labeled videos that were classified with a 13-layer CNN to then viewed with the use of t-Distributed Stochastic Neighbor Embedding [Zhang et al., 2018]. Zhang et al. made use of 277 echocardiograms collected over a 10-year period for view classification. Kusunose et al. mentioned that other authors have reached an accuracy of 91-94 for 15-view classification while their work mentioned a 98.1 accuracy for five-predefined views [Kusunose, 2021].

2.4 Auto-encoders

Laumer et al. proposed a novel autoencoder-based framework to learn human interpretable representation of cardiac cycles from cardiac ultrasound data [Laumer et al., 2020].

Ouyang et al. presented echo-dynamic dataset as the first annotated medical video dataset with 10,036 videos. Additionally, authors reported the use of three CNN architectures varying filters in each layer to assess ejection fraction to near-expert performance. It is worthwhile to note that authors got best performance with mean absolute error of 5.44% using clip length of 16 and frame rate of 4. Such error is near-expert performance as they can get 4-5% for skilled echocardiographers in controlled settings [Ouyang et al., 2019].

Ghorbani et al. applied convolutional neural networks of cardiac ultrasound to identify local structures, estimate cardiac function and predict pathologies. Their deep learning model, EchoNet, can identify up to 10 cardiac biometrics which results in decreasing repetitive task in the clinical flow, provide interpretation to less experienced cardiologist, and predict phenotypes. This work can predict age, sex, weight and height from echocardiogram images. Authors mention that the increase of data does not improve model training. The homogenisation of cardiac views prior to model training improved training speed and computation time [Ghorbani et al., 2020].

2.5 Segmentation

With the challenges of limited sampling of cardiac cycles and the considerable inter-observer variability, Ouyang et al. presented a CNN model with residual connections and spatiotemporal convolutions that surpass human performance of segmentation of left ventricle, estimation of ejection fraction and assessment of cardiomyopathy. Their model

reached Dice similarity coefficient of 0.92, predicts ejection fraction with mean absolute error of 4.1% and classify heart failure based on reduced ejection fraction [Ouyang et al., 2020].

Meyer et al. used Prominence Iterative Dijkstra’s algorithm (ProID), based on the identification of ventricle boundaries with iterative Dijkstra’s algorithm, for ventricle detection and volumen estimation [Meyers et al., 2021]. ProID employs echocardiogram-specific cost-matrix to address contrast-to-noise and resolution limitations problems [Brindise et al., 2020].

2.6 Contrastive Learning

Methods on Contrastive Learning apparently address the challenge of required labelled data to identify pathologies in the images of detect certain cardiac views. Recently, Chartsias et al. use contrastive learning to train imbalanced cardiac datasets and they compared a naive baseline model to achieve a F1 score of up to 26% [Chartsias et al., 2021]. Saeed et al. recently investigated contrastive pretraining to improve the DeepLabV3 and UNET segmentation networks of cardiac structures in ultrasound imaging. Authors showed comparable results with state-of-the-art fully supervised algorithms and presents better results compared to EchoNet-Dynamic and CAMUS [Mohamed et al., 2021].

2.7 AI-guided US imaging

Near-human quantification of LV and EF has been investigated, however Asch et al. pointed out that boundary identification is prone to errors when low quality images or artifacts are used. Asch et al. pointed out that data and materials were not publicly available and they made use of AutoEF by Caption Health Co. Authors used a database of 50000 echocardiography datasets over a period of 10 years of various clinical US systems. The training datasets included multiple views of 2 and 4-chamber views and LV EF values where clinicians use conventional methods (biplane Simpson technique) [Asch et al., 2019].

Asch et al. [Asch et al., 2021].

Hong et al. reported the evaluation of image quality assessment to demonstrate that AI can recognise nuances of varying image quality during scanning [Hong et al., 2021].

Narang et al. reported the acquisition of 10 echocardiography views of novice users using deep-learning-based software [Narang et al., 2021]. Narang et al. mentioned that CNNs were used with stacks of networks and transformations. The AI-guided software consists of three estimates: (1) quality image assessment, (2) ”6-dimensional geometric distance with position and orientation between the current probe location and the location anticipated to optimise the image”; and (3) corrective probe manipulation. [Narang et al., 2021]. Authors mention that algorithms do not use trackers, fiducial marks or additional sensors to make guidance estimations [Narang et al., 2021].

Cheema et al. reported the use of AI-enabled guidance to sonographer which was created from the use of 500000 hand movements. Cheema et al. reported that such feature was the first cardiac authorised by Food and Drug Administration in 2020. Authors 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 steering of user’s transducer position and hand movement [Cheema et al., 2021].

