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 RESPONSE

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TABLE OF AUTHORITIES

EXHIBITS

Exhibit	Description
2001	Complaint for Patent Infringement, *Univ. of British Columbia v. Caption Health, Inc.*, No. 5:24-cv-03200-EKL (N.D. Cal. May 28, 2024), ECF No. 1
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)
2004	GE HealthCare Techs. Inc. Corporate Family Report (July 24, 2025)
2005	Non-Final Rejection, App. No. 16/146770 (June 2, 2020)
2006	Non-Final Rejection, App. No. 17/558271 (June 4, 2024)
2007	Ex. C to Joint Amended and Supplemented Claim Construction and Prehearing Statement, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. Oct. 10, 2025), ECF No. 87-3
2008	Defendants' Notice of Motion and Motion to Stay Case Pending *Inter Partes* Review, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. June 27, 2025), ECF No. 72
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)
2010	Order Setting Initial Case Management Conference & ADR Deadlines, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. May 31, 2024), ECF No. 9
2011	Defendants' First Amended Invalidity Contentions, *Univ. of British Columbia v. Caption Health, Inc.*, No. 3:24-cv-03200 (N.D. Cal. Aug. 22, 2025)
2012	Decl. of Dorianne Salmon in Support of UBC's Opp. to Defendants' Motion to Stay Pending *Inter Partes* Review, *Univ. of British*

Exhibit	Description
	Columbia v. Caption Health, Inc., No. 24-cv-03200 (N.D. Cal. July 11, 2025), ECF No. 77-1
2013	Appendix A to Defendants' First Amended Invalidity Contentions, dated August 22, 2025
2014	Exhibit E to Infringement Contentions
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2019	Administrative Motion Regarding Case Schedule and Motion to Stay, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. July 3, 2025), ECF No. 75
2020	Plaintiff UBC's Motion for Leave to Amend Infringement Contentions regarding US Patent Nos. 11,129,591 and 10,751,029, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. May 9, 2025), ECF No. 65
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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
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2025	Joint Claim Construction and Prehearing Statement Pursuant to Pat. L.R. 4-3, *Univ. of British Columbia v. Caption Health, Inc.*, No. 24-cv-03200 (N.D. Cal. May 30, 2025), ECF No. 68
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2027	UBC's Additional Proposed Terms for Construction, dated Sept. 5, 2025
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2029	UBC's Supplemental Preliminary Claim Constructions, dated Sept. 19, 2025
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2034	’029 Patent Grants Spreadsheet
2035	Krizhevsky, Sutskever, and Hinton, *ImageNet classification with deep convolutional neural networks* (“AlexNet”) (2012)
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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
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2044	Japanese Patent No. 7,284,298
2045	Japanese Patent App. No. 2021 to 572915 Notice of Reasons for Refusal dated Nov. 24, 2022 (English translation)
2046	November 25, 2025 Email from Tina Williams
2047	Plaintiff UBC’s Opening Claim Construction Brief, Redacted Version (Dkt. 92)
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2049	Declaration of Dr. Milan Sonka (“Sonka”)
2050	Curriculum vitae of Dr. Milan Sonka
2051	Deposition Transcript of Dr. Rahul Deo (Session I) (April 17, 2026)
2052	Deposition Transcript of Dr. Rahul Deo (Session II) (April 17, 2026)

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2053	*Caption Health v. Univ. of British Columbia*, IPR2025-01066, Paper 15 (Institution Decision) (Dec. 19, 2025)
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2066	F. Isensee, et. al., *nnU-Net: Self-adapting Framework for U-Net-Based Medical Image Segmentation*, arXiv:1809.10486 (Sept. 72, 2018)
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LISTING OF THE CHALLENGED CLAIMS

Limitation	Claim Language
Claim 1	
[1(pre)]	1. 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)]	deriving one or more extracted feature representations from the set of ultrasound images;
[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
[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.
Claim 2	
[2]	The method of claim 1 wherein the image property is a view category.
Claim 3	
[3]	The method of claim 2 wherein deriving the one or more extracted feature representations from the ultrasound images comprises, for each of the ultrasound images, deriving a first feature representation associated with the ultrasound image.
Claim 4	
[4]	The method of claim 3 wherein deriving the one or more extracted feature representations comprises, for each of the ultrasound images, inputting the ultrasound image into a commonly defined first feature extracting neural subnetwork to generate the first feature representation associated with the ultrasound image.
Claim 5	
[5]	The method of claim 4 wherein deriving the one or more extracted feature representations comprises concurrently inputting each of a plurality of the ultrasound images into a respective implementation of the commonly defined first feature extracting neural network.
Claim 6	

[6]	The method of claim 4 wherein the commonly defined first feature extracting neural network includes a convolutional neural network.
Claim 7	
[7]	The method of claim 4 wherein deriving the one or more extracted feature representations comprises inputting the first feature representations into a second feature extracting neural network to generate respective second feature representations, each associated with one of the ultrasound images and wherein the one or more extracted feature representations include the second feature representations.
Claim 8	
[8]	The method of claim 7 wherein the second feature extracting neural network is a recurrent neural network.
Claim 9	
[9]	The method of claim 2 wherein determining the quality assessment value comprises inputting the one or more extracted feature representations into a quality assessment value specific neural network and wherein determining the image property comprises inputting the one or more extracted feature representations into an image property specific neural network.
Claim 10	
[10]	The method of claim 9 wherein inputting the one or more extracted feature representations into the quality assessment value specific neural network comprises inputting each of the one or more extracted feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork and wherein inputting the one or more extracted feature representations into the image property determining neural network comprises inputting each of the one or more extracted feature representations into an implementation of a commonly defined image property specific neural network.
Claim 11	
[11]	The method of claim 2 wherein 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 comprises producing signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by at least one display in association with the set of ultrasound images.

Claim 12	
[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)]	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.
Claim 13	
[13]	The method of claim 12 wherein each of the image properties is a view category.
Claim 14	
[14(pre)]	The method of claim 13 wherein the neural network includes a feature extracting neural network, an image property specific neural network, and a quality assessment value specific neural network and wherein:
[14(a)]	the feature extracting neural network is configured to take an input set of the plurality of sets of ultrasound training images as an input and to output one or more extracted feature representations;
[14(b)]	the image property specific neural network is configured to take the one or more extracted feature representations as an input and to output a representation of an image property associated with the input set of ultrasound training images; and
[14(c)]	the quality assessment specific neural network is configured to take the one or more extracted feature representations as an input and to output a quality assessment value associated with the input set of ultrasound training images.
Claim 15	

[15]	The method of claim 14 wherein the feature extracting neural network is configured to, for each of the ultrasound training images included in the input set of ultrasound training images, derive a first feature representation associated with the ultrasound image.
Claim 16	
[16]	The method of claim 15 wherein the feature extracting neural network includes, for each of the ultrasound images included in the input set of ultrasound training images, a commonly defined first feature extracting neural network configured to take as an input the ultrasound training image and to output a respective one of the first feature representations.
Claim 17	
[17]	The method of claim 16 wherein more than one implementation of the commonly defined first feature extracting neural networks are configured to concurrently generate the first feature representations.
Claim 18	
[18]	The method of claim 16 wherein the commonly defined first feature extracting neural network is a convolutional neural network.
Claim 19	
[19]	The method of claim 16 wherein the feature extracting neural network includes a second feature extracting neural network configured to take as an input the first feature representations and to output respective second feature representations, each associated with one of the ultrasound images included in the input set of ultrasound training images and wherein the one or more extracted feature representations include the second feature representations.
Claim 20	
[20]	The method of claim 19 wherein the second feature extracting neural network is a recurrent neural network.
Claim 21	
[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)]	derive one or more extracted feature representations from the set of ultrasound images;
[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.
Claim 22	
[22]	The system of claim 21 wherein the image property is a view category.
Claim 23	
[23]	The system of claim 22 wherein the at least one processor is configured to, for each of the ultrasound images, input the ultrasound image into a commonly defined first feature extracting neural subnetwork to generate a first feature representation associated with the ultrasound image.
Claim 24	
[24]	The system of claim 23 wherein the at least one processor is configured to, for each of the ultrasound images, input the ultrasound image into a commonly defined first feature extracting neural subnetwork to generate the first feature representation associated with the ultrasound image.
Claim 25	
[25]	The system of claim 24 wherein the at least one processor is configured to concurrently input each of a plurality of the ultrasound images into a respective implementation of the commonly defined first feature extracting neural network.
Claim 26	
[26]	The system of claim 24 wherein the at least one processor is configured to input the first feature representations into a second feature extracting neural network to generate respective second feature representations, each associated with one of the ultrasound images and wherein the one or more extracted feature representations include the second feature representations.
Claim 27	
[27]	The system of claim 22 wherein the at least one processor is configured to input the one or more extracted feature

	representations into a quality assessment value specific neural network and to input the one or more extracted feature representations into an image property specific neural network.
Claim 28	
[28]	The system of claim 27 wherein the at least one processor is configured to input each of the one or more extracted feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork and to input each of the one or more extracted feature representations into an implementation of a commonly defined image property specific neural network.
Claim 29	
[29]	The system of claim 22 wherein the at least one processor is configured to produce signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by at least one display in association with the set of ultrasound images.
Claim 30	
[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)]	means for deriving one or more extracted feature representations from the set of ultrasound images;
[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.

