UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

CAPTION HEALTH, INC.,
Petitioner,

v.

UNIVERSITY OF BRITISH COLUMBIA,
Patent Owner.

IPR2025-01422

Patent No. 10,751,029

PATENT OWNER'S PRELIMINARY RESPONSE

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2002	Decision Referring the Petition to the Board, *Caption Health, Inc. v. Univ. of British Columbia*, IPR2025-01066, Paper 13 (Oct. 10, 2025)
2003	GE HealthCare Techs. Inc. Corporate Structure Tree (July 24, 2025)
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2009	Order Denying Motion to Stay and Granting Motion to Seal, Univ. of British Columbia v. Caption Health, Inc. No. 24-cv-03200, (N.D. Cal. Aug. 6, 2025)
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2022	Civil Minutes, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. Aug. 6, 2025), ECF No. 81
2023	UBC's list of claim terms, dated April 11, 2025
2024	Defendants' Amended and Supplemented Proposed Claim Terms from U.S. Patent No. 11,129,591 for Construction Pursuant to L.R. 4-1, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. Apr. 11, 2025)
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2032	U.S. Pub. No. US2019/0266716 ("Rothberg")
2033	U.S. Pub. No. US2009/0088640 ("Park")

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2034	’029 Patent Grants Spreadsheet
2035	Krizhevsky, Sutskever, and Hinton, *ImageNet classification with deep convolutional neural networks* (“AlexNet”) (2012)
2036	Zhang, Lipton, Li, and Smola, *Dive into Deep Learning*, Chapter 8.1 Deep Convolution Neural Networks (AlexNet), https://d2l.ai/chapter_convolutional-modern/alexnet.html
2037	Ghada Zamzmi, et al., *Harnessing Machine Intelligence in Automatic Echocardiogram Analysis: Current Status, Limitations, and Future Directions* (Apr. 27, 2021)
2038	Geoffrey Hinton, The Nobel Prize, https://www.nobelprize.org/prizes/physics/2024/hinton/facts/
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2040	U.S. Patent No. 10,878,311
2041	App. No. 16/146,770 Non-Final Rejection dated June 2, 2020
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2043	App. No. 18/431,566 Non-Final Rejection dated May 10, 2024
2044	Japanese Patent No. 7,284,298
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I. INTRODUCTION

Patent Owner University of British Columbia ("UBC") submits this Preliminary Response ("POPR") to the Petition of Caption Health, Inc. ("Caption Health" or "Petitioner") challenging claims 1-30 (the "Challenged Claims") of U.S. Patent No. 10,751,029 (Ex1001, the "'029 patent").

The '029 patent relates to ultrasound image analysis and explains that "[a]ccurate diagnosis…requires high quality ultrasound images, which may need to show or contain different specific features and structures depending on various properties of the images." Ex1001, 1:22-25. However, "[s]ome ultrasound systems may not provide feedback to operators regarding quality of the image and/or other image properties." *Id.*, 1:25-27. Because of this, "[i]nexperienced ultrasound operators may have a great deal of difficulty using such known systems to recognize features in the ultrasound images[,] and thus can fail to capture diagnostically relevant ultrasound images." *Id.*, 1:27-31.

The '029 patent ameliorated this problem by employing neural networks to derive extracted feature representations from ultrasound images and, based on the derived extracted feature representations, determine a quality assessment value/image property for the images. *Id.*, independent claims 1, 21, 30. The '029 patent explains that the quality assessment value and image property could then be displayed for the ultrasound operator, enabling real-time feedback and facilitating more accurate analysis/diagnosis. *Id.*, 2:24-31, 4:61-5:33.

The ’029 patent also improves on existing systems by disclosing “training a neural network…using [a] set of ultrasound training images as an input to the neural network” together with quality assessment values/image properties associated with the training images. *Id.*, independent claim 12.

Petitioner asserts four grounds of unpatentability against the Challenged Claims. Petition, 9. Claims 1, 12, 21, and 30 are independent.

Ground	**Prior Art**	**Basis**	**Claims Challenged**
A	Krishnan	§102	1-3, 9, 11, 21-22, 27, 29-30
B	Krishnan in view of Chen (“Krishnan-Chen”)	§103	3-8, 23-26
C	Krishnan in view of Aase (“Krishnan-Aase”)	§103	9-10, 27-28
D	Krishnan in view of Chen and Wu (“Krishnan-Chen-Wu”)	§103	12-20

The Petition should be denied for three reasons.

<u>First</u>, the Petition does not comply with 37 C.F.R. §42.104(b)(3), which requires a petition to state “[h]ow the challenged claim is to be construed.” Here, the Petition fails to offer a construction for “quality assessment value.” Meanwhile, Petitioner is simultaneously advancing a narrower construction in the parallel litigation (“score of diagnostic image quality”). Petitioner offers no plausible explanation for this inconsistency, and the Petition should be denied accordingly.

Revvo Techs., Inc. v. Cerebrum Sensor Techs., Inc., IPR2025-00632, Paper 20, 3-4 (Nov. 3, 2025) (precedential).

Second, the Petition does not demonstrate a reasonable likelihood of prevailing as to any independent Challenged Claim (and therefore any Challenged Claim). Each independent Challenged Claim requires either (1) deriving extracted feature representations using a neural network, when "extracted feature representations" is properly construed[1] (limitations 1(b), 21(b), 30(b)); or (2) inputting training images into a neural network (limitation 12(d)).

The Petition relies solely on Krishnan to teach the relevant limitations. *See* Petition, 24-26 (1(b)), 39 (21(b)), 45-47 (30(b)), 78-79 (12(d)). However, unlike the claimed inventions, Krishnan derives extracted features from images using known methods that do not employ neural networks. And once the features are extracted from the images, Krishnan discloses that only those extracted features—not the images—may be input into its alleged neural network (for either image analysis or training purposes).

Third, even if the Office is not inclined to adopt UBC's proposed construction of "extracted feature representations" at the institution stage, the Petition should still

[1] As explained in §IV, "extracted feature representations" should be construed as "feature representations that are learned using a neural network."

be denied because, even taking the Petition's arguments at face value, the Petition fails to demonstrate a reasonable likelihood that at least 20 out of the 30 Challenged Claims are unpatentable. Specifically, the Petition's analysis is either: (1) facially deficient, regardless of UBC's proposed construction (claims 12-20 and 30); or (2) based on cross references that leave the work to be done by the Office (claims 21-29 and claim 6). Thus, the Petition should be denied because "maintaining a trial in this case would require the Board and Patent Owner to expend resources addressing multiple claims and grounds that do not meet the reasonable likelihood standard, as well as grounds that have not been sufficiently developed." *Zhuhai CosMX Battery Co. v. Ningde Amperex Tech. Ltd.,* IPR2025-00405, Paper 24, 3 (Oct. 15, 2025).

For at least these reasons, UBC respectfully submits that the Director should deny institution.

II. BACKGROUND

A. Summary of the '029 Patent

1. Specification

As described above, the '029 patent discloses systems and methods for analyzing ultrasound images with a neural network and for training the neural network. Regarding analyzing the images, the '029 patent discloses an exemplary analyzer 14 in Figure 1.

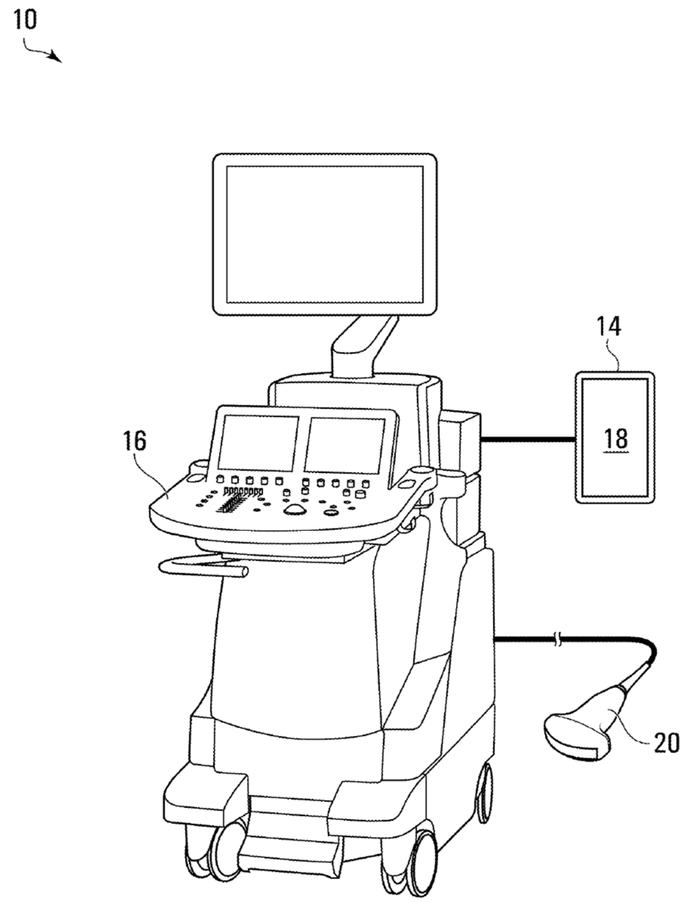


FIG. 1

Ex1001, Fig. 1.

The ’029 patent explains that “the analyzer 14 may receive signals representing a set of ultrasound images of the subject.” *Id.*, 6:23-25. “The analyzer 14 may then derive one or more extracted feature representations from the received set of ultrasound images” (*id.*, 6:35-37) and “determine, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images” (*id.*, 6:42-45). “The analyzer 14 may also determine, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images." *Id.*, 6:56-58. An exemplary image property is view category. *Id.*, 6:58-60; *see also, e.g., id.*, 20:41-59 (disclosing that, with respect to echocardiography, examples of image properties include the view category, left ventricular ejection fraction, and left atrial ejection fraction).

"The analyzer 14 may then produce signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images." *Id.*, 7:4-7. Then, in some embodiments, "the analyzer 14 may produce signals for causing a representation of the quality assessment value and a representation of the view category to be displayed by the display 18 in association with the set of ultrasound images." *Id.*, 7:7-11.