2.8 3D US

Considering that 3D left ventricle (LV) can provide full volume information of the heart than 2D echocardiography, Dong et al. proposed a real-time framework VoxelAtlasGAN that made use of cGAN [Dong et al., 2018]. VoxelAtlasGAN framework with mean surface distance of 1.85 mm, mean hausdorff distance of 7.66mm, mean dice 0.953 and correlation of EF 0.918 and the mean inference speed of 0.1 s demonstrated potential for clinical application [Dong et al., 2018]. Dong et al. in 2020 applied transformers to obtain translations parameters that passed to VoxelAtlasGAN [Dong et al., 2020]. AtlasNET framework ended up with "mean surface distance, mean hausdorff surface distance, and mean dice index were 1.52 mm, 5.6 mm and 0.97 respectively" [Dong et al., 2020]

Smistad et al. 2021 made use of CETUS 3D US LV segmentation dataset and weakly annotated datasets for real-time 3D left ventricle segmentation and estimation of ejection fraction [Smistad et al., 2021b]. Authors presented the impact of pre-training that resulted in an improvement of Dice score. It is important to note that VoxelAtlasGAN and AtlasNet by Dong et al. presented a better dice score. Smistad et al. 2021 concluded that a limited labelled datasets of 15 patients demonstrate good accuracy and models were able to generalise to new data and ultrasound scanners [Smistad et al., 2021b].

2.9 Transformers

Rubin et al. noted the shortcoming of transformers of extensive computation for training that lead to use detection transformer (DETR) which make smaller models reducing model size and acceleration inference [Rubin et al., 2021]., Rubin et al. considered the detection of needles in real-time ultrasound video sequences 12,000 needle insertions (2 million of individual frames). Video sequences (up to 60 sec in time) were divided into 30-frame clips (1 sec in time).

Reynaud et al. 2021 adapted Residual Autoencoder Network and BERT model to predict ejection fraction which is different from what is commonly use with segmentation methods [Reynaud et al., 2021]. Reynaud et al. applied their model to Echonet-Dynamic dataset which only contains 10,030 echocardiograms containing one to three or more cardiac cycles with only cardiac cycle with ES and ED annotations. Due to the distribution between ES and ED, the sequence length was 128 frames. As Echonet-Dynamic datasets contains unlabelled ES and ED, Reynaud et al. applied (a) Guided Random Sampling (b) Mirroring Methods. Code is available at <https://github.com/HReynaud/UVT>.

2.10 Others

Rank-2 non-negative matrix factorization [Yuan et al., 2017] to generate End-Systole and End-Diastole for apical 4 view. Recently Robust Non-negative Matrix Factorization seems to be implement low-computation cost algorithms to automatic segment mitral valve [Dukler et al., 2018].

Salte et al. classified three standard apical views from data of 200 patients to perform strain measurements with deep learning architectures [Salte et al., 2021]. Salte et al. made use of the work [Østvik et al., 2021] inception and dense network were used to classify, recurrent network to detect event timing and u-net-based network for segmentation [Salte et al., 2021]. Authors compared the results with the commercially available semiautomatic speckle-tracking software (EchoPAC v202), reporting evidence of the comparable GLS measurements to other semiautomatic methods [Salte et al., 2021].

3 Spatiotemporal Features

3.1 Deep Residual Learning

Ouyang et al. benchmarked various spatiotemporal convolutions (Sports-1M, Kinetics, UCF101, and HMDB51) [Ouyang et al., 2019] based on deep residual learning (He et al. 2015 and Tran et al. 2018).

3.2 LSTM

Recently, Smistad et al. 2021 presented the use of LSTM to address the single frame segmentation of end-diastole and end-systole to address segmentation flickering and reduce temporal errors [Smistad et al., 2021a]. One of the challenges is architecture design to add ConvLSTMs to which authors experiment at the location at the encoder, decoder, last layer and in bottleneck, to which authors mention that the use of the ConvLSTM layers in the encoder of the temporal NN gave the best results [Smistad et al., 2021a]. Authors mention that interpolation of the annotations of the entire cardiac cycle did not capture the complex motion with the use of 7 frames to which they suggest to use advanced speckle tracking such as Echo-PWC-Net [Østvik et al., 2021].

Lu et al. made use of U-Net and LSTM to model Left Ventricular cardiac motion [Lu et al., 2020].

