

Supplemental Online Content

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eMethods 1. Background

eMethods 2. Workflow Description

eMethods 3. THCP Training Details

eMethods 4. Model Development

eTable. Trained Health Care Provider Scan Distribution

eFigure 1. Workflow for Image Capture in Each Zone

eFigure 2. Overview of Model Development (Left), Key Features (Middle), and User Interface With All Features (Right) for Caption AI Lung Guidance Software

eFigure 3. Representative Diagnostic Quality Ultrasound Lung Clips Acquired With the Caption Lung AI by Lung Ultrasound Novice THCP

eReferences.

This supplemental material has been provided by the authors to give readers additional information about their work.

eMethods 1. Background

The lung ultrasound guidance is partly inspired by previously developed echocardiography guidance, wherein the user is provided with real-time assessments of relative image quality and prescriptive instructions on how to manipulate the probe to improve image quality.¹ In contrast to the cardiac application, where the heart has a complex three-dimensional structure that can be visualized with ultrasound and used to infer probe position from an image, lung ultrasound is more defined by an arrangement of anatomical features and artifacts in two-dimensional images. Additionally, lung ultrasound exams are typically based on exploring different zones of the lung, rather than capturing precise imaging planes as done for echocardiography. Rapid assessment of the lungs, as performed in emergency settings, is often performed with an 8-zone protocol that includes two anterior and two lateral zones on each side.²⁻⁴ As a result, we developed a unique approach for lung ultrasound guidance (eFigure 1) that includes the following features to enable the non-expert operator to acquire diagnostic quality images of the lungs across various zones:

1. Diagnostic quality meter and auto capture – this feature provides real-time estimates of the relative diagnostic quality of images. By manipulating the probe to increase the quality meter to a level considered diagnostic in quality, this feature provides critical continuous feedback to help non-experts move toward appropriate probe positions. When the quality meter reaches a level that corresponds to diagnostic quality, the auto capture feature will automatically initiate a recording as long as the quality level is prospectively maintained.
2. Landmark annotation of images – this feature aims to help the operator understand what landmarks are visible in the current image by providing annotation of features in real-time. Because different sets of lung zones share common anatomical features, we

grouped annotations into two sets of zones (eFigure 2). For zones 1-3 and 5-7, including both anterior and upper lateral zones, the landmarks used to define canonical images include pleural line, A-lines, and rib shadows.⁵ For zones 4 and 8, the lower lateral zones which visualize the costophrenic angles of the lung, the included landmarks are the diaphragm, liver or spleen, spine, and curtain sign.^{5,6} As the user scans a given zone, detected landmarks are annotated in the image in real time, providing guidance on what structures are being visualized to help the user arrive at an image close to the reference image provided in the software.

3. B-line detection and autocapture – while the non-expert operator is scanning each lung zone, the algorithm is continuously assessing the presence of B-lines by annotating them in real-time and estimating a B-line score from 0-10. Any time the score exceeds a threshold level corresponding to the presence of at least 1 B-line, the user is instructed to maintain the probe position to auto capture the visualized B-lines.

eMethods 2. Workflow Description

The user interface is designed to aid medical professionals without prior ultrasound experience to perform diagnostic imaging. The user interface guides operators through an 8-zone lung ultrasound workflow with the goal of capturing one or more diagnostic quality clips within each zone. For each zone, the static guidance feature indicates the approximate starting location of the probe on the surface of the body, which helps the user select an initial probe position and begin scanning that zone. A reference image for each zone is also provided, which shows the relevant landmarks and their typical arrangement for that zone. When the user begins scanning, the model interprets the acquired images in real time and provides the user with immediate feedback through two means: landmark annotation, and quality meter scoring (eFigure 2). The landmark annotation detects and annotates landmarks of interest on the images, providing the operator with understanding of visualized features and artifacts. This allows the operator to manipulate the probe to achieve an arrangement of landmarks similar to that of the reference image.

Additionally, the quality meter score provides the operator with an estimate of relative diagnostic quality as the probe is manipulated to produce a diagnostic quality view. When the image quality reaches a threshold level considered to be diagnostic, an auto capture is initiated to record the current ultrasound imagery as part of the overall study. The auto capture duration varies from 4 to 6 seconds, depending on the persistence of the quality meter above the diagnostic quality threshold. If the user is unable to achieve a diagnostic quality image within the first 60 seconds of scanning a given zone, the “Save Best Clip” (SBC) feature becomes available, which allows the user to record the clip of a fixed duration (2 seconds for Zones 1-3, 5-7, and 4 seconds for Zones 4 and 8) with the highest quality score over the prior scanning session for that zone.