In this way, the disclosed invention may allow for "near real-time or real-time feedback to the operator," which "may help the operator improve their skills and/or improve image quality for subsequently captured images." *Id.*, 7:15-18; *see also id.*, 7:18-32.

Regarding training the neural network for image analysis, Figure 11 shows a schematic view of neural network trainer 502, which may be included in system 10 shown in Figure 1. *Id.*, 15:37-41.

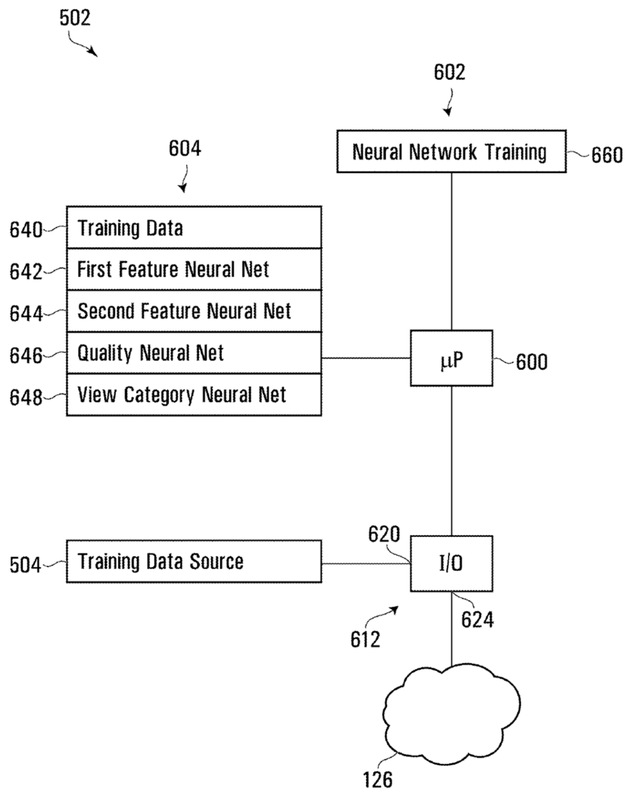


FIG. 11

Ex1001, Fig. 11.

Figure 12 depicts a flowchart for directing the trainer processor 600 shown in Figure 11 to perform neural network training. *Id.*, 16:14-21. Trainer processor 600 receives signals representing ultrasound training images (702), signals representing quality assessment values (704), and signals representing image properties (706). *Id.*, 16:23-17:26.

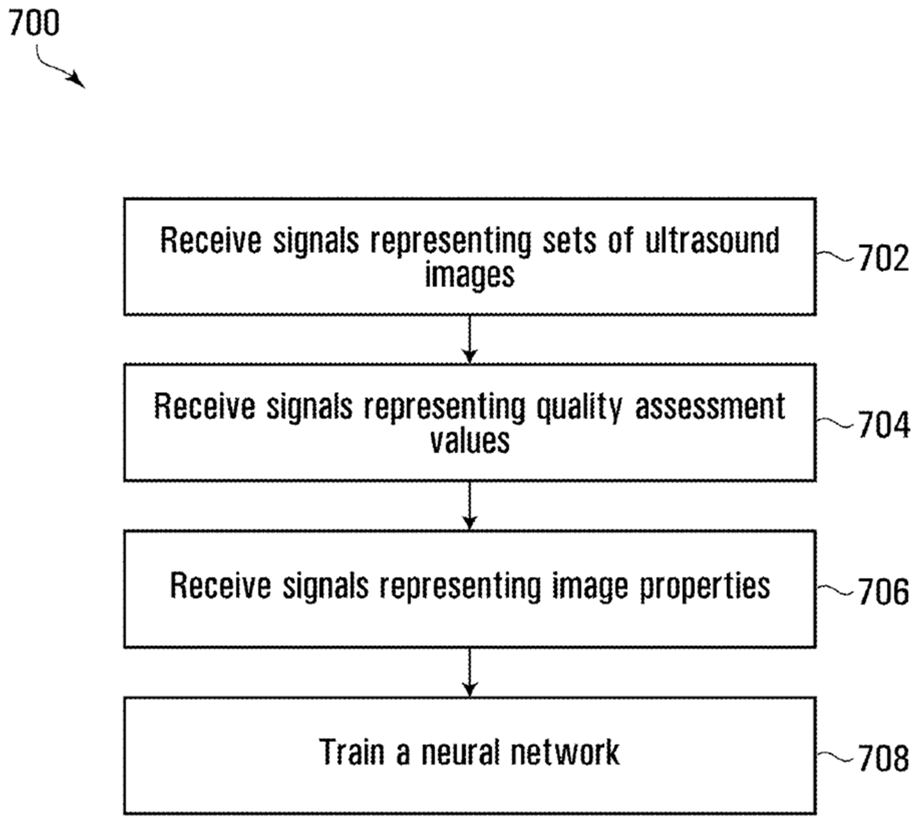


FIG. 12

Ex1001, Fig. 12.

In block 708, the neural network is trained "using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network."[2] *Id.*, 17:27-33; *see also id.*, 17:33-44 (describing training the neural network 300 shown in Figure 4).

Accordingly, the '029 patent discloses that the neural network is trained using ultrasound images as inputs, rather than extracted features from the images.

2. Claims

For context, the independent claim language is reproduced below with limitations relevant to this POPR underlined.

> [1(pre)] A computer-implemented method of facilitating ultrasonic image analysis of a subject, the method comprising:
>
> [1(a)] receiving signals representing a set of ultrasound images of the subject;
>
> [1(b)] <u>deriving one or more extracted feature representations from the set of ultrasound images</u>;
>
> [1(c)] determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images;
>
> [1(d)] determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images; and

[2] All emphases added unless otherwise noted.

> [1(e)] producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

Id., claim 1.

> [12(pre)] A computer-implemented method of training one or more neural networks to facilitate ultrasonic image analysis, the method comprising:
> [12(a)] receiving signals representing a plurality of sets of ultrasound training images;
> [12(b)] receiving signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images;
> [12(c)] receiving signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images; and
> [12(d)] <u>training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network</u>.

Id., claim 12.

> [21(pre)] A system for facilitating ultrasonic image analysis comprising at least one processor configured to:
>
> [21(a)] receive signals representing a set of ultrasound images of the subject;
>
> [21(b)] <u>derive one or more extracted feature representations from the set of ultrasound images</u>;
>
> [21(c)] determine, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images;
>
> [21(d)] determine, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images; and
>
> [21(e)] produce signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

Id., claim 21.

> [30(pre)] A system for facilitating ultrasonic image analysis, the system comprising:
>
> [30(a)] means for receiving signals representing a set of ultrasound images of the subject;
>
> [30(b)] <u>means for deriving one or more extracted feature representations from the set of ultrasound images</u>;

> [30(c)] means for determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images;
>
> [30(d)] means for determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images; and
>
> [30(e)] means for producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

Id., claim 30.

B. The Alleged Prior Art

1. Krishnan

Krishnan is directed to medical imaging and describes "systems and methods for processing a medical image to automatically identify the anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image." Ex1005, [0002].

Krishnan's Figure 1 depicts an automatic feature analysis module 102 for extracting features from images, decision support modules 103/104/105, and a learning engine 109 within a classification module 108. *Id.*, [0017] ("[T]he feature analysis module (102) implements methods for automatically extracting one or more types of features/parameters from input medical image data and combining the extracted features/parameters in a manner that is suitable for processing by the decision support modules (103, 104 and/or 105).”), [0023].

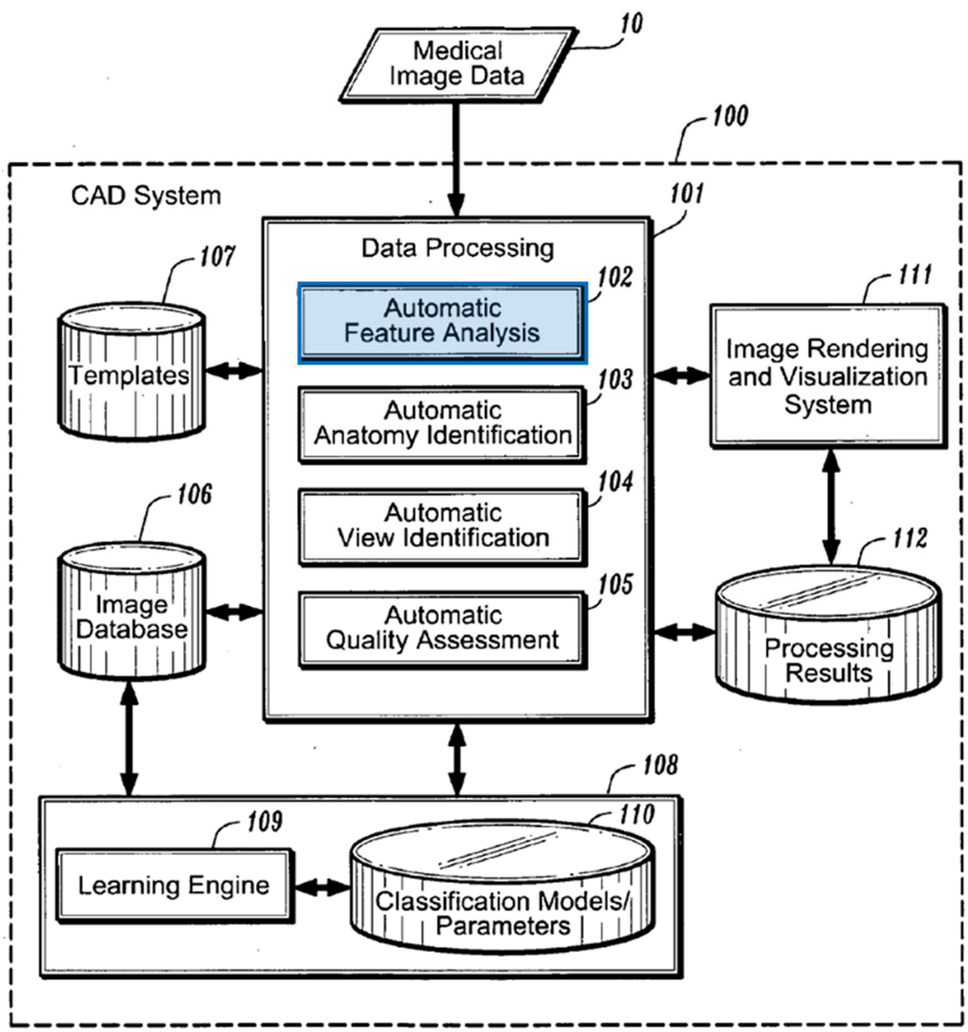


FIG. 1

Ex1005, Fig. 1.[3]

[3] All color annotations added.