Bar et al. assessed surgical workflow recognition and report a deep learning system in which clips of one second to create a short-term spatio-temporal model based on inflated 3D network with non-local to obtain SoftMax probability vector to feed LSTM to produce final phase predictions [Bar et al., 2020]

4 Validation and Usability Studies

Francesconi et al. 2021 presented technical validation by intra-operator reproducibility of two measurements (intima-media thickness and distension) by one expert and usability of integrated system in a laboratory setting with 12 healthy volunteers [Francesconi et al., 2021].

5 Cardiac Motion Estimation

Cardiac motion estimation has an important role in echocardiography due to the computation of myocardial deformation indices. [Aviles et al., 2017] propose a method to estimate cardiac motion of ultrafast ultrasound data by combining low-rank data representation with topology preservation to overcome the challenges of non-rigid registration that involves complex heart motion and distortions. [Young et al., 2021] proposed a method to build 3D recovery models from 2D echocardiography data with the only assumption that the probe is fixed for one cardiac cycle. [Evain et al., 2022] proposed a deep learning model PWC-Net, achieving an average endpoint error of " 0.07 ± 0.06 mm per frame and 1.20 ± 0.67 mm between ED and ES on their simulated dataset". See [Østvik et al., 2021] for further details on Echo-PWC-Net and other networks.

6 Datasets in echocardiography

6.1 CAMUS (2D US)

CAMUS dataset, Cardiac Acquisitions for Multi-structure Ultrasound Segmentation, was published in 2019 by Leclerc et al. 2019 [Leclerc et al., 2019]. CAMUS is the largest publicly-available and fully-annotated dataset of two and four-chamber acquisition from 500 patients. Datasets is categorised in image quality (good, medium, and poor) and LV_{EF} ($\leq 45\%$ (pathological risk) , $\geq 55\%$, else). The dataset reflects a daily clinical practice data where images quality and a range of pathological cases. Dataset was collected with GE Vivid E95 ultrasound scanners (GE Vingmed Ultrasound, Horten Norway) with a GE M5S probe (GE Healthcare, US). The datasets is available electronically to download at <https://www.creatis.insa-lyon.fr/Challenge/camus/>.

6.2 EchoNet-Dynamic (2D US)

Ouyang et al. published a large datasets of 10,030 annotated echocardiogram videos [Ouyang et al., 2019, Ouyang et al., 2020]. Datasets were labelled left ventricle volumes by sonographers to calculate ejection fraction. Datasets were acquired by skilled sonographers using iE33, Sonos, Acuson SC2000, Epiq 5G or Epiq 7C ultrasound machines and processed images were stored in a Philips Xcelera system. The datasets is available electronically to download at <https://echonet.github.io/dynamic/index.html#dataset>.

6.3 CETUS (3D US)

Challenge on Endocardial Three-dimensional Ultrasound Segmentation (CETUS) dataset was published in 2016 by Bernard et al. [Bernard et al., 2016]. CETUS contains 45 sequences of 3D ultrasound volumes of one cardiac cycle from 45 patients were equally acquired from three different hospitals with three different brands of ultrasound machines (GE, Philips and Siemens) [Bernard et al., 2016]. The studied population of 45 participants is composed of 15 healthy subjects, 15 with previous myocardial infarction, 15 with dilated cardiomyopathy. The datasets is available electronically to download at https://www.creatis.insa-lyon.fr/EvaluationPlatform/CETUS/about_database.html.

6.4 Synthetic cardiac motion

Alessandrini et al. in 2018 published "a open access library of 105 synthetic sequences encompassing i) healthy and ischemic motion patterns, ii) most common apical probe orientations iii) vendor specific image quality from 7 different systems" [Alessandrini et al., 2018]. See previous work of Alessandrini et al. in 2015 [Alessandrini et al., 2015].

7 Tools

7.1 Annotation tools

Recently, Smistad et al. 2021 published the first web-based tool for annotation of medical ultrasound video to do image classification, segmentation, bounding box and landmark annotation [Smistad et al., 2021c]. AW tool has been used since 2016 at different projects

to perform segmentation of the left ventricle, cardiac view classification, and detection of nerves and blood vesels [Smistad et al., 2021c].