Finally, the software continuously monitors images for the presence of B-lines and estimates a

B-line score, and if B-lines are detected, they are annotated on the screen, and an autocapture for B-lines will be initiated if they persist on the screen for more than a predefined duration of 0.5 seconds. In each zone, the software will allow for up to 4 clips to be recorded in that zone, including both diagnostic quality related auto captures, SBC clips, and B-line auto captures, before automatically proceeding to the next zone. At the completion of the 8-zone protocol, users are presented with a summary page that highlights detected findings in each zone (i.e., B-lines) and allows for review of clips captured in each zone.

eMethods 3. THCP Training Details

The training session for non-physician THCPs was composed of the following components:

- 1) A 30-minute presentation on the Lung Guidance AI software's user interface, workflow, and basic principles of lung ultrasound. This covered the 8-zone acquisition protocol and the appearance of normal lung in anterior and lateral zones, including the costophrenic angle.
- 2) A four-hour hands-on session where THCPs used the Lung Guidance AI to acquire clips on both male and female subjects across a range of BMIs. This session was conducted collectively for all participants. Overall, each non-physician THCPs received 2.5 hours of supervised lung ultrasound practice with the software.
- 3) Following a one-hour washout period, testing to ensure THCPs could successfully operate the software to acquire a full 8-zone lung exam using AI on three test subjects, including at least one male or female and different BMIs. The focus was on understanding the software workflow rather than assessing clip quality.

Physician THCPs underwent a similar training, primarily focusing on components 1 and 3 due to their prior experience with lung ultrasound.

We acknowledge that, due to some LUS training, the non-physician THCPs may not reflect the average novice user.

eMethods 4. Model Development

To develop the aforementioned features for lung ultrasound guidance, a segmentation-based deep learning algorithm to analyze individual ultrasound frames was chosen (eFigure 1). This model, which consists of a MobileNetV3 backbone followed by DeepLabV3+ as well as custom upsampling layers, provides classification predictions at the pixel-level across two sets of classes representing anatomical features and artifacts.^{7,8} A combination of expert sonographers and physicians labeled approximately 20,000 individual ultrasound frames, derived from ~3,700 clips in ~1000 patients, by drawing semantic segmentation labels for a subset of the output classes for each frame. The training data was acquired on multiple ultrasound probes, including Butterfly IQ+ (42%), Philips Sparq (32%), GE Vscan CL (14%), and others. Patients were well balanced across sex (52% male / 48% female), body mass index (12% BMI<20, 52% BMI 20-30, 28% BMI 30-40, 7% BMI>40), and age (33% <60, 44% 60-80, 23% >80).

Outputs of the segmentation model were post-processed using standard morphological image processing techniques to generate point and line-based annotations from the model outputs. The image quality meter was constructed by mapping measurements describing the connected components of model outputs for several classes to image diagnostic quality scores in the 0-100% range using a set of exponential equations. For upper zones, the pleural line, A-lines, and rib shadows were included in the quality meter score, while in zones 4 and 8, the diaphragm, liver/spleen, spine, and curtain sign were included in the quality meter score. An auxiliary B-line scoring model was developed using outputs of the segmentation model as inputs to a support vector regression (SVR) model, which provided a score from 0-10 representing the relative coverage of B-lines within the intercostal spaces. The segmentation model, B-line scoring model,

and all post-processing were implemented in a software development kit (SDK), with the
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segmentation model converted to TensorFlow Lite to optimize for speed, and the entire software was developed as an iOS application for the clinical study.