Krishnan's feature extraction is described in more detail with respect to Figure 2. Specifically, Krishnan describes performing feature extraction according to "known" methods such as "segmentation" or "filtering"—not learning the extracted features using a neural network.

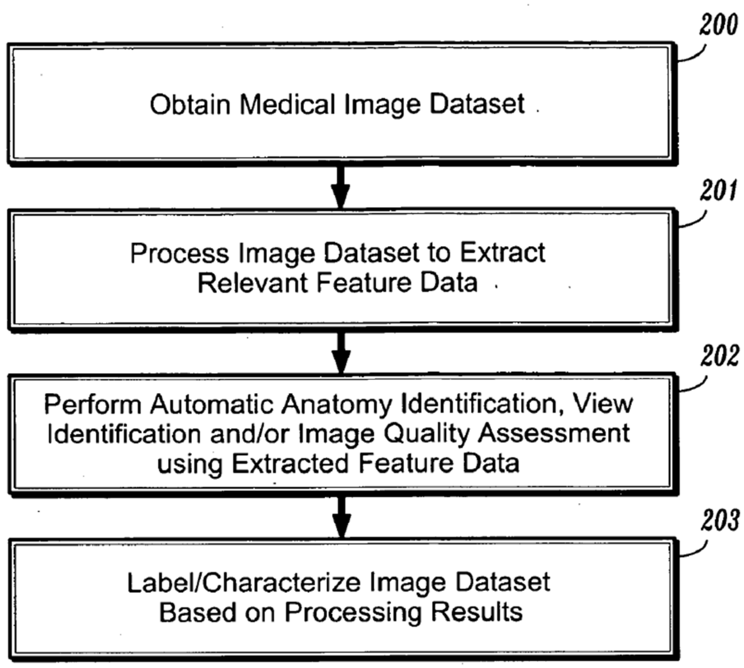


FIG. 2

Ex1005, Fig. 2.

> [T]he image dataset will be processed to determine or otherwise extract relevant feature data from the image dataset (step 201)…<u>Feature extraction can implement known segmentation and/or filtering methods</u> for segmenting features or anatomies of interest <u>by reference to known or anticipated image characteristics</u>, such as

> edges, identifiable structures, boundaries, changes or transitions in colors or intensities, changes or transitions in spectrographic information, etc[.], using known methods.

Id., [0034]. Critically, Krishnan does not disclose that learning module 109 is associated with feature extraction module 102. Rather, Krishnan discloses that classification module 108/learning engine 109 may support "classification" methods performed by "classifiers" (e.g., modules 103/104/105) (*id.*, [0023]), which may be "built using neural networks" (*id.*, [0044]).

> <u>[T]he various modules (103), (104)[,] and (105) can implement classification methods that utilize the classification module (108)</u> to process extracted feature data to classify the image dataset under consideration. In the exemplary embodiment of FIG. 1, the classification module (108) comprises a learning engine (109) and knowledge base (110) to implement a principle (machine) learning classification system. The learning engine (109) includes methods for training/building one or more classifiers using training data that is learned from the database (106) of previously diagnosed/labeled cases. <u>The classifiers are implemented by the various decision</u>

support modules (102~105) for performing their respective functions.[4]

Id., [0023]. In Figure 5, Krishnan discloses analyzing images using the "classifiers." Ex1005, [0042]-[0044].

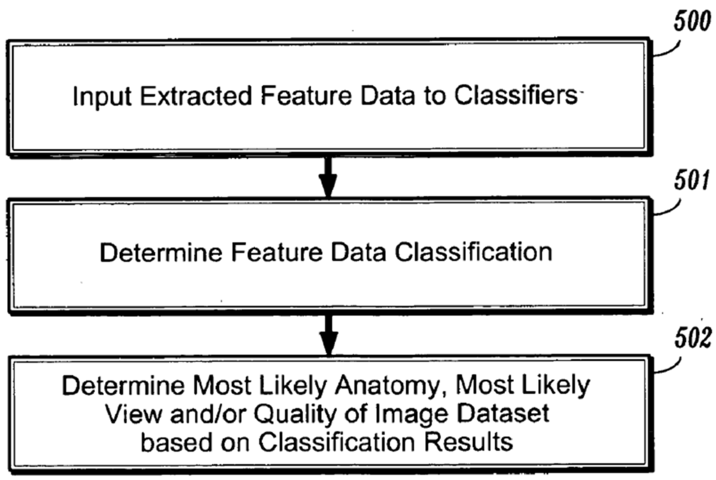


FIG. 5

Ex1005, Fig. 5.

In this embodiment, "feature data extracted from the image dataset would be input to classifiers (step 500) that are trained or designed to process the feature data to classify the image data (step 501)." *Id.*, [0042]. "The classification results would

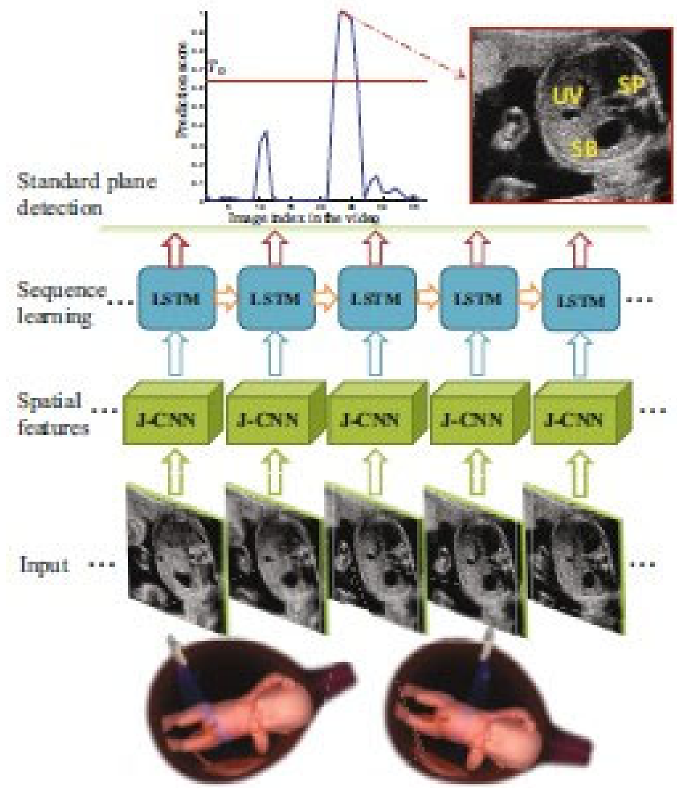
[4] Although Krishnan refers to module 102 as implementing a "classifier" in this sentence, this is clearly an error because the first sentence in the paragraph states that only modules 103/104/105 "can implement classification methods."

be used to determine the most likely anatomy or view, or assess image quality (step 502)." *Id*. "For example, a bank of classifiers could be constructed to classify the images <u>based on the features extracted</u>." *Id*., [0043]. "These classifiers would use the set of <u>features as an input</u>, and classify the image as belonging to a particular anatomy, view, or level or quality." *Id*.

Thus, Krishnan does not disclose that the "classifier" neural networks take images as input, e.g., to derive extracted features from the images or to train the classifiers. Instead, the classifiers take extracted "features as an input." *Id.*

2. Chen

Chen is directed to automatically detecting standard fetal ultrasound planes from ultrasound videos using neural networks. Ex1009, Abstract. Specifically, Chen describes integrating deep convolutional neural networks (CNN) and recurrent neural networks (LSTM model) to identify fetal ultrasound standard planes. *See id*., 509.

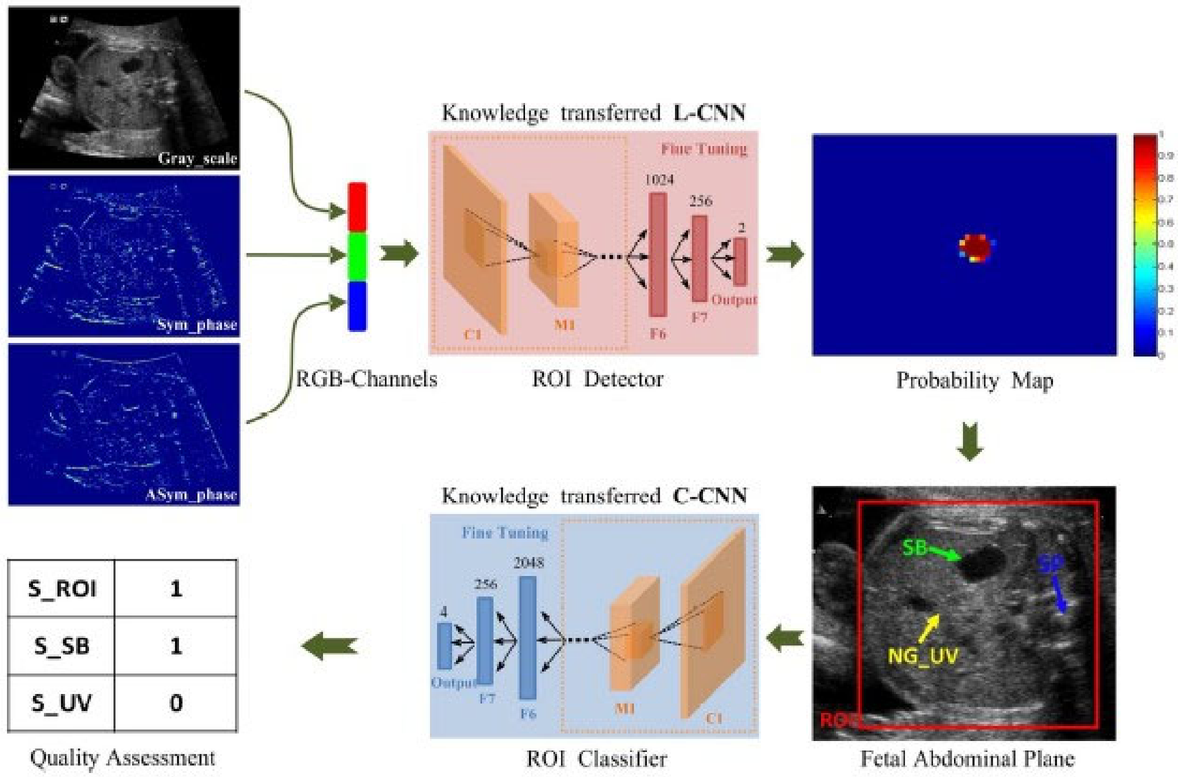


Ex1009, Fig. 2 (left side).