8 Methods and materials

8.1 Proposed model

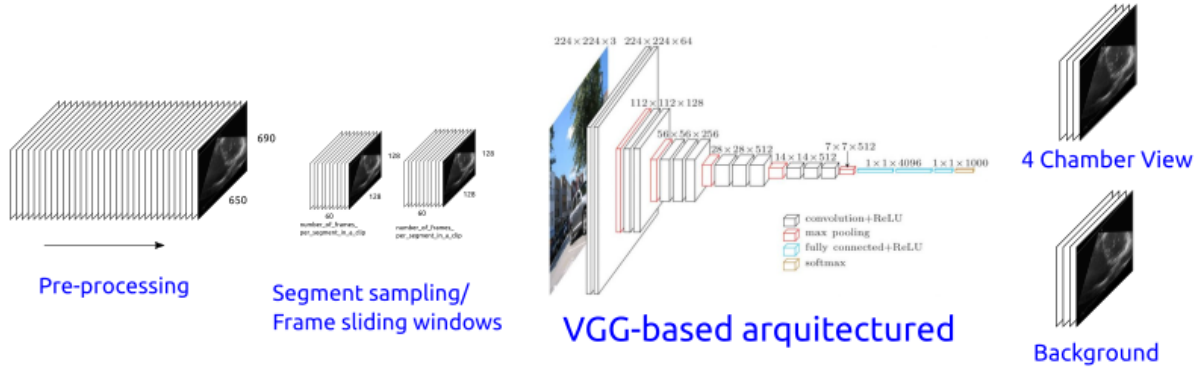


Figure 1: VGG-based architecture (a) description... (b) description... Figure is adapted from the works of

9 Datasets

9.1 VITAL

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

9.2 Ethics statement

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

10 Potential future work

2D velocity vector fields of flow blow can help to detect abnormal flow patterns as done in fetal and neonatal echocardiograhhy [Meyers et al., 2021]. Use LV A4C echos that can create synthetic Ulstraound 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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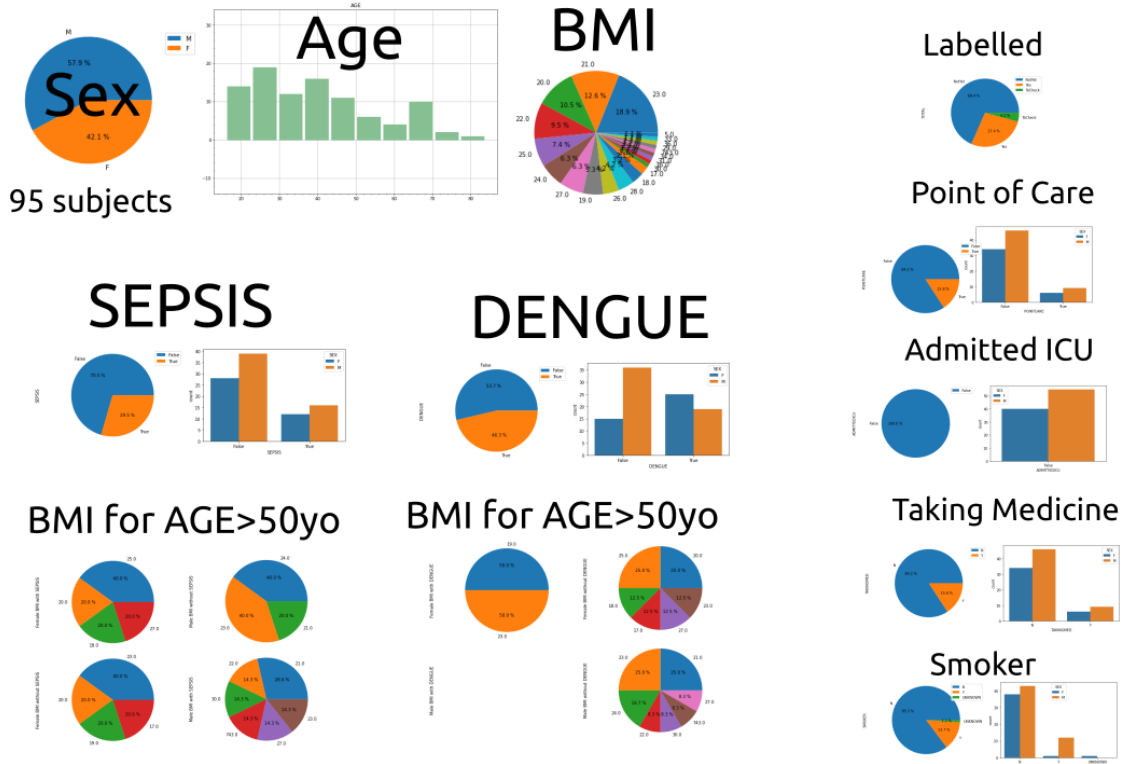


Figure 2: Patient demographics (a) description... (b) description... Figure is adapted from the works of

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