eTable. Trained Health Care Provider Scan Distribution

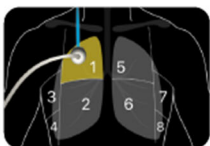
Trained HCP profile	Site Name	No. of unique trained HCPs	No. studies scanned (%)
Physician / LUS Expert		4	38 (21.6%)
Physician 1	4		12 (6.8%)
Physician 2	4		6 (3.4%)
Physician 3	1		12 (6.8%)
Physician 4	1		8 (4.55%)
Registered Nurse		12	82 (46.6%)
Nurse 1	2		16 (9.1%)
Nurse 2	1		4 (2.3%)
Nurse 3	1		3 (1.7%)
Nurse 4	1		5 (2.8%)
Nurse 5	1		8 (4.6%)
Nurse 6	1		7 (4.0%)
Nurse 7	1		2 (1.1%)
Nurse 8	1		9 (5.1%)
Nurse 9	1		3 (1.7%)
Nurse 10	1		8 (4.6%)
Nurse 11	1		8 (4.6%)
Nurse 12	3		9 (5.1%)
Phlebotomist			
Phlebotomist 1	2	1	19 (10.8%)
Pharmacy technician			
Pharmacy tech 1	2	1	7 (4.0%)
Medical assistant		3	30 (17.1%)
Medical assistant 1	2		5 (2.8%)
Medical assistant 2	3		8 (4.6%)
Medical assistant 3	3		17 (9.7%)
Total		21	176 (100.0%)

HCP, health care provider; LUS, lung ultrasound

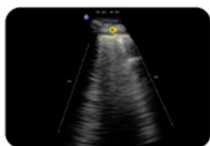
eFigure 1. Workflow for Image Capture in Each Zone

The three methods for automated image capture include diagnostic quality-based auto capture (Step 3a), “Save Best Clip” feature (Step 3b), and B-line related auto capture.

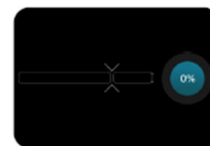
Step 1 Placement



Probe Position

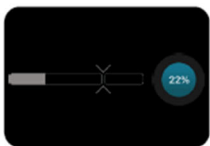


Landmark Guidance

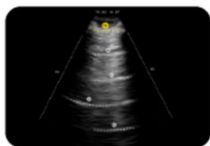


Quality Meter

Step 2 Optimizing



Increase Quality

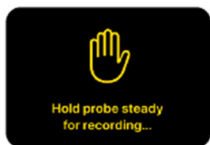


Annotations Appear



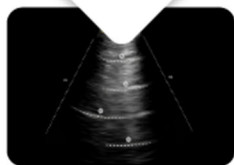
Increase Quality

Step 3a Auto Capture



2-4 seconds

System automatically captures as long as diagnostic quality is maintained.



Step 3b Save Best Clip

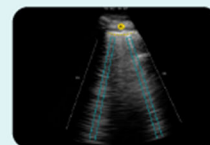


Tap Button

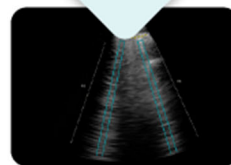
User selects Save Best Clip to save the best available 2 second clip.