I. INTRODUCTION

Patent Owner University of British Columbia ("UBC") submits this Patent Owner Response 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. It addresses the problem that "[i]nexperienced ultrasound operators may have a great deal of difficulty using…known systems to recognize features in the ultrasound images[,] and thus can fail to capture diagnostically relevant ultrasound images." Ex1001, 1:27-31.

The '029 patent solves this problem by employing neural networks to derive extracted feature representations from ultrasound images and, based on those learned representations, determine quality assessment values and image properties that can be displayed to the operator in real time. *Id.*, cl.1, 21, 30; *id.*, 2:24-31. 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.*, cl.12.

Petitioner asserts four grounds of unpatentability. 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-Chen	§103	3-8, 23-26
C	Krishnan-Aase		9-10, 27-28
D	Krishnan-Chen-Wu		12-20

Petitioner fails to meet its burden to show that any challenged claim is unpatentable.

Ground A (anticipation) fails for two reasons. First, the Petition fails to show that Krishnan's feature extraction module learns extracted features using a neural network, which limitations 1(b)/21(b)/30(b) require when properly construed. Second, as to limitations 1(c)/21(c)/30(c), the Petition fails to show that Krishnan discloses a "quality assessment value" under the construction that Petitioner is bound by in this IPR, which is "score of diagnostic image quality."

Ground B fails because the Petition fails to articulate a coherent obviousness combination that satisfies the particularity requirement of 35 U.S.C. §312(a)(3). Instead, Petitioner first proposes wholesale replacement of Krishnan's architecture—which employs non-neural network techniques for generating hand-crafted extracted features and separate modules that receive those features as inputs—with Chen's end-to-end integrated neural network architecture. Petitioner then proposes a mutually exclusive theory that "adds" Chen's neural network to Krishnan, all the while implausibly alleging that the combination would require little or no modification. Petitioner's expert then compounded this problem at deposition by offering contradictory and elusive testimony as to what the proposed combination is and how it would be achieved. A POSITA would not have been motivated to combine Krishnan's and Chen's fundamentally incompatible architectures and would not have had a reasonable expectation of success in doing so.

Ground C fails because Petitioner fails to articulate a viable combination of Krishnan and Aase. Petitioner appears to propose feeding Krishnan's hand-crafted extracted features into Aase's neural networks, thereby breaking apart Aase's integrated neural network architecture and providing Aase's neural network inputs it was not designed to receive. Petitioner fails to address the material modifications that would need to be made in order to combine these two fundamentally different architectures. Petitioner's expert's deposition only exacerbated this problem. A POSITA would not have been motivated to combine Krishnan's and Aase's fundamentally different architectures, and the proposed combination would not have been expected to succeed.

Ground D fails for multiple reasons. As a threshold and dispositive issue, the Petition relies solely on Krishnan for limitation 12(d). This limitation, however, requires inputting training images into a neural network—which Krishnan does not disclose. More generally, the Petition does not even attempt to propose a coherent, particular combination of Krishnan, Chen, and Wu and a particular motivation to combine. Petitioner's expert then offered contradictory and shifting explanations at deposition—testifying that the combination could be anything from wholesale replacement of Krishnan's architecture to keeping some components of Krishnan's architecture while omitting others.

For at least these reasons, the Board should find that Petitioner has not met its burden to show that any challenged claim is unpatentable.

II. BACKGROUND

A. Overview of the Technology

At the time of the '029 patent's priority date (August 2018), ultrasound imaging in healthcare continued its major reliance on sonographer experience, expertise, and ability to navigate the ultrasound scanning exams using the intimate knowledge of human anatomy. Sonka, ¶56. Ultrasound is inherently noisy—signal reflection and tissue-associated speckle can obscure anatomy, and free-hand probe positioning introduces variability in image quality and anatomical views that is unique to ultrasound and absent in fixed-geometry modalities such as CT, MRI, and PET. *Id.* These limitations created an unmet need to assist operators with automated feedback regarding diagnostic image quality and anatomical view identification across the broad spectrum of ultrasound exam types. *Id.*, ¶¶57-59.

Prior to 2012, attempts to address these challenges relied exclusively on conventional computer vision techniques. *Id.*, ¶¶60, 62. Image analysis methods of that era required features to be hand-designed by human experts—one by one—and then computed from images using fixed algorithms such as edge-based segmentation, thresholding, region growing, template matching, deformable models, and other segmentation or filtering approaches. *Id.*, ¶¶63-64, 73-74. These engineered feature descriptors could then be input into a separately-trained classifier to produce outputs such as view labels or quality assessments. *Id.*, ¶74. Machine learning techniques available before the deep learning era could optimize parameters for otherwise fixed segmentation methods, but they could not design new features—that capability remained exclusively dependent on human expertise. *Id.*, ¶64. Similarly, image quality assessment methods were limited to analytical measures of general properties like signal-to-noise ratio, rather than learned assessments of diagnostic or clinical usability. *Id.*, ¶65.

In 2012, a technological revolution arrived with the introduction of AlexNet, which demonstrated that a deep convolutional neural network trained on large datasets could dramatically outperform hand-crafted features. *Id.*, ¶61; *see* Ex1029; Ex2035; Ex2061. However, deep learning for medical image analysis did not emerge as a practical methodology until years later. Sonka, ¶62.

Deep learning is a fundamentally different approach. Rather than requiring human-designed features, deep neural networks facilitate direct feature derivation from training data—raw images are input to an end-to-end network, and entire feature representations are derived jointly during model training to be maximally useful for a given task. *Id.*, ¶¶72-73. This stands in stark contrast to conventional approaches, where features are extracted from individual images using hand-designed formulas and then fed as numerical descriptors to a separately trained model. *Id.*, ¶74.

Critically, these two paradigms are fundamentally incompatible in their processing pipelines. Conventional systems like Krishnan (Ex1005; filed 2005) invariably utilize non-neural techniques for feature extraction. The "known segmentation and/or filtering methods" (Ex1005, [0034]) disclosed in Krishnan could only have referred to methods available when it was filed in 2005, none of which involved neural networks. Sonka ¶¶63, 66. Deep learning systems like the '029 patent, by contrast, use images directly as inputs to neural networks that simultaneously learn optimal feature representations and produce classification outputs. *Id.*, ¶76. Thus, "deriv[ing]" extracted features in the '029 patent (automated neural network learning) and the extraction of features in Krishnan describe fundamentally different processes. *Id.*, ¶77; *see generally id.*, ¶¶56-78.

B. Summary of the ’029 Patent

The ’029 patent discloses systems and methods for analyzing ultrasound images with a neural network and for training the neural network. Ex1001, Abstract; Sonka, ¶79. Regarding analyzing the images, the ’029 patent discloses an exemplary analyzer 14 in Figure 1. *Id.*

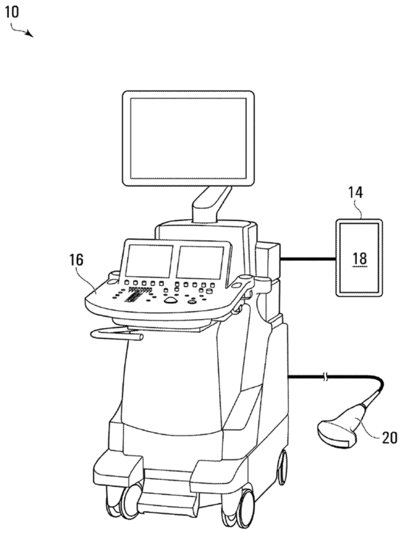

FIG. 1

Ex1001, Fig. 1.

“[T]he analyzer 14 may receive signals representing a set of ultrasound images of the subject.” Ex1001, 6:23-25; Sonka, ¶80. “The analyzer 14 may then derive one or more extracted feature representations from the received set of ultrasound images” (Ex1001, 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). Sonka, ¶80. “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." Ex1001, 6:56-58; Sonka, ¶80. An exemplary image property is view category. Ex1001, 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); Sonka, ¶80.

"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." Ex1001, 7:4-7; Sonka, ¶81. 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." Ex1001, 7:7-11; Sonka, ¶81.

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." Ex1001, 7:15-18; *see also id.*, 7:18-32; Sonka, ¶82.

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. Ex1001, 15:37-41; Sonka, ¶83.