Chen's neural networks do not output any quality assessment value. Thus, Chen's neural networks are only trained to output identified fetal ultrasound standard planes. *See id.*, 509 ("ROI classifier is first trained based on the joint learning of convolutional neural networks (J-CNN) across multi-tasks to locate the most discriminative regions for US standard plane detection."). Chen states that it discloses "a general framework [that] can be easily extended to other [ultrasound] standard plane or anatomical structure detection," but fails to specifically explain how its framework would be modified to work with other implementations. *See id.*

3. Wu

Wu is directed to quality assessment of fetal ultrasound images. Ex1010, Abstract. Wu utilizes two deep convolutional neural networks (denoted L-CNN and C-CNN). The L-CNN extracts features from images to identify a region of interest (ROI) in the image, and the C-CNN receives the region of interest as input and outputs a quality assessment value. *See id.*, 2, 4 ("For the L-CNN, the input sources include the original US image, symmetric and asymmetric phase features. The L-CNN will help to locate the ROI of fetal abdominal region, which is the input of the C-CNN. The knowledge learned from the L-CNN will be introduced to the C-CNN as initialization for the learning of four-class differentiation of [ultrasound] images.").



Ex1010, Fig. 3.

Wu states that its "proposed [quality assessment] scheme can be easily generalized to other types of fetal [ultrasound] views," but does not specifically describe how its system would be modified to do so. *See id.*, 3.

III. LEVEL OF ORDINARY SKILL

The Petition proposes that a POSITA "would include a person with an advanced degree in Computer Engineering, Computer Science, Physics, or other field related to computer imaging, and at least 1 year of research experience training machine learning models to analyze ultrasound data." Petition, 9.

Patent Owner disagrees that a POSITA would have needed "at least 1 year of research experience training machine learning models to analyze ultrasound data." Rather, Patent Owner submits that an individual with one of the advanced degrees Petitioner identifies and at least 1 year of research or work experience training machine learning models to analyze medical imaging data (e.g., ultrasound, CT, PET, MRI, etc.) would also have qualified as a POSITA. Additionally, further education could substitute for experience and vice versa.

IV. CLAIM CONSTRUCTION

Regarding claim 30, Petitioner identifies several §112(f) constructions the parties have agreed to in the parallel litigation. Petition, 10-12. UBC applies these constructions in the analysis below. Relevant to limitation 30(b) ("means for deriving one or more extracted feature representations from the set of ultrasound images"), Petitioner states "the corresponding structure/algorithm identified in the specification for performing the recited function is: 'a processor and memory operating a neural network.'" Petition, 10.

Petitioner further states: "[e]xcept for terms drafted in means-plus-function format, the claim terms of the Patent do not require an express construction. The prior art addressed herein discloses the claimed features under any reasonable interpretation of the claim language." Petition, 10.

However, as explained below, the Petition applies an overbroad interpretation of "extracted feature representations,"[5] e.g., when analyzing limitations 1(b), 21(b), and 30(b).[6] Accordingly, UBC asserts that "extracted feature representations" should be construed as "feature representations that are learned using a neural network." This is the construction UBC proposes in the parallel litigation. *See* Ex2007, 7.

When "extracted feature representations" is appropriately read in the context of the '029 patent specification, the term plainly requires "feature representations that are learned using a neural network." And as explained below, when the term is properly construed, the prior art does not disclose at least limitations 1(b), 21(b), and 30(b).

The '029 patent describes "feature representations" as encodings of image patterns of one or more images. *See, e.g.*, Ex1001, 11:30-35 ("[T]he commonly defined first feature extracting neural networks (e.g. 304, 306, and 308 shown in

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[5] Claims 1, 3-5, 7, 9-10, 14, 19, 21, 26-28, and 30 of the '029 patent recite "extracted feature representations."

[6] Although Petitioner does not offer a construction for this term, its proposed construction in the parallel litigation is "data representing extracted features," which is overly broad and inconsistent with the '029 patent specification.

FIG. 4) may be each configured to <u>extract features that are encodings of image patterns</u> of a single echo frame which are correlated with the image quality and view category of the single input echo frame."); *id.*, 11:35-39 ("In some embodiments these <u>features (encodings or mappings)</u> may be in the form of a vector of real-valued numbers (after the flatten operation), and each number may be considered as the level of presence of a specific spatial pattern in the input echo frame."); *id.*, 12:28-31 ("As a result, in some embodiments, the <u>features</u> extracted by the LSTM networks <u>may be encodings of both spatial and temporal patterns</u> of a multitude of echo frames.").

The '029 patent's figures and corresponding descriptions uniformly disclose that these extracted feature representations (i.e., encodings of image patterns) are learned using a neural network. *See, e.g.*, *id.*, 8:43-45 (disclosing that Figure 2 depicts "location 154 for storing first feature extracting neural network parameter data, location 156 for storing second feature extracting neural network parameter data"); *id.*, 11:30-32 (disclosing that Figure 4 depicts feature extractor neural networks 304, 306, and 308); *id.*, 11:28-29 (disclosing that Figures 5, 6, and 7 depict feature extractor neural networks 310, 312, and 314); *id.*, 16:3-5 (disclosing that Fig. 11 depicts "location 642 for storing first feature extracting neural network data, location 644 for storing second feature extracting neural network"); *id.*, 22:24-32 (disclosing that Fig. 13 depicts "three first feature extracting neural network or CNN threads" 752, 754, and 756).

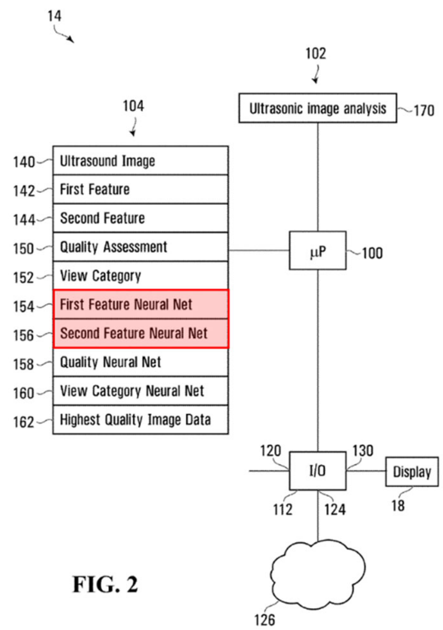

FIG. 2

Ex1001, Fig. 2 (depicting locations 154/156 for storing feature extracting neural network parameter data).

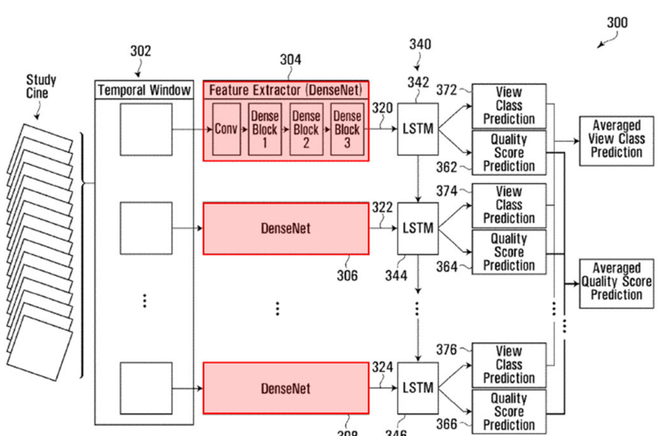

FIG. 4

Ex1001, Fig. 4 (depicting feature extractor neural networks 304, 306, and 308).

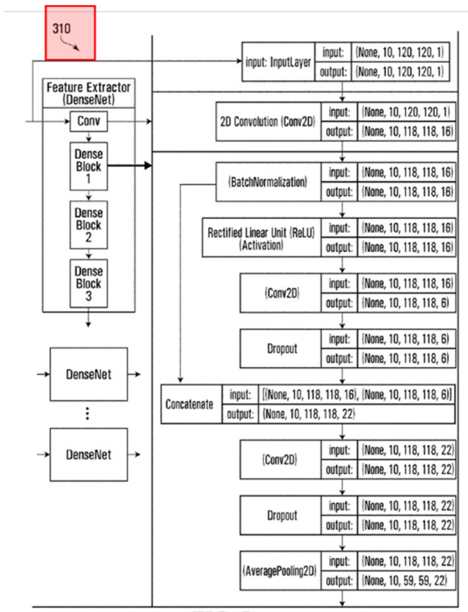

FIG. 5

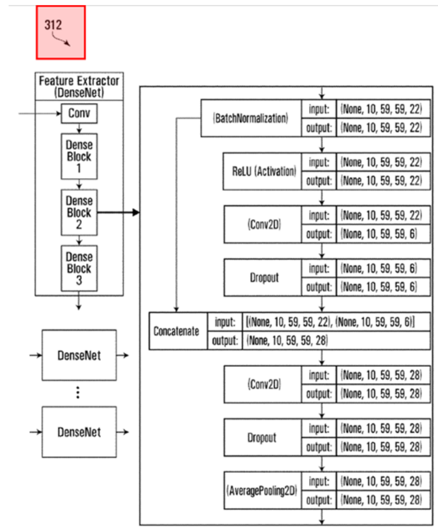

FIG. 6

Ex1001, Fig. 5 (depicting feature extractor neural network 310).