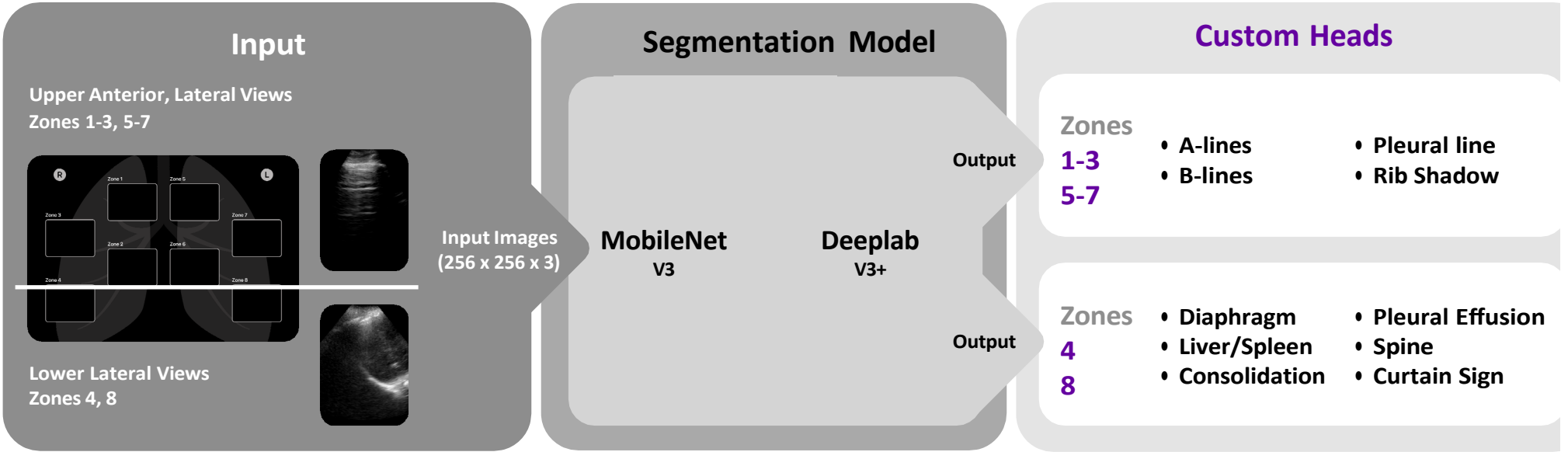
B-Line Auto Capture



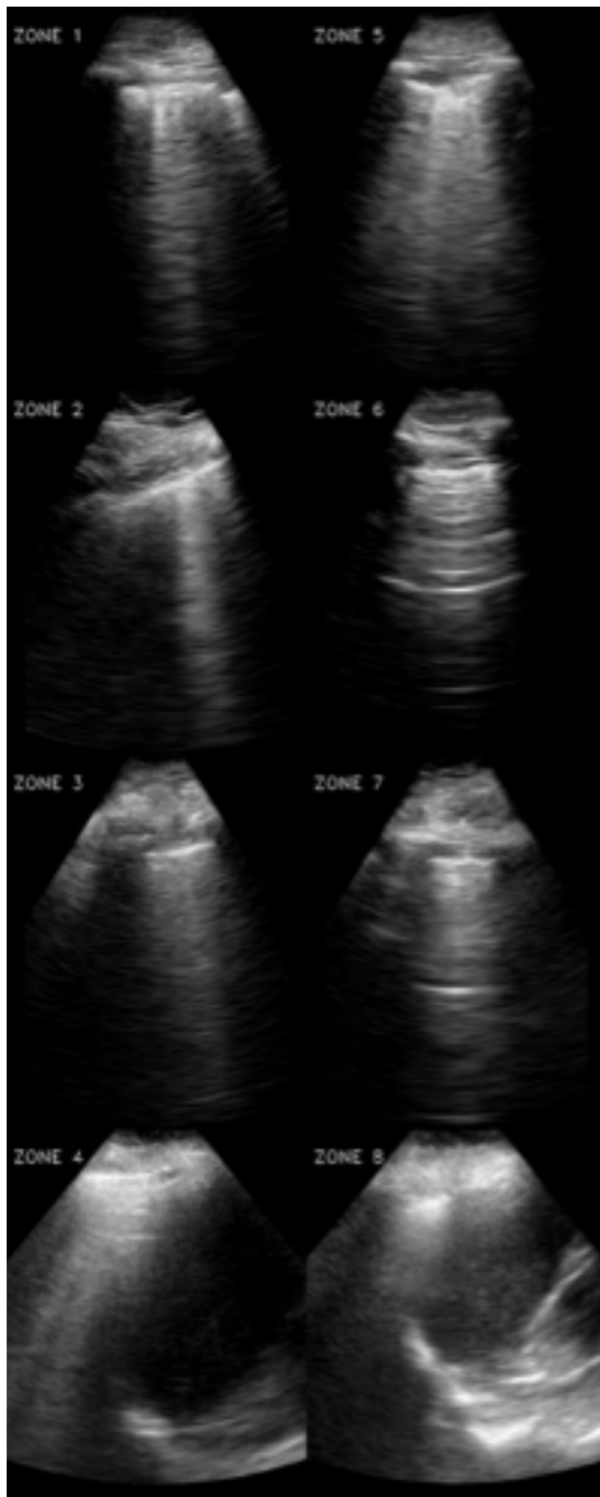
The system monitors for B-Lines in the background, automatically capturing pathology when it is seen.



eFigure 2. Overview of Model Development (Left), Key Features (Middle), and User Interface With All Features (Right) for Caption AI Lung Guidance Software



eFigure 3. Representative Diagnostic Quality Ultrasound Lung Clips Acquired With the Caption Lung AI by Lung Ultrasound Novice THCP



eReferences.

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