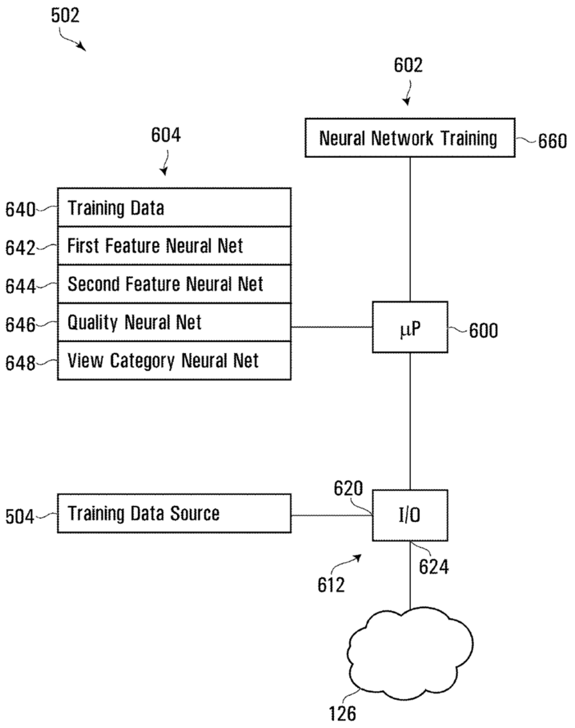

FIG. 11

Ex1001, Fig. 11.

Figure 12 depicts a flowchart for directing the trainer processor 600 shown in Figure 11 to perform neural network training. Ex1001, 16:14-21; Sonka, ¶84. Trainer processor 600 receives signals representing ultrasound training images (702), signals representing quality assessment values (704), and signals representing image properties (706). Ex1001, 16:23-17:26; Sonka, ¶84.

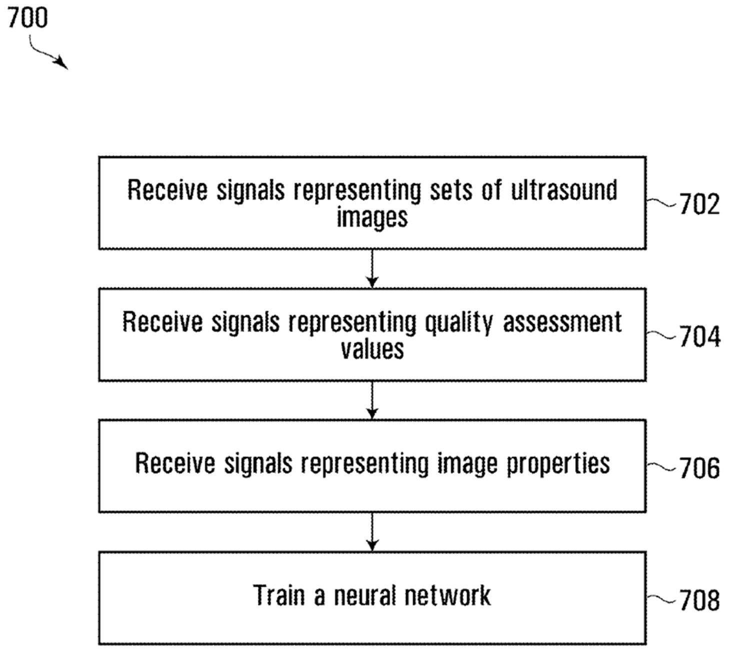

FIG. 12

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."[1] Ex1001, 17:27-33; *see also id.*, 17:33-44 (describing training the neural network 300 shown in Figure 4); Sonka, ¶85.

Accordingly, the '029 patent discloses that the neural network is trained using ultrasound images as inputs, rather than features (descriptors) separately defined and

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[1] All emphases added unless otherwise noted.

extracted from the ultrasound images prior to the neural network training. Sonka, ¶86.

C. Prosecution History

The application leading to the issuance of the ’029 patent was filed 8/30/2019 and claimed priority provisional application 62/725,913 (filed 8/31/2018). Ex1001, (22), (63), (60); Sonka, ¶87.

The Examiner initially issued a non-final office action rejecting then-pending claims 1-30 as anticipated by U.S. 2019/0125298. Ex1004, 265-79; Sonka, ¶88. U.S. 2019/0125298 is the publication of an application that later issued as U.S. 11,129,591, which Petitioner challenged in a separate IPR (IPR2025-01066; institution denied). Ex2052; Sonka, ¶89. After applicant explained that the application was commonly-owned, the Examiner withdrew the rejection and allowed the claims. Ex1004, 345-56; Sonka, ¶¶89, 92. Applicant submitted Krishnan (Ex1005) during prosecution, and the Examiner signed an information disclosure statement indicating Krishnan was considered. Ex1004, 302, 298, 416; Sonka, ¶¶91-92.

D. The Alleged Prior Art

1. Krishnan (Ex1005)

Krishnan is directed to providing decision support for 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]; Sonka, ¶114.

Figure 1 depicts a high-level block diagram of Krishnan's system 100. Ex1005, [0016]; Sonka, ¶115. The system includes a data processing module 101, which comprises automatic feature analysis module 102, anatomy identification module 103, view identification module 104, and image quality assessment module 105. *Id.*

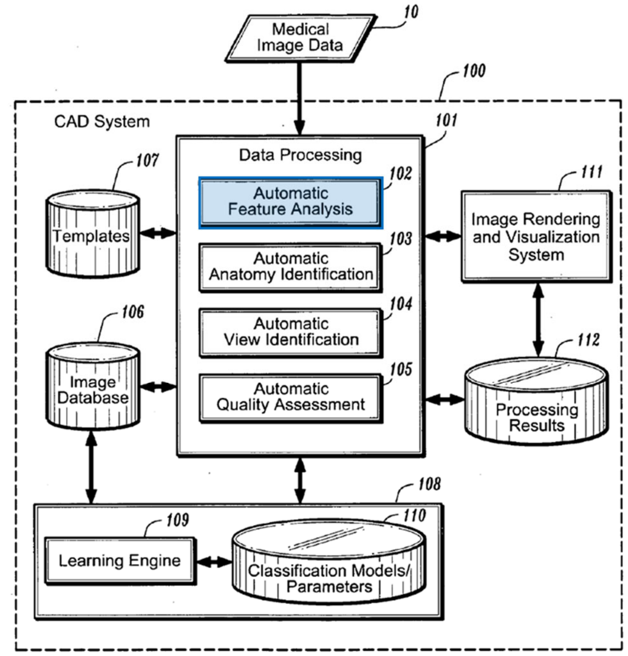

FIG. 1

Ex1005, Fig. 1.[2]

Feature analysis module 102 "implements methods for automatically extracting one or more types of features/parameters from input medical image data

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[2] All color annotations added.

and combining the extracted features/parameters in a manner that is suitable for processing by the decision support modules (103, 104 and/or 105)." Ex1005, [0017]; Sonka, ¶116.

Anatomy identification module 103 "implements methods for using the extracted features/parameters to automatically identify anatomical objects." Ex1005, [0018]; Sonka, ¶117. Paragraph 18 of Krishnan refers to anatomy identification module as module 102, which is a typographical error because Figure 1 illustrates that anatomy identification module is module 103. Sonka, ¶118.

View identification module 104 "implements methods for using the extracted features/parameters to automatically identify the view of an acquired image." Ex1005, [0019]; Sonka, ¶119. Paragraph 19 refers to view identification module as module 103, which is a typographical error because Figure 1 illustrates view identification module as module 104. Sonka, ¶120.

Quality assessment module 105 "implements methods for using the extracted features/parameters to assess a level of diagnostic quality of an acquired image data set and determine whether errors occurred in the image acquisition process." Ex1005, [0020]; Sonka, ¶121.

Thus, feature analysis module 102 is the only module that receives images (Ex1005, [0017]), whereas modules 103/104/105 "use[] the extracted features/parameters" output by module 102 as an input, not the images themselves (*id.*, [0018]-[0020]). Sonka, ¶122.

Krishnan discloses three alternative embodiments for implementing modules 103/104/105: database querying methods, template-based methods, and classification methods. Ex1005, [0021]-[0023]; Sonka, ¶122.

When describing the "classifier" embodiment, Krishnan discloses that "the various modules (103), (104) and (105) can implement classification methods that utilize the classification module (108) to process extracted feature data to classify the image dataset under consideration." Ex1005, [0023]; Sonka, ¶123. Krishnan further discloses that "classification module (108) comprises a learning engine (109) and knowledge base (110) to implement a principle (machine) learning classification system," and that "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." *Id.* "The classifiers are implemented by the various decision support modules (102~105) for performing their respective functions." *Id.*

As Dr. Sonka explains, Krishnan discloses that only modules 103/104/105 may be implemented using classification methods according to the third alternative embodiment (described in more detail as to Figure 5). Sonka, ¶123. The generic reference to "102~105" at the conclusion of paragraph 23 is a typographical error, which is clear because the paragraph's first sentence explicitly lists only modules

103/104/105 as implementing "classification methods." Ex1005, [0023]; Sonka, ¶123.

Krishnan's process is described in more detail with respect to Figure 2. Sonka, ¶124.