Ex1001, Fig. 6 (depicting feature extractor neural network 312).

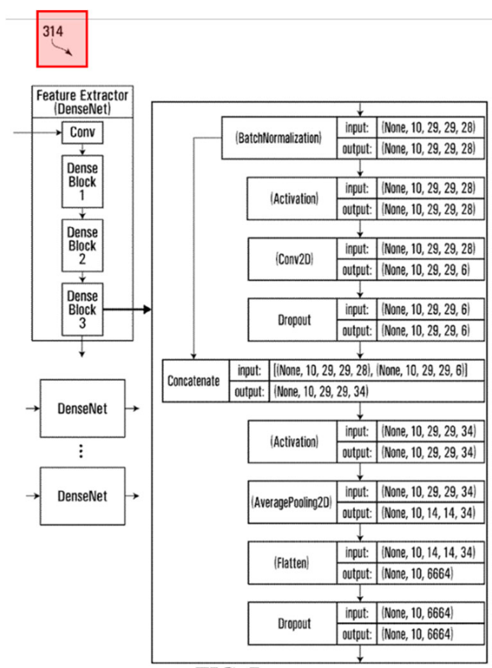

FIG. 7

Ex1001, Fig. 7 (depicting feature extractor neural network 314).

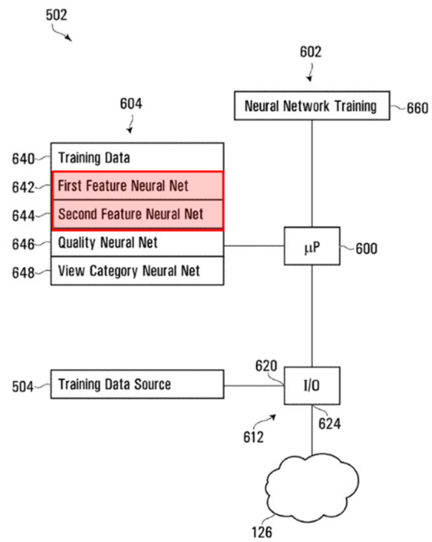

FIG. 11

Ex1001, Fig. 11 (depicting locations 642/644 for storing feature extracting neural network data).

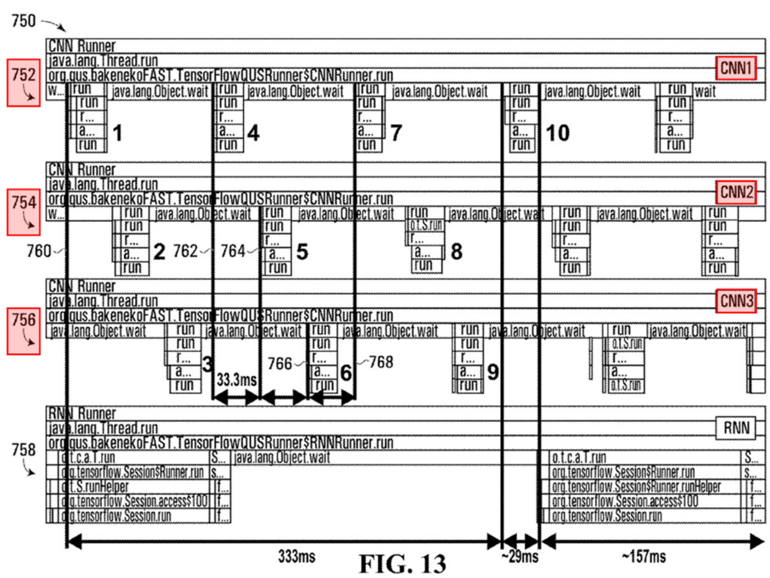

FIG. 13

Ex1001, Fig. 13 (depicting three first feature extracting neural network threads 752/754/756, which are implemented as convolutional neural networks).

Further, whenever the specification mentions "deriving extracted feature representations," it explains this is performed using a neural network. *See e.g., id.*, 6:35-41 ("The analyzer 14 may then derive one or more extracted feature representations from the received set of ultrasound images. In some embodiments, the analyzer 14 may implement a neural network including a feature extracting neural network and the analyzer 14 may input the set of ultrasound images into the feature extracting neural network in order to derive the one or more extracted feature representations"); *see id.*, 10:9-31 (explaining with respect to Figure 3 that "block 204 directs the analyzer processor 100 to derive one or more extracted feature representations from the set of ultrasound images received at block 202" and that the extracted feature representations are learned upon inputting images into various neural networks); *id.*, 10:32-12:51 (describing further details about implementing neural networks for deriving extracted feature representations).

V. THE PETITION SHOULD BE DENIED

A. Petitioner's Failure to Construe "Quality Assessment Value" Does Not Comply With 37 C.F.R. §42.104(b)(3)

37 C.F.R. §42.104(b)(3) requires a petition to state "[h]ow the challenged claim is to be construed." Relatedly, the Director has confirmed that "when a petitioner takes alternative positions before the Board and a district court, that petitioner should, at a minimum, explain why alternative positions are warranted." *Revvo*, IPR2025-00632, Paper 20, 3-4.

Here, the Petition states: "[e]xcept for terms drafted in means-plus-function format, the claim terms of the Patent do not require an express construction." Petition, 10. However, in the parallel litigation, Petitioner asserts that "quality assessment value"—which is recited in each independent Challenged Claim—should have a narrower construction of "score of diagnostic image quality." Ex1015, 84; Ex2007, 1.

Petitioner cannot offer a sufficient reason for this inconsistency. Indeed, the District Court has not construed "quality assessment value," so this cannot not explain the inconsistency. *See Revvo*, IPR2025-00632, Paper 20, 5 ("For example, if a party advances a narrow construction in the district court and the district court declines to adopt the narrow construction, the party would have sufficient reason for advancing the broader, court-adopted construction in a proceeding before the Board.") (quotations and citation omitted). Rather, the only plausible explanation is that Petitioner believes a narrower construction provides a noninfringement argument. For example, in the parties' joint claim construction statement, Petitioner agreed that its narrowed construction of "quality assessment value" was among the terms that are "most significant to resolution of the case." Ex1015, 3-4 ("[T]he Parties identify the terms listed below as most significant to resolution of the case…'quality assessment value.'").

Petitioner's inconsistent claim construction position for noninfringement purposes is exactly what the Board's rules were designed to discourage, and the Petition should be denied accordingly. *Revvo*, IPR2025-00632, Paper 20, 4 ("[T]he rules discourage petitioners from seeking broader constructions at the Board to support a patentability challenge while seeking narrower constructions in litigation to avoid infringement liability.").

B. The Petition Fails to Demonstrate a Reasonable Likelihood of Unpatentability as to Any Challenged Claim

1. Independent Claims 1, 21, 30: Krishnan Fails to Teach Limitations 1(b), 21(b), 30(b) When Those Limitations Are Properly Construed

a. The Petition Fails to Show That Krishnan Discloses Any Learning in Its Feature Extraction Step

Limitations 1(b), 21(b), 30(b) each recite "deriv[ing] one or more extracted feature representations from the set of ultrasound images." Ex1001, claims 1, 21, 30. As discussed in §IV, "extracted feature representations" should be construed to require "feature representations that are learned using a neural network."

The Petition relies solely on Krishnan to teach limitations 1(b), 21(b), and 30(b). Petition, 24-26 (1(b)), 39 (21(b)), 45-47 (30(b)). As properly construed, Krishnan fails to disclose these limitations.

Starting with limitations 1(b) and 21(b), the Petition asserts that automatic feature analysis module 102 discloses this limitation. Petition, 24 (citing Krishnan's automatic feature analysis module 102 in Figure 1, Krishnan's paragraphs 17 and

34, and Krishnan's Figure 2); *id.*, 39 (for limitation 21(b), pointing back to analysis of limitation 1(b)).

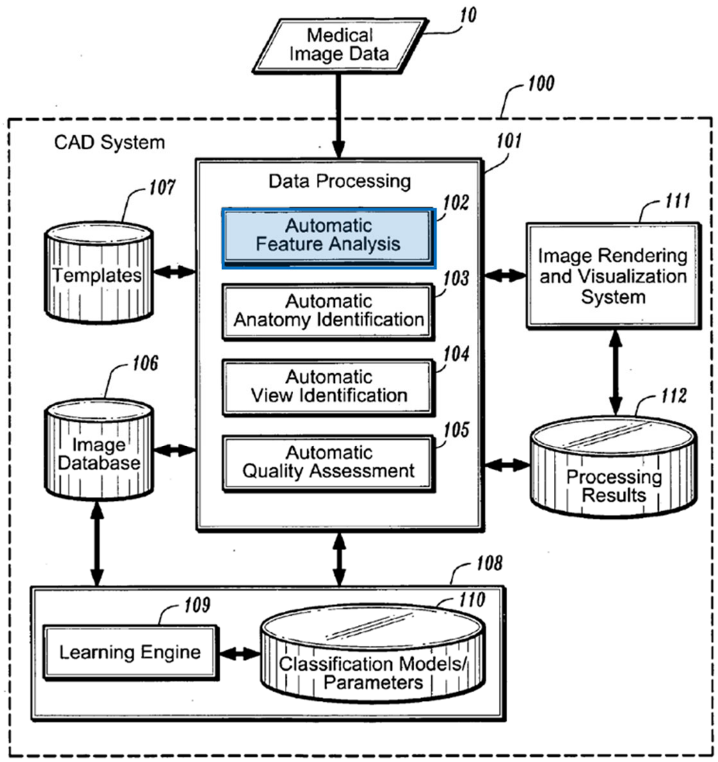

FIG. 1

Ex1005, Fig. 1.