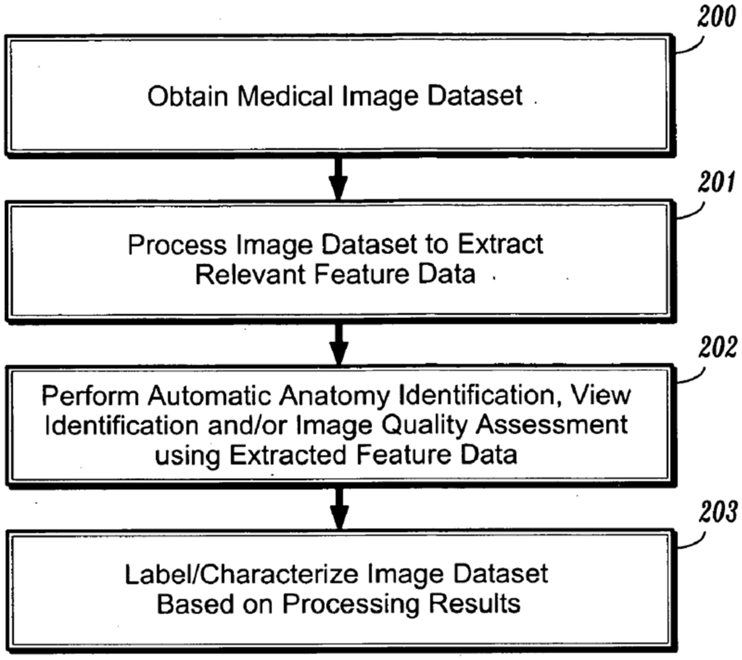


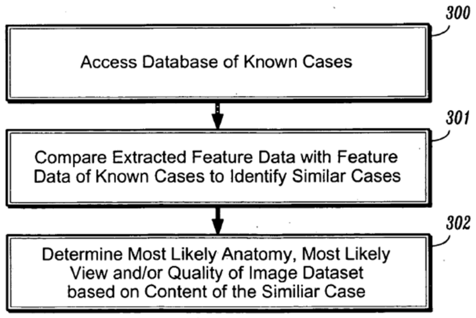
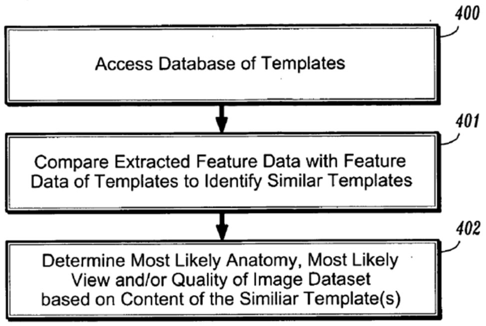
FIG. 2

EX1005, Fig. 2.

The process involves obtaining the medical imaging dataset (step 200), processing the image dataset to extract relevant feature data (step 201; performed by module 102), performing automatically anatomy identification, and/or image quality assessment using extracted feature data (step 202; performed by modules 103/104/105), and labeling/characterizing the image dataset based on processing results (step 203). *Id.*, [0033]-[0034], [0036]; Sonka, ¶125.

As to step 201, Krishnan describes performing feature extraction according to "known" methods such as "segmentation" or "filtering"—not learning the extracted features using a neural network. Ex1005, [0034]; Sonka, ¶125.

Krishnan illustrates the alternative approaches for step 202—i.e., steps performed by modules 103/104/105—in Figures 3 (database querying), 4 (template processing), and 5 (classifiers). Ex1005, [0035]; Sonka, ¶¶125-126. As to each approach, Krishnan discloses the modules "utilize the <u>extracted features</u> to provide automated decision support functions." Ex1005, [0035]; *see also id.*, [0037]-[0040] (describing Figure 3), [0041] (describing Figure 4); Sonka, ¶¶126-28.

 **FIG. 3**	 **FIG. 4**
Ex1005, Fig. 3.	Ex1005, Fig. 4.

As to the classification methods alternative embodiment (Figure 5), Krishnan discloses inputting extracted feature of images into the "classifiers" (step 500). Ex1005, [0042]-[0044]; Sonka, ¶129.

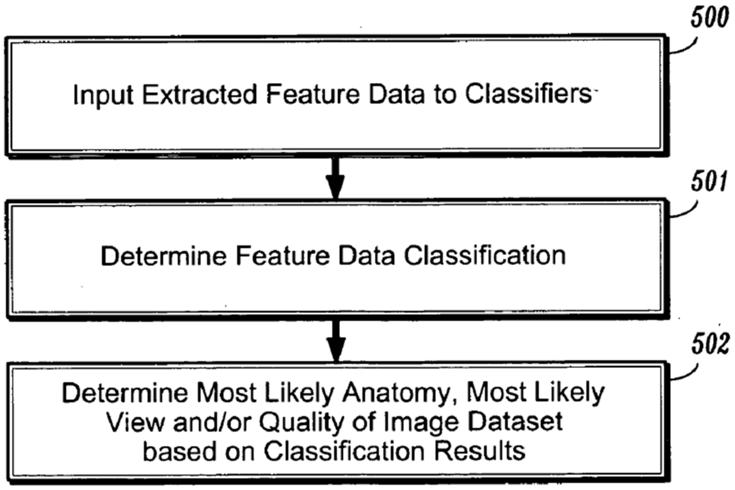


FIG. 5

Ex1005, Fig. 5.

Specifically, "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)." Ex1005, [0042]; Sonka, ¶130.

"The classification results would be used to determine the most likely anatomy or view, or assess image quality (step 502)." Ex1005, [0042]; Sonka, ¶131. "[A] bank of classifiers could be constructed to classify the images <u>based on the features extracted</u>." Ex1005, [0043]; Sonka, ¶131. "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." Ex1005, [0043]; Sonka, ¶131. Krishnan discloses that the "classifiers" (i.e., modules 103/104/105) (Ex1005, [0023]) may be "built using neural networks" (*id.*, [0044]). Sonka, ¶131.

Critically, Krishnan does not disclose that classification module 108/learning engine 109/knowledge base 110 shown in Figure 1 are associated with feature extraction module 102. Sonka, ¶132. Rather, Krishnan discloses that 108/109/110 may support "classification methods" performed by modules 103/104/105. Ex1005, [0023]; Sonka, ¶132. Further, modules 103/104/105 still "process extracted feature data" received from module 102 when implementing classification methods. *Id.* In other words, regardless of whether modules 103/104/105 are implemented in alternative embodiments according to database querying, template-based, or classification methods, the module 102's function is the same—it extracts feature data according to known non-neural network techniques and provides the feature data as an input to modules 103/104/105. Sonka, ¶132. The "classifiers" may separately be "built using neural networks" (Ex1005, [0044]), and modules 103/104/105 may utilize classification methods to process the feature data that has already been extracted by module 102 according to non-neural network techniques. Sonka, ¶132.

Thus, Krishnan does not disclose implementing module 102 using classification methods, where the "classifiers" may be built using neural networks. Sonka, ¶133. Rather, Krishnan discloses that only modules 103/104/105 may be implemented—according to one alternative embodiment—using classification methods, and module 102 would still perform feature extraction using "known" segmentation and/or filtering methods. *Id*.

Given that Krishnan excludes module 102 from using classification methods and discloses that modules 103/104/105 receive extracted features from module 102 regardless of which of the three alternative embodiments for modules 103/104/105 is employed, a POSITA would have understood the "known" techniques module 102 employs for feature extraction would not have employed neural networks. Sonka, ¶134. This is also consistent with the fact that the shift from non-learning-based feature extraction to neural network-based feature learning did not occur until 2012 with the introduction of AlexNet. *Id*. At the time of Krishnan's filing in 2005, "known segmentation and/or filtering methods" would have been understood by a POSITA to refer exclusively to conventional, non-learning-based techniques such as edge detection, thresholding, region-based methods, watersheds, and dynamic programming-based optimization approaches—none of which involve neural networks. *Id*.

Moreover, the extracted features input into modules 103/104/105 are not the same thing as the images. Sonka, ¶135. Krishnan's feature extraction is a separate preprocessing step, and the extracted features are engineered attributes of the images, not the images themselves. *Id*.

As previously described, Krishnan discloses the feature extraction that 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 spectographic information." Ex1005, [0034]; Sonka, ¶136. Krishnan discloses that "[t]hese features could include any kind of characteristic that could be extracted from the image" and provides "a particular shape or texture"[3] as examples. Ex1005, [0034]; Sonka, ¶136.

Thus, the extracted features are information collected from image content (e.g., edges, regions, intensities, etc.) and are more limited than the raw image. Sonka, ¶137. They capture only certain aspects of what the image depicts. *Id*. Thus, a POSITA would have understood the extracted features are not the holistic visual image content, rather they are image features/descriptors a human designer expected to be useful for a specific task such as identifying the anatomy and view, diagnostic image quality, etc. *Id*.

Krishnan makes this distinction clear when it describes 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

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[3] "[A] particular shape or texture" again suggests that the features are extracted using non-neural network techniques. Sonka, ¶136 n.5.

the medical images" and disclosing embodiments where a "database could be constructed with either the images, or with just the feature representations of the images." Ex1005, [0016], [0040]; Sonka, ¶138.

And as described above regarding Figures 1 and 2, Krishnan discloses a sequential pipeline where features are extracted by module 102 (step 201) and then, in step 202, modules 103/104/105 receive extracted features as inputs. Sonka, ¶139. After module 102 extracts features, it would not be possible to reverse the process and reconstruct the original image from the features. *Id*.

Krishnan discloses, e.g., that "[a] set of typical apical four chamber views would reveal a number of features, such as the presence of four chambers, and a general shape for the heart." Ex1005, [0038]; Sonka, ¶140. However, these are features meant for computational analysis. Their quantitative representation (e.g., a numeric vector of values) would not allow a technician or clinician to interpret the anatomical structures, the view, or the image quality visually from these features. Sonka, ¶140. Moreover, these features could not be used to display the heart's anatomy. *Id*.

Thus, even in the alternative embodiment in which modules 103/104/105 employ classification methods, Krishnan does not disclose that these modules take images as input—e.g., to derive extracted features from the images or to train the classifiers. Sonka, ¶141. Instead, according to all three alternative embodiments, modules 103/104/105 take extracted features produced by module 102 as an input. Ex1005, [0018]-[0020], [0034]-[0037], [0042]-[0043]; Sonka, ¶141.

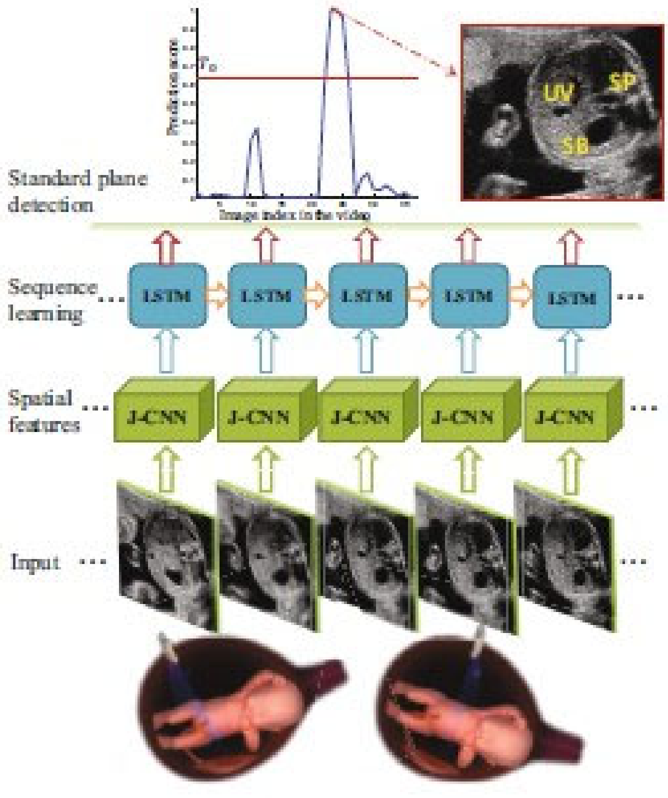
2. Chen (Ex1009)

Chen is directed to automatically detecting standard fetal ultrasound planes from ultrasound videos using neural networks. Ex1009, Abstract; Sonka, ¶142. Specifically, Chen describes "a knowledge transferred recurrent neural network (T-RNN)," "which is a hybrid model integrating deep convolutional neural networks (CNN) and recurrent neural networks (LSTM model)." Ex1009, 509; Sonka, ¶142. The T-RNN detects fetal ultrasound standard planes from ultrasound video sequences. *See* Ex1009, 514; Sonka, ¶142.

Chen uses joint learning of CNNs ("J-CNN") (Ex1009, 509), and the J-CNN takes raw ultrasound image frames as input—not extracted features. *See* Ex1009, 510 (table 1 showing input is a "227x227x1" image frame), 511 ("Given the input frame I_{mk}, the probability map of the ROI [regions of interest] is computed by the J-CNN model…"); Ex2052, 13:8-10 (Dr. Deo confirming Chen's J-CNN takes raw ultrasound image frames as input); Sonka, ¶143.

The J-CNN extracts "deep learning based spatial feature representations" from each frame. Ex1009, 508; *see id.*, 511 ("Features in the penultimate layer (i.e., activations of F6 layer) of the J-CNN model are then extracted from the ROI of each frame"); Sonka, ¶144. These learned spatial features are then input into the LSTM, and "the temporal information is explored via the LSTM model based on the features of ROIs in consecutive frames extracted from the J-CNN model." Ex1009, 509; Sonka, ¶144.

Inputting images into the J-CNN and spatial features into the LSTM is depicted below in Figure 2. Sonka, ¶145.



Ex1009, Fig. 2 (left side).

Critically, Chen's feature extraction (J-CNN) and classification (LSTM) are integrated in a single end-to-end system. Sonka, ¶146. They are not separate modules like Krishnan's module 102 and modules 103/104/105. *See* Ex1009, 509 (describing the T-RNN as "a hybrid model integrating deep convolutional neural networks

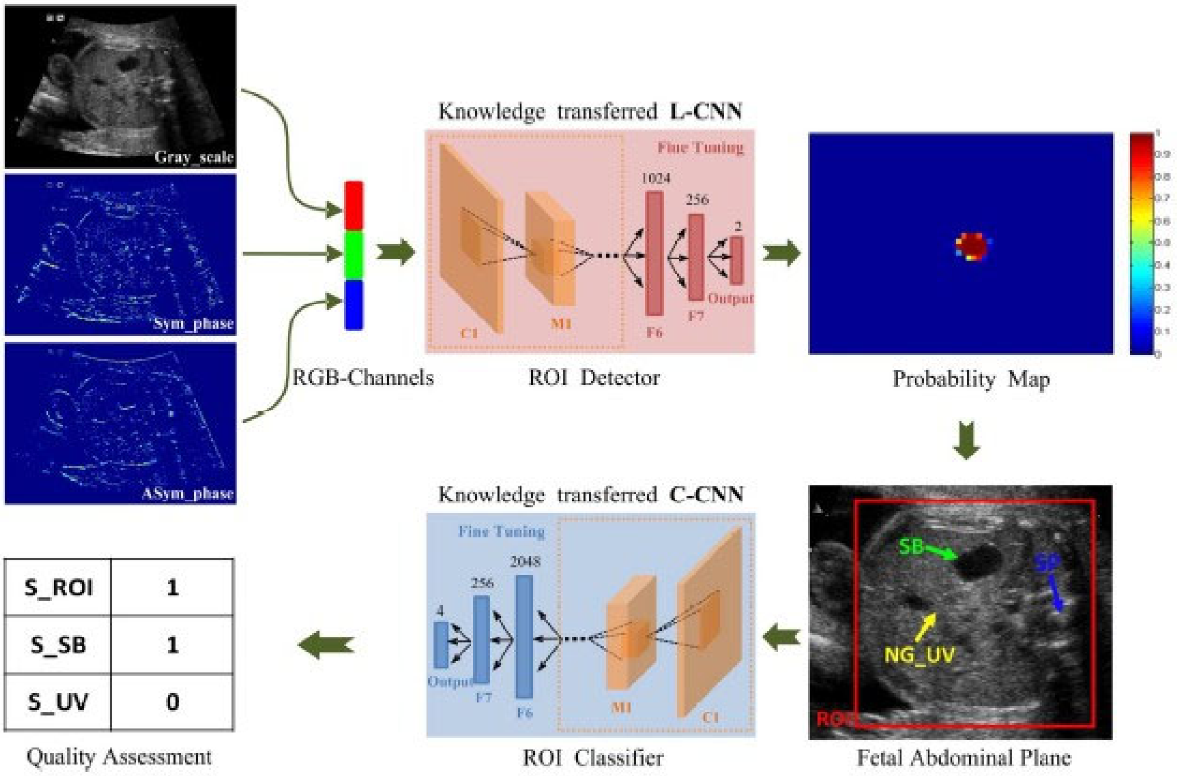
(CNN) and recurrent neural networks (LSTM model)"); Sonka, ¶146.

Chen's neural networks do not output any quality assessment value. Sonka, ¶147. Thus, Chen's neural networks are only trained to output identified fetal ultrasound standard planes. *See* Ex1009, 509; Sonka, ¶147. Chen states that it discloses "a general framework [that] can be easily extended to other [ultrasound] standard plane or anatomical structure detection," but does not specifically explain how its framework would be modified to work with other implementations. Ex1009, 509; Sonka, ¶147.

3. Wu (Ex1010)

Wu is directed to quality assessment of fetal ultrasound images. Ex1010, Abstract; Sonka, ¶148. Wu utilizes two deep convolutional neural networks (denoted L-CNN and C-CNN) in a sequential pipeline. Ex1010, Fig. 3; Sonka, ¶148.

Wu's L-CNN takes the original ultrasound image together with symmetric and asymmetric phase features as its three inputs. Ex1010, 4; *id.,* 5-6 (describing computation of phase features); Sonka, ¶149. These inputs are spatial image data, unlike the engineered feature descriptors that Krishnan's module 102 outputs. Sonka, ¶149.



Ex1010, Fig. 3.