However, as explained in §II.B.1, Krishan discloses that automatic feature analysis module 102 uses "known methods" such as segmentation or filtering to extract features by reference to "known or anticipated image characteristics." Ex1005, [0034] ("Feature extraction can implement known segmentation and/or filtering methods for segmenting features or anatomies of interest by reference to known or anticipated image characteristics, such as edges, identifiable structures, boundaries, changes or transitions in colors or intensities, changes or transitions in spectrographic information, etc, <u>using known methods</u>.”).

In other words, Krishnan’s approach relies on hand-crafted, manually-generated features that are detected using non-learning based methods (e.g., segmentation, filtering) that were known in 2005 at the time of the filing of the application leading to the publication of Krishnan. *See* Ex1005, Cover.

As also explained previously, any “learning” in Krishnan is associated with classifiers 103/104/105, which may be built with neural networks. *Id.*, [0023], [0044]. But these classifiers “would use the set of [extracted] features as an input” (*id.*, [0043]) and would not employ neural networks to learn the extracted features.

Thus, when limitations 1(b) and 21(b) are properly construed such that “extracted feature representations” are “feature representations that are learned using a neural network,” Krishnan fails to disclose these limitations.

Turning to limitation 30(b), the Petition is unclear, but Petitioner appears to argue that feature extraction module 102 may employ a neural network. Petition, 45-46 (identifying module 102 as a “classifier,” asserting that “classifiers can be ‘built using neural networks,’” and asserting that “the use of artificial neural networks to perform feature extraction tasks, including, for example, segmentation or identification objects in medical images was well-known prior to the priority date of the Patent”) (citing Ex1007 and Ex1014).

Notably, the Petition elsewhere appears to admit that automatic feature analysis model 102 does not employ a neural network for learning extracted feature representations. For example, when summarizing Krishnan, the Petition omits automatic feature analysis module 102 when discussing modules that may employ "machine learning." Petition, 15 (stating that "modules 103-105 shown in Figure 1 perform their respective functions using machine learning") (citing Ex1005, [0023]); *see also id.* ("For example, the various modules 103-105 may be implemented using one or more trained classifiers that have been built by the learning engine 109 using training data such as previously diagnosed/labeled images from the database 106.").

Regardless, the Petition's assertion that Krishnan discloses learning extracted features with a neural network is incorrect. As previously explained, feature analysis module 102 employs "known" segmentation or filtering methods—which are not learning-based. Ex1005, [0034]. Further, to the extent isolated sentences in Krishnan refer to module 102 as a "classifier," those are clearly errors because Krishnan elsewhere only refers to modules 103/104/105 as the modules that "can implement classification methods." *Id.*, [0023].

Perhaps recognizing that Krishnan does not disclose employing a neural network for feature extraction, Petitioner cites Ex1007 and Ex1014 to argue that this was "well-known" prior to the '029 patent's priority date. Petition, 46. However, Krishnan only discloses using "known," non-learning-based feature extraction methods such as segmentation and filtering as of its filing/publication date in 2005. Ex1005, [0034]. Ex1007 and Ex1014 are dated at least 10 years after Krishnan's 2005 filing/publication, and thus do not inform—and certainly do not expand—the scope of the "known" feature extraction methods Krishnan discloses. Ex1007 (filed in 2015 and published in 2018); Ex1014 (publication dated in 2016).

Thus, as with limitations 1(b) and 21(b), Krishnan does not disclose limitation 30(b) because Krishnan does not disclose learning extracted features with a neural network.

b. Other Extrinsic Evidence Demonstrates That Krishnan's Feature Extraction Step Cannot Involve Learning

Although Krishnan makes clear that its feature extraction does not involve learning extracted feature representations using a neural network, additional evidence also demonstrates that Krishnan—which was filed/published in 2005—does not disclose learning extracted features.

The shift from non-learning-based methods for feature extraction as disclosed in Krishnan to new methods involving feature learning did not occur until 2012, when the deep learning revolution made feature learning viable at scale. For example, the 2012 paper "*ImageNet classification with deep convolutional neural networks*" ("AlexNet") demonstrated that a large convolutional neural network trained on 1.2 million images could achieve a top-5 error rate of 17%, far below previous approaches using hand-crafted features (26.2% with SIFT + Fisher vectors). *See* Ex2035, Abstract.

Prior to this, computer-vision pipelines used manually engineered features like SIFT and SURF, and progress relied on creating clever methods for feature extraction. *See* Ex2036, 1. Further, it was known that conventional approaches using such manually engineered features were problematic. *See e.g.*:

> Although model-based methods for echo quality assessment can achieve good performance, these methods are view-specific because they require to generate a specific model or template for each view. In addition, the accurate generation of the template relies heavily on human experts or the image's contrast. For example, methods [that] are designed for a specific B-mode view (A4C [] or PLAX []), require manual annotation [], and...rely heavily on the presence of the sharp edges in the image...would fail when applied to low contrast images.

Ex2037, 8.

The AlexNet results, however, showed that learned features can outperform hand-crafted ones. *See id*. (explaining that "for much of the intervening time between the early 1990s and the watershed results of 2012 (Krizhevsky et al., 2012)," features were manually engineered and that deep networks were not trained on large datasets). The impact was so significant that the Royal Swedish Academy of

Sciences recognized one of the authors, Hinton, "for foundational discoveries and inventions that enable machine learning with artificial neural networks" including devising algorithms for "autonomously find[ing] properties in data." *See* Ex2038; Ex2039.

This additional context underscores that Krishnan plainly does not disclose using neural networks to learn extracted features.

2. Independent Claim 12: Krishnan, Chen, and Wu, Alone or in Combination, Fail to Render Obvious Limitation 12(d)

Limitation 12(d) recites "training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, <u>using the set of ultrasound training images as an input to the neural network</u> and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network." Ex1001, Claim 12. In other words, this limitation requires inputting training images into a neural network to train the network.

Petitioner relies on Krishnan in view of Chen and Wu for claim 12. Petition, 69-79. However, for limitation 12(d), the Petition cites neither Chen nor Wu and instead relies solely on Krishnan. *Id.*, 78-79. As explained below, Krishnan does not disclose this limitation. Further, if the Office is inclined to consider Chen or Wu's disclosures for limitation 12(d) notwithstanding the Petition's failure to cite them, these references fail to make up for Krishnan's deficiencies.

a. Krishnan Fails to Disclose Limitation 12(d)

The Petition argues that "Krishnan trains one or more neural network classifiers." Petition, 78 (citing Ex1005, [0023], [0044]). The Petition also argues that a "POSITA would also understand that training the neural network would consist of using…training images as input to the neutral network and adjusting the neural network parameters based on…training labels associated with the images being the 'desired output of the neural network.'" *Id.* (citing Ex1002, ¶273 and Ex1018, [0037], [0040]-[0041]).

Notably, Petitioner does not cite disclosures in Krishnan (or Chen or Wu for that matter) regarding its assertion that training Krishnan's classifiers would involve inputting training images into them. Instead, Petitioner cites Ex1018 ("Pagoulatos"), which is a patent application filed/published in 2017 that is not part of Petitioner's proposed obviousness ground.

Petitioner's failure to cite Krishnan is not surprising, as Krishnan does not disclose neural network "classifiers" that take ultrasound training images as inputs (for either image analysis or training purposes). Instead, the "classifiers" take extracted features from images as inputs. In this regard, Pagloulatos' disclosures regarding training a different neural network should be disregarded as they are irrelevant to how Krishnan's classifiers would be trained.

In more detail, Krishnan's disclosures regarding the inputs to its "classifiers" are best understood with reference to Figure 5.

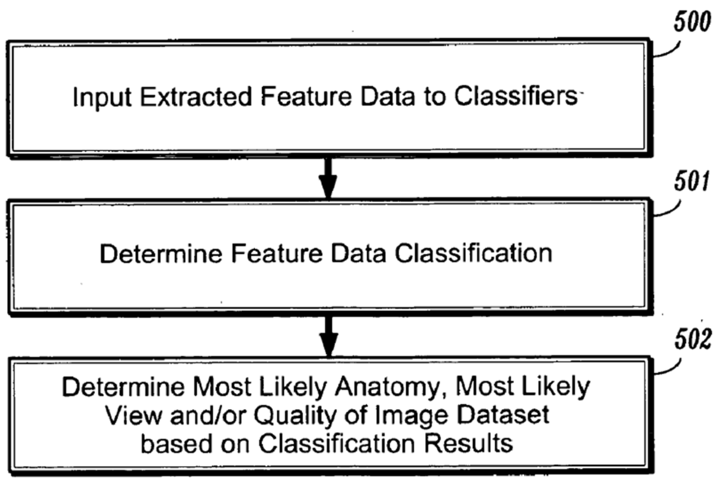

FIG. 5

Ex1005, Fig. 5.

Krishnan discloses that "feature data extracted from the image dataset would be input to classifiers (step 500) that are trained or designed to process the feature data to classify the image data (step 501)." *Id.*, [0042]. "The classification results would be used to determine the most likely anatomy or view, or assess image quality (step 502)." *Id.* "For example, a bank of classifiers could be constructed to classify the images based on the features extracted." *Id.*, [0043]. "These classifiers would use the set of features as an input, and classify the image as belonging to a particular anatomy, view, or level or quality." *Id.*

Thus, Krishnan discloses that the "classifiers" take extracted features (not images) as inputs, which directly contradicts Petitioner's unsupported assertion that the classifiers take images as inputs (either for image analysis or training purposes).