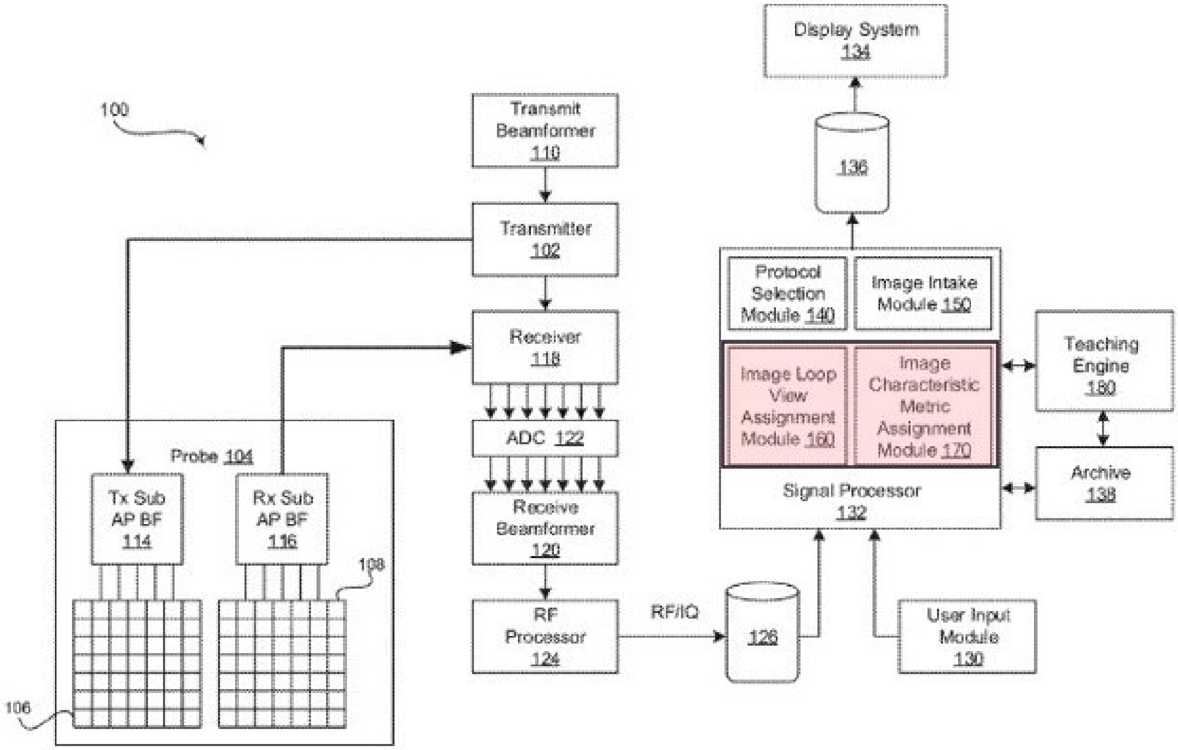
Wu's L-CNN and C-CNN are integrated through knowledge transfer. The L-CNN extracts features from images to identify a region of interest (ROI) in the image, the C-CNN receives the ROI as an input, and "[t]he knowledge learned from the L-CNN will be introduced to the C-CNN as initialization for the learning of four-class differentiation of [ultrasound] images." *See id.*, 4; Sonka, ¶150. The C-CNN further outputs a quality assessment. Ex1010, 3, Abstract; Sonka, ¶151.

Wu's L-CNN for feature extraction and C-CNN for quality assessment thus are integrated. Sonka, ¶152. In other words, they are not independent modules that could be separated and recombined with other systems without modification. *Id.*

Notably, Wu does not perform view identification—it is limited to quality assessment. Ex1010, Abstract; Sonka, ¶153. Wu states that its "proposed [quality assessment] scheme can be easily generalized to other types of fetal [ultrasound] views," but Wu does not specifically describe how its system would be modified to do so. *See* Ex1010, 3; Sonka, ¶153.

4. Aase (Ex1006)

Aase is directed to automatic selection of ultrasound image loops from continuously captured ultrasound stress echocardiographic images. Ex1006, Abstract; Sonka, ¶154. Central to Aase are image loop view assignment module 160 and image characteristic metric assignment module 170. Ex1006, Fig. 2; Sonka, ¶154.



Ex1006, Fig. 2.

Module 160 utilizes deep learning or neural networks to analyze the anatomical structures within the ultrasound frames and automatically assign a "view type" to each captured loop. Ex1006, [0032]-[0033]; Sonka, ¶155. Module 170 utilizes deep learning or neural networks to provide an "image characteristic metric" (e.g., score of image quality) to the image loops. Ex1006, [0035]; Sonka, ¶155.

Aase's modules 160 and 170 each receive image loops as input—not extracted features. Ex1006, [0033] (as to 160, disclosing that "the input layer may have a neuron for each pixel or a group of pixels from an image loop 220, 320"), [0035] (as to 170, disclosing that "[t]he input layer may include a neuron for each pixel or a group of pixels from an image loop 220, 320"); Sonka, ¶155.

The feature extraction processing for modules 160 and 170 is embedded in the initial layers within these modules' neural networks. *See* Ex1006, [0033] ("Each neuron of each layer may perform a processing function and pass the processed ultrasound image information to one of a plurality of neurons of a downstream layer for further processing."); *id.*, [0035]; Sonka, ¶156.

Because feature extraction is embedded within its neural networks, the feature extraction and classification functions of modules 160 and 170 are integrated. Sonka, ¶157. In other words, they are not independent modules that could be separated and recombined with other systems without modification. *Id.*

Since the neural networks of modules 160 and 170 expect specific learned feature representations produced by these initial layers, Aase's subsequent classification layers would not perform as designed if they were to receive features they were never trained on. Sonka, ¶158.

III. LEVEL OF ORDINARY SKILL

The Petition proposes 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; Sonka, ¶27. UBC recognizes that Petitioner proposed the same definition of a POSITA in the Petition for *inter partes* review of U.S. 11,129,591, and the Board adopted Petitioner's definition in its decision denying institution. *See* IPR2025-01066, Petition at 11; *see id.*, Ex2053, 10-11; Sonka, ¶28. For purposes of this IPR only, UBC applies Petitioner's definition of a POSITA. Sonka, ¶29.

UBC's expert, Dr. Sonka, satisfies this POSITA definition. For example, Dr. Sonka has advanced degrees in Electrical Engineering and Technical Cybernetics–Digital Image Analysis (i.e., fields related to computer imaging) and, as of August 31, 2018, had several years of research experience training machine learning models to analyze ultrasound data. *See* Sonka, ¶30; Ex2050; Ex2054-59.

IV. CLAIM CONSTRUCTION

A. "Extracted Feature Representations" (Independent Claims 1, 21, and 30 and Dependent Claims 3-5, 7, 9-10, 14, 19, and 26-28)

The Petition applies an overbroad interpretation of "extracted feature representations," e.g., when analyzing limitations 1(b)/21(b)/30(b). Sonka, ¶94. "[E]xtracted feature representations" should be construed as "feature representations that are learned using a neural network," which is the construction UBC proposes in the parallel litigation. *See* Ex2007, 7; Sonka, ¶94.

When "extracted feature representations" is appropriately read in the context of the claim language requiring "deriv[ing]" the features and the specification, the term plainly requires "feature representations that are learned using a neural network." Sonka, ¶96. And when the term is properly construed, the prior art does not disclose at least limitations 1(b), 21(b), and 30(b). *Id.*

The Federal Circuit has recognized that "when a patent 'repeatedly and consistently' characterizes a claim term in a particular way, it is proper to construe the claim term in accordance with that characterization." *GPNE Corp. v. Apple Inc.*, 830 F.3d 1365, 1370-71 (Fed. Cir. 2016) (finding the district court did not err in characterizing a "node" as a "pager" when the specification "repeatedly and exclusively" used the words "pager" and "pager units" to describe the devices in the patented system); *Wis. Alumni Rsch. Found. v. Apple Inc.*, 905 F.3d 1341, 1351 (Fed. Cir. 2018); *Federal Express Corp. v. Qualcomm Inc.*, No. 2024-1235, 2026 WL

1162769, *2-3 (Fed. Cir. Apr. 29, 2026) (nonprecedential) ("Although the patent acknowledges that 'the specification and examples be considered as exemplary only,' the specification is nonetheless instructive in understanding the disputed term…").

That is precisely the case here. Sonka, ¶97. The '029 patent specification repeatedly and consistently describes the "extracted feature representations" as feature representations that are learned using a neural network, and a POSITA would have understood that learning extracted features using a neural network was central to the claimed invention of the '029 patent. *Id.*

As a preliminary matter, the '029 patent describes "feature representations" as encodings of image patterns of one or more images. *See, e.g.*, Ex1001, 11:30-39, 12:28-31; *see* Sonka, ¶98.

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 (Figure 2 depicts storage memory 104, which includes a plurality of storage locations, including "location 154 for storing first feature extracting neural network parameter data, location 156 for storing second feature extracting neural network parameter data"), 11:30-32 (Figure 4 depicts feature extractor neural networks 304, 306, and 308), 11:28-29 (Figures 5, 6, and 7 depict feature extractor neural networks 310, 312, and 314), 16:3-5 (Fig. 11

depicts storage memory 604 and "location 642 for storing first feature extracting neural network data, location 644 for storing second feature extracting neural network"), 22:24-34 (Fig. 13 depicts "three first feature extracting neural network or CNN threads" 752, 754, and 756); Sonka, ¶99.

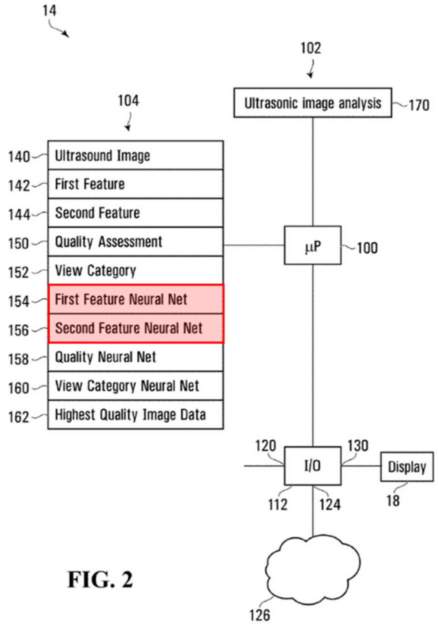


FIG. 2

Ex1001, Fig. 2

(locations 154/156 for storing feature extracting neural network parameter data)

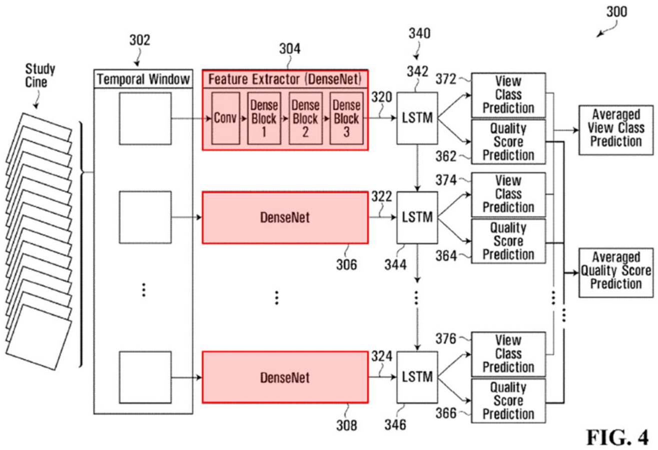


FIG. 4

Ex1001, Fig. 4

(feature extractor neural networks 304/306/308)

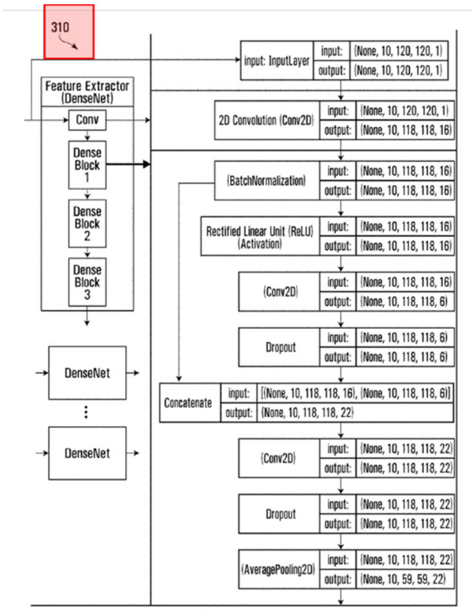


FIG. 5

Ex1001, Fig. 5

(feature extractor neural network 310)

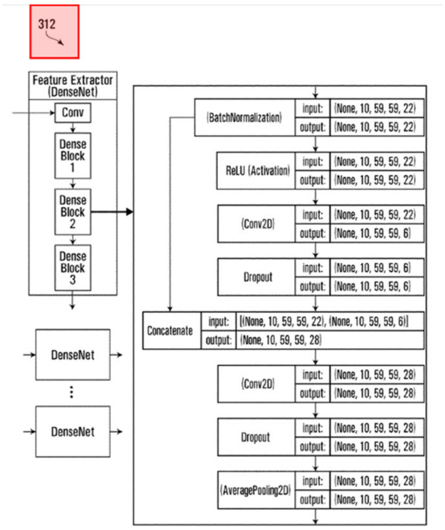


FIG. 6

Ex1001, Fig. 6

(feature extractor neural network 312)

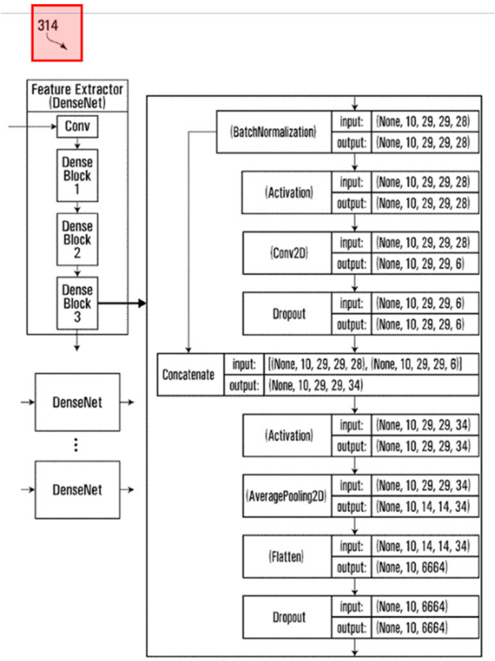


FIG. 7

Ex1001, Fig. 7

(feature extractor neural network 314)

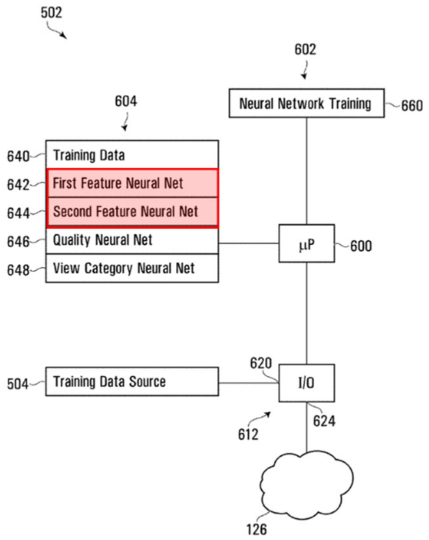


FIG. 11

Ex1001, Fig. 11

(locations 642/644 for storing feature extracting neural network data)

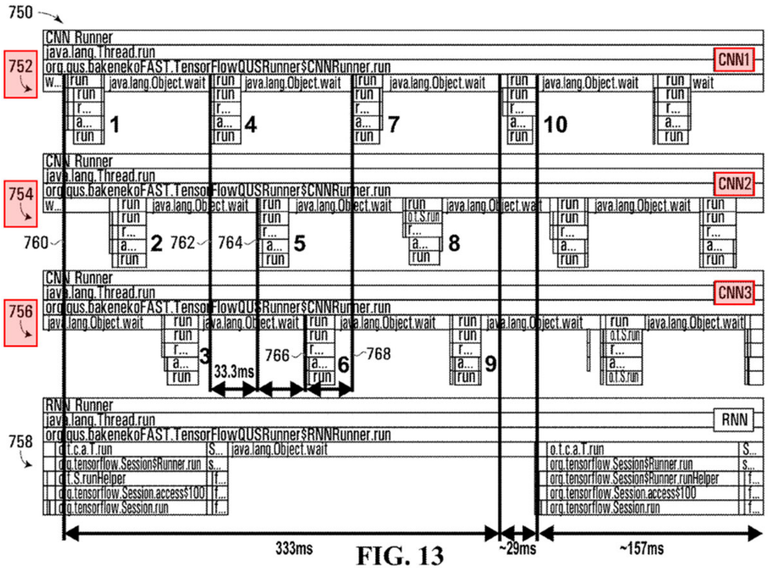


FIG. 13

Ex1001, Fig. 13

(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 (in Figure 3, "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 the extracted feature representations are learned upon inputting images into various neural networks); *id.*, 10:32-12:51 (further details about implementing neural networks for deriving extracted feature representations); Sonka, ¶100.

The Figure 3 description further supports that the "extracted feature representations" are learned using a neural network. Figure 3 is a "flowchart depicting blocks of code for directing the analyzer processor 100 shown in FIG. 2 to perform ultrasonic image analysis functions in accordance with various embodiments..." Ex1001, 9:9-13; Sonka, ¶101.

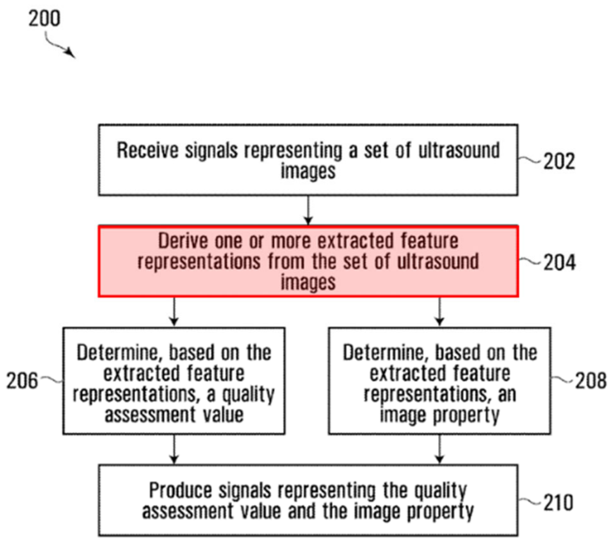


FIG. 3

Ex1001, Fig. 3.