Further, Krishnan makes plain that the extracted features that are input into the classifiers are not the same thing as the images. Specifically, Krishnan establishes that feature extraction is a separate preprocessing step such that the extracted features are engineered attributes of the images, not the images themselves. As previously explained, Krishnan discloses the feature extraction that automatic feature analysis module 102 performs can utilize "known segmentation and/or filtering methods" to isolate "features or anatomies of interest" based on expected image characteristics, such as "edges, identifiable structures, boundaries, changes or transitions in colors or intensities, changes or transitions in spectrographic information." *See id.*, [0034]. "These features could include any kind of characteristic that could be <u>extracted from the image</u>, such as a particular shape or texture." *See id*. Thus, Krishnan discloses that the extracted features are merely a collection of information (e.g., edges, regions, intensities, etc.) pulled from image content, rather than the holistic visual content of an image.

In other words, the extracted features are more limited than the raw image as they capture only certain aspects of what the image depicts. Krishnan highlights this distinction by describing the feature extraction step as "automatically extract[ing] and process[ing] relevant information from the medical image data to provide various decision support function(s) for evaluating the medical images" and explaining embodiments where a "database could be constructed with either the images, or with just the feature representations of the images." *See id.*, [0016], [0040].

Figure 1 illustrates the pipeline from start to end, where the feature analysis module 102 first operates on the input medical image data 10 to extract relevant feature data, which is then passed to the decision-support modules (i.e., the "classifiers" including automatic anatomy identification module 103, automatic view identification module 104, and automatic quality assessment module 105) for classification and interpretation.

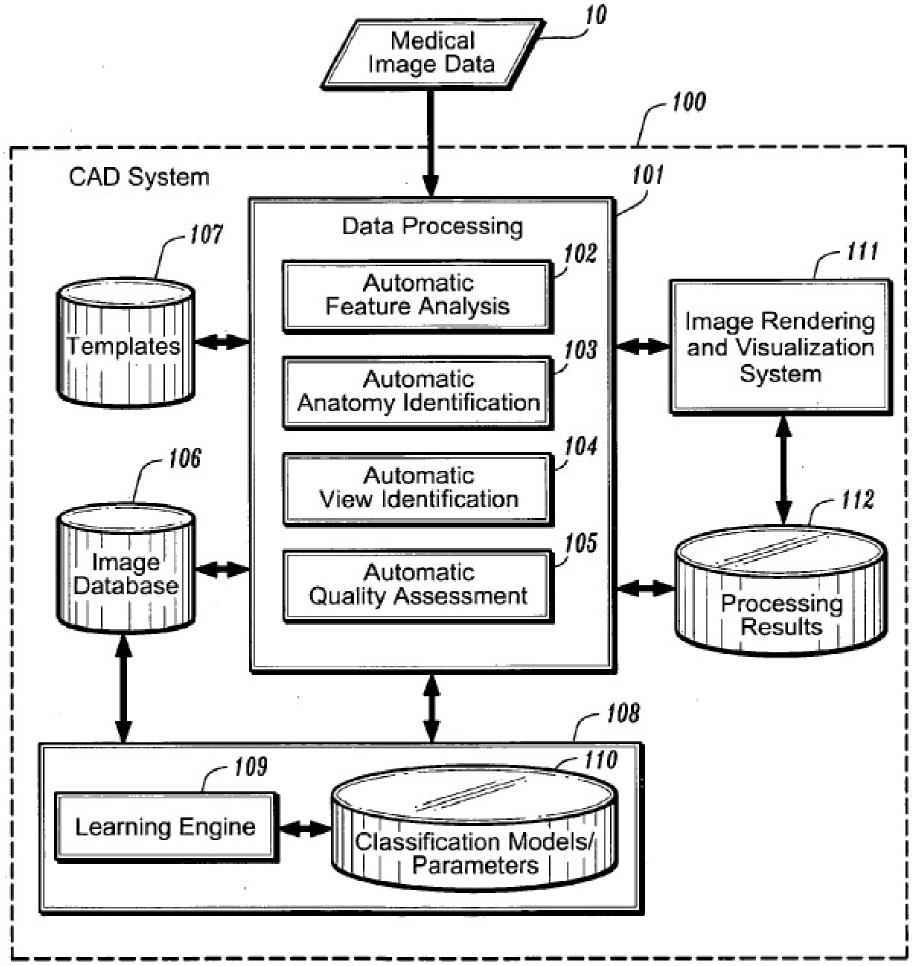

FIG. 1

Ex1005, Fig. 1.

Crucially, this sequential pipeline cannot be reversed to determine the original image based on its features. For example, Krishnan explains that an apical four-chamber echocardiographic view will typically exhibit certain features, such as the presence of four chambers, general shape of the heart, and lack of aortic outflow track. *See id.*, [0038]. However, these features are meant to be used for computational analysis and cannot display the heart's anatomy or allow a clinician to visually interpret cardiac structures.

Figure 2 further underscores this sequential pipeline by depicting "process image dataset to extract relevant feature data" (step 201) as preceding and feeding into "perform automatic anatomy identification, view identification and/or image quality assessment using extracted feature data" (step 202).

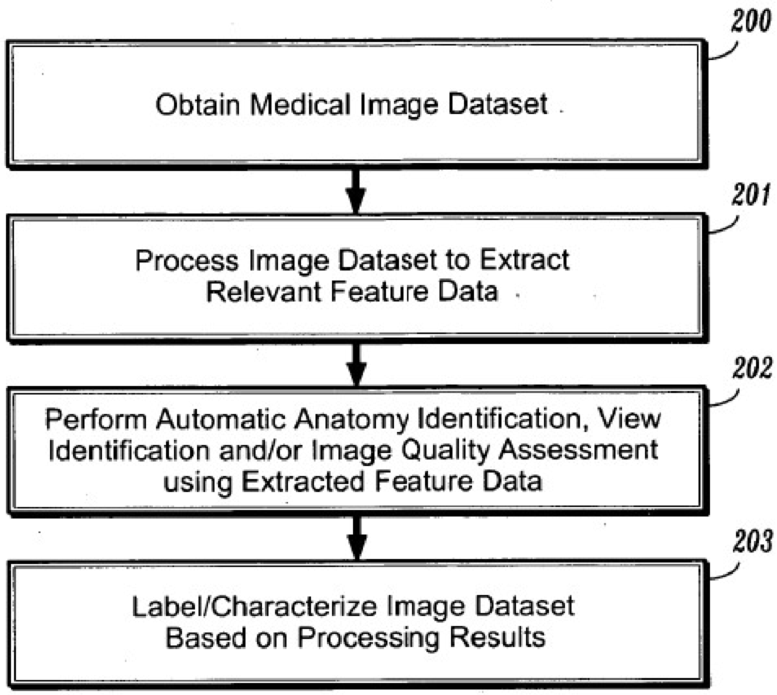

FIG. 2

Ex1005, Fig. 2.

Thus, Krishnan treats feature extraction as a distinct preliminary step, meaning that its neural network classifiers (used in step 202) do not receive images as input during analysis or training, as claimed.

In sum, Krishnan makes clear that its alleged neural network "classifiers" take extracted features as inputs—not the images as limitation 12(d) requires.

b. Petitioner Has Failed to Demonstrate That a POSITA Would Have Been Motivated to Combine Krishnan with Chen and Wu With a Reasonable Expectation of Success

As noted previously, neither the Petition nor Dr. Deo's declaration provide any specific citations to Chen and Wu for limitation [12(d)]. Petition, 78-79; Ex1002, ¶¶272-73. Thus, the disclosures of Chen and Wu should not be considered for this limitation. Nevertheless, if the Office is inclined to consider them, the combination of Krishnan with these references fails to make up for Krishnan's deficiencies.

With respect to rationale to combine and reasonable expectation of success, the Petition relies on general statements by Chen and Wu that their implementations can be extended or generalized to other contexts without any specific explanation about how Krishnan would be modified with the implementations of Chen and Wu. For example, the Petition states that "[it] would have been natural and obvious to a POSITA to combine the teachings of Krishnan, Chen, and Wu by using the neural network architecture disclosed in Chen and Wu to perform the same features described in Krishnan" and then mentions that "Chen and Wu describe techniques for training" Krishnan's classifiers. Petition, 71-72; *id.*, 72 (citing without further support Chen's statement that it discloses "a general framework [that] can be easily extended to other [ultrasound] standard plane or anatomical structure detection problems"); *id.*, 72-73 (citing without further support Wu's statement that its "proposed [quality assessment] scheme can be easily generalized to other types of fetal [ultrasound] views").

However, the Petition fails to explain with any specificity how either of the training frameworks of Chen and Wu would be modified to work with Krishnan's implementation. *Id.*, 72-73. Thus, the Petition fails to provide sufficient evidence regarding a POSITA's alleged motivation to combine. *See ActiveVideo Networks, Inc. v. Verizon Commc'ns, Inc.*, 694 F.3d 1312, 1328 (Fed. Cir. 2012) (citing *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 418 (2007)) (finding generic statements regarding motivation to combine to be deficient because they "fail[ed] to explain why a [POSITA] would have combined elements from specific references *in the way the claimed invention does*") (emphasis in original).

Additionally, Dr. Deo's declaration does not make up for the deficiencies of the Petition. Dr. Deo's declaration provides generalized statements about motivation to combine the references, but stops short of specifically explaining how Krishnan would be modified with Chen and Wu to result in claim 12. For example, Dr. Deo first states that "it would have been intuitive to a POSITA to use recurrent neural networks—like those disclose in Chen and Wu—to improve view identification and quality assessment in Krishnan" and that "[i]t would likewise be intuitive, and a

POSITA would be motivated, to use the 'training' techniques disclosed in Chen and Wu." Ex1002, ¶261. Dr. Deo then lists excerpts from Chen and Wu regarding techniques for training and then repeats his assertions regarding motivation to combine. *See id*. ("a POSITA would have been further motivated to implement the training methods described in Chen and Wu").

With respect to reasonable expectation of success, the only support that Dr. Deo provides is the same general statements by Chen and Wu cited in the Petition, which state that their implementations can be extended or generalized to other contexts. *See id*., ¶262. However, like the Petition, Dr. Deo fails to specifically explain how either the frameworks of Chen and Wu would be modified to work with other implementations. *See id*.

Accordingly, Petitioner has failed to demonstrate how the references would be combined and why a POSITA would have been motivated to combine them with a reasonable expectation of success.

c. Petitioner's Assertions Regarding Obviousness And Reasonable Expectation of Success Are Belied by Krishnan and Other Extrinsic Evidence

Petitioner's assertions regarding obviousness and reasonable expectation of success when modifying Krishnan in view of Chen and Wu (*see* Petition, 71-72) are not only conclusory/unsupported—they also are belied by Krishnan's disclosures and other extrinsic evidence.

As discussed above in §II.B.1, Krishnan describes first extracting features from images, which then are provided to "classifiers" (e.g., neural networks) that perform quality assessment. *See, e.g.*, Ex1005, [0017] ("[T]he feature analysis module (102) implements methods for automatically extracting one or more types of features/parameters from input medical image data and combining the extracted feature/parameters in a manner that is suitable for processing by the decision support modules"); *see id.*, [0042] ("[T]he feature data extracted from the image dataset would be input to classifiers (step 500) that are trained or designed to process the feature data to classify the image data (step 501).").

Krishnan further discloses that the component that performs feature analysis/extraction is separate from the "learning engine." For example, Krishnan makes clear that learning engine 109 is associated with the classification module 108, which includes classification models/parameters 110. *See id.*, Fig. 1. Learning engine 109—or any other type of learning module—is not associated with automatic feature analysis module 102 that implements feature extraction. *See id.* (showing automatic feature analysis 102 to be separate from learning engine 109 and reliance on templates 107); *see also id.*, [0017] (describing feature analysis module 102 without any learning step).

Modifying Krishnan's described methods to be implemented using neural networks that input images to learn extracted features (and are trained with input images rather than extracted features) would not have been obvious and would not have been expected to succeed. Although non-learning-based feature extraction methods like those disclosed in Krishnan had shortcomings, it was known that applying deep learning to images rather than extracted features to implement an end-to-end neural network architecture handling feature extraction and quality assessment like in the ’029 Patent was not a simple matter. This is evidenced not only by Petitioner’s failure to propose an unpatentability ground that adds up to the claimed limitations, but also by the recognition of others in the field that the ’029 patent was pioneering with respect to its deep learning approach for deriving extracting features from images. For example, the ’029 patent or the publication leading to the ’029 patent (U.S. Pat. Pub. No. 2020/0069292, “the ’292 application”) has been cited by patent families across major medical-imaging and technology companies. *See e.g.*, Ex2040 (General Electric Company patent); Ex2041, 9 (App. No. 16/146,770 Non-Final Rejection citing ’292 application during prosecution of Ex2039); Ex2042 (Ultrasound AI Inc. patent); Ex2043, 11 (App. No. 18/431,566 Non-Final Rejection citing ’292 application during prosecution of Ex2041); Ex2044 (Google patent); Ex2045, 3 (Reasons for refusal citing ’292 application during prosecution of Ex2043). Such recognition would not exist had the ’029 patent merely provided known feature engineering techniques like in Krishnan.

Thus, a POSITA would not have found it obvious to modify Krishnan to implement a neural network that derives extracted features from images or is trained by receiving images as input and outputting quality assessment values and image properties. Moreover, a POSITA would not have reasonably expected success.

C. Even Taking the Petition's Arguments at Face Value, the Petition Fails to Demonstrate a Reasonable Likelihood of Unpatentability as to at Least 20 Out of the 30 Challenged Claims (Regardless of UBC's Proposed Claim Construction)

Even if the Office is not inclined to adopt UBC's proposed construction of "extracted feature representations" at the institution stage, the Petition should still be denied because, even taking the Petition's arguments at face value, the Petition fails to demonstrate a reasonable likelihood that at least 20 out of the 30 Challenged Claims are unpatentable. Specifically, as explained in more detail below, the Petition's analysis is either: (1) facially deficient, regardless of whether the Office adopts UBC's proposed claim construction (claims 12-20 and 30); or (2) based on cross references that leave the work to be done by the Office (claims 21-29 and claim 6).

Thus, the Petition should be denied because "maintaining a trial in this case would require the Board and Patent Owner to expend resources addressing multiple claims and grounds that do not meet the reasonable likelihood standard, as well as grounds that have not been sufficiently developed." *Zhuhai*, IPR2025-00405, Paper 24, 3 ("Because the Board must institute on all grounds or none, *SAS Institute Inc.*

v. Iancu, 584 U.S. 357, 364-65 (2018), and because the Board must address all grounds in its final written decision, maintaining a trial in this case would require the Board and Patent Owner to expend resources addressing multiple claims and grounds that do not meet the reasonable likelihood standard, as well as grounds that have not been sufficiently developed. That is not an efficient or respectful use of Office or party resources and thus institution is denied.") (footnote omitted).

1. The Petition's Analyses of Claim 12 (and Therefore Dependent Claims 13-20) and Claim 30 Are Deficient

As described in §§V.B.2 and V.B.1, the Petition's analysis of claims 12 and 30 is deficient and does not satisfy Petitioner's burden. Specifically, limitation 12(d) requires "training a neural network…using [a] set of ultrasound training images as an input to the neural network," which neither Krishnan nor the Krishnan-Wu-Chen combination disclose. Further, because the Petition does not establish a reasonable likelihood that Krishnan (or Krishnan-Wu-Chen) renders claim 12 unpatentable, the Petition also does not establish a reasonable likelihood that the claims depending from claim 12 (claims 13-20) are unpatentable.

Regarding claim 30, limitation 30(b) recites "means for deriving one or more extracted feature representations from [a] set of ultrasound images." The Petition proposes that the "structure/algorithm identified in the specification for performing the recited function is: 'a processor and memory operating a neural network.'" However, for the reasons described in §V.B.1, Krishnan does not disclose a processor/memory operating a neural network where the neural network performs the claimed function of deriving the extracted feature representations.

2. The Petition's Analyses of Claim 21 (and Therefore Dependent Claims 22-29) and Claim 6 Are Based on Cross References That Leave the Work to Be Done By the Office

The Petition's claim 21 analysis is reproduced below and consists of a cursory paragraph and table cross referencing the Petition's claim 1 analysis:

> Claim 21 is substantially the same as claim 1 except, whereas claim 1 recites a method, claim 21 recites a system comprising a "processor configured to" perform the same steps recited in claim 1. As previously explained, Krishnan discloses a computer-implemented method that anticipates claim 1, where the steps of the method are carried out by a data processor (101). *See* Section IX.B.1. For the same reasons provided above with respect to claim 1, and as cross-referenced in the table below for convenience, claim 21 is also anticipated by Krishnan. Ex1002, ¶¶103-131,145-162.

Limitation	**Reasoning**	**Krishnan Citations (Ex1005)**
[21(pre)]	*See* Section IX.B.1.a) [1(pre)]	[0016], [0026], [0045]
[21(a)]	*See* Section IX.B.1.b) [1(a)]	[0016], [0032]-[0033], FIG. 1 (10)
[21(b)]	*See* Section IX.B.1.b) [1(b)]	[0016]-[0017], FIG. 1 (102)
[21(c)]	*See* Section IX.B.1.c) [1(c)]	[0016], [0020], [0032], FIG. 1 (105)
[21(d)]	*See* Section IX.B.1.d) [1(d)]	[0005], [0016], [0019], FIG. 1 (104)
[21(e)]	*See* Section IX.B.1.e)) [1(e)]	[0019]-[0020], [0024], [0036]

Petition, 38-39.

In other words, rather than explain how the prior art discloses claim 21's limitations, the Petition puts the burden on UBC and the Office to refer to other sections of the Petition to understand the challenge. And because claims 22-29 depend from claim 21, the Petition's deficient claim 21 analysis also infects the Petition's analysis of those claims.

As another example,[7] the Petition's claim 6 analysis consists entirely of a cross reference to another Petition section:

> Claim 6 depends from claim 4 and is rendered obvious by Krishnan-Chen for the same reasons already provided in Section IX.C.2. Ex1002, ¶¶221-223.

Petition, 59.

The Petition's analysis of at least claims 21-29 and 6 is thus exactly the type that the Director has found supports denial because it improperly "leav[es] the work to be done by the Office." *See Zhuhai*, IPR2025-00405, Paper 24, 2-3 ("Although the Board did not abuse its discretion in instituting review, as a matter of policy, it is not an efficient use of Office resources to institute and maintain a trial when a

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[7] These are just two examples of the Petition's deficient analysis. There are additional places where the Petition's analysis is nothing more than a cross reference to other sections with no prior art citations. *See, e.g.*, Petition, 39 (claim 22), 42 (30(pre)).

petition presents a multitude of unfocused grounds leaving the work to be done by the Office…For some of these grounds, the Petition presents arguments for claims 1–6 but does not include separate arguments for claims 12 and 16–26. Instead, the Petition includes tables setting forth the limitation for each of claims 12, 16–19, and 21–26 (e.g., [12.pre] for claim 12's preamble) and referring to arguments made in other sections of the Petition to explain the challenge.").

VI. CONCLUSION

For the reasons set forth above, the Petition fails to demonstrate a reasonable likelihood that any of the challenged claims of the '029 patent are unpatentable.

Dated: November 20, 2025

Respectfully submitted,

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CERTIFICATE OF WORD COUNT UNDER 37 CFR § 42.24(d)

Under 37 C.F.R. § 42.24(d), the undersigned certifies that the word count for this Patent Owner's Preliminary Response to the Petition for *inter partes* review totals 8,184, excluding the parts exempted by 37 C.F.R. § 42.24(a). The word count was made using the built-in word count function in the Microsoft® Word software used to prepare this document.

Dated: November 20, 2025

Respectfully submitted,

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CERTIFICATE OF SERVICE

Pursuant to 37 C.F.R. § 42.6(e), I certify that I caused to be served a true and correct copy of the foregoing: PATENT OWNER'S PRELIMINARY RESPONSE and accompanying exhibits by email to the electronic service addresses for Petitioner on the date indicated below:

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