Figure 3's flowchart 200 "begins with block 202 which directs the analyzer processor 100 shown in FIG. 2 to receive signals representing a set of ultrasound images of a subject." Ex1001, 9:16-19; Sonka, ¶102. Then, "[i]n various embodiments, execution of blocks 204, 206 and 208 of the flowchart 200 may result in the analyzer processor 100 being directed to <u>input the received set of ultrasound images into a neural network 300 shown in FIG. 4</u>, to generate an output of a quality assessment value and an image property, which in some embodiments may be a view category." Ex1001, 9:65-10:4; Sonka, ¶102.

The images are input into a neural network in block 204 in order to "derive" extracted feature representations. Ex1001, 10:9-31 ("Referring to FIG. 3, block 204 directs the analyzer processor 100 to <u>derive</u> one or more extracted feature representations from the set of ultrasound images received at block 202…In some embodiments, block 204 may direct the analyzer processor 100 to <u>derive</u> the first feature representations by <u>inputting each image</u> of the set of ultrasound images (shown at 302 in FIG. 4) <u>into a commonly defined first feature extracting neural network</u>…"); Sonka, ¶103.

Expert testimony further supports UBC's construction. As Dr. Sonka explains, when reading the claims in the context of the specification, a POSITA would have understood that the "extracted feature representations" are feature representations learned using a neural network. Sonka, ¶¶95-96. This is because the claim language itself refers to "deriv[ing]" the features, the specification repeatedly and consistently characterizes extracted feature representations as being learned using a neural network, and a POSITA would have understood that learning extracted features with a neural network was central to the claimed invention. *Id.*, ¶¶97-103.

Dr. Deo's testimony is also consistent with UBC's construction. Dr. Deo opines that the '029 patent "discloses <u>and claims</u> an echocardiographic image analysis workflow shown in Figure 3." Ex1002, ¶62. Dr. Sonka agrees. Sonka, ¶104. Dr. Deo also opines that Figure 3's workflow uses a neural network in block 204, which is the feature extracting step. *See* Ex1002, ¶62; Sonka, ¶105. And Dr. Deo testified at deposition that there are no specific alternative embodiments that do not use a neural network for block 204. *See* Ex2051, 44:8-45:4; Sonka, ¶106.

UBC's proposed construction is also consistent with the claim differentiation doctrine because it does not result in any claims that depend from claims 1 and 21 being redundant. Sonka, ¶108. Certain dependent claims specify details regarding the neural network involved in extracting features, e.g., a "commonly defined first feature extracting neural subnetwork," whereas claims 1 and 21 are broader in that they only require that the extracted features be learned using a neural network. *See* Ex1001, cl.4-8, cl.23-26; Sonka, ¶108.

B. "Quality Assessment Value" (Independent Claims 1, 12, 21, and 30 and Dependent Claims 9, 10, 11, 14, and 27-29)

Although UBC does not propose a construction for "quality assessment value," Petitioner is bound in this IPR and in any other proceeding before the Office to apply the construction "score of diagnostic image quality." Paper 15, 3; Sonka,

¶109. UBC reserves the right to challenge this construction in other proceedings, but because Petitioner is bound by it, UBC applies this construction to Petitioner's grounds below. Sonka, ¶109.

C. Means-Plus-Function (Claim 30)

Regarding claim 30, Petitioner identifies several agreed-to §112(f) constructions. Petition, 10-12; Sonka, ¶110.

Term (claimed function underlined)	**Corresponding Structure**
[30(a)]: "means for <u>receiving signals representing a set of ultrasound images of the subject</u>"	a processor with I/O interface
[30(b)]: "means for <u>deriving one or more extracted feature representations from the set of ultrasound images</u>"	a processor and memory operating a neural network
[30(c)]: "means for <u>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</u>"	a processor and memory operating a neural network

[30(d)]: "means for <u>determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images</u>"	a processor and memory operating a neural network
[30(e)]: "means for <u>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</u>"	a processor and memory

See Ex2031, §I.A; Petition, 10-12; Sonka, ¶111.

V. PETITIONER HAS NOT ESTABLISHED BY A PREPONDERANCE OF THE EVIDENCE THAT ANY CHALLENGED CLAIM IS UNPATENTABLE

"In an IPR, the petitioner has the burden from the onset to show with particularity why the patent it challenges is unpatentable. *See* 35 U.S.C. § 312(a)(3) (requiring IPR petitions to identify 'with particularity...the evidence that supports the grounds for the challenge to each claim')." *Harmonic Inc. v. Avid Tech., Inc.*, 815 F.3d 1356, 1363 (Fed. Cir. 2016). "The petition must specify where each element of the claim is found in the prior art patents or printed publications relied upon." 37 C.F.R. §42.104(b)(4).

Petitioner has not established by a preponderance of the evidence that any challenged claim is unpatentable for the reasons explained below. *See* Sonka, ¶160.

A. Ground A: Krishnan Does Not Anticipate Claims 1-3, 9, 11, 21-22, 27, and 29-30

1. Krishnan Fails to Disclose That "Deriving One or More Extracted Feature Representations" From Ultrasound Images Is Performed Using a Neural Network (Limitations 1(b)/21(b)/30(b))

a. Limitations 1(b)/21(b)

When properly construed, limitations 1(b) and 21(b) require "deriv[ing] one or more extracted feature representations from the set of ultrasound images," where the extracted feature representations are "feature representations that are learned using a neural network." §IV.A; Sonka, ¶161.

The Petition asserts that Krishnan's automatic feature analysis module 102 discloses these limitations. Petition, 24-26 (for 1(b), citing Krishnan's automatic feature analysis module 102 in Figure 1, paragraphs 17 and 34, and Figure 2); *id.*, 39 (for 21(b), pointing to limitation 1(b) analysis); Sonka, ¶162.

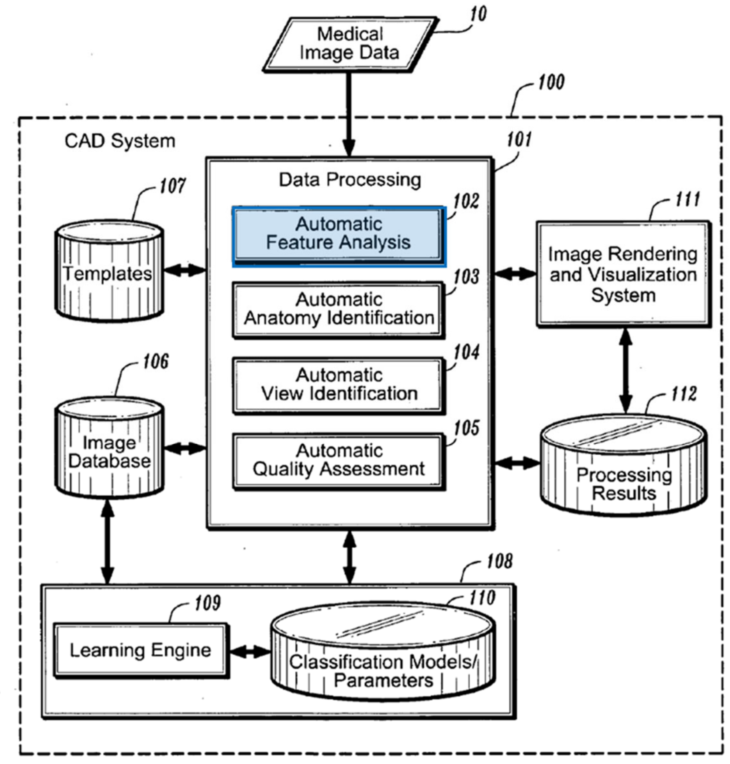


FIG. 1

Ex1005, Fig. 1.

As a threshold matter, the Petition does not allege that Krishnan's module 102 is a neural network for these limitations. Sonka, ¶163. This is dispositive under UBC's proposed construction and demonstrates that claims 1 and 21 have not been shown to be unpatentable. *Id*. Indeed, the Petition does not even cite the Figure 5 embodiment for these limitations, which is the only embodiment employing classification methods/classifiers that may be built using neural networks. *Id*. Moreover, Dr. Deo confirmed during his deposition that he did not opine that module 102 performs feature extraction using a neural network. Ex2051, 83:2-7; Sonka, ¶163. And Petitioner has conceded in the parallel district court litigation that module

102 employs "non-neural network techniques." Ex2048, 18; Sonka, ¶163.

Even if Petitioner belatedly attempts to argue that any module in Krishnan learns extracted features using a neural network, Petitioner would be incorrect. *Id.*, ¶164. Specifically, even if the Petition had cited the Figure 5 embodiment, automatic feature analysis module 102 is not a neural network and does not employ neural network techniques. *Id.* As explained in §II.D.1, Krishnan does not disclose that the neural network techniques associated with classification module 108/learning engine 109/knowledge base 110 are associated with feature extraction module 102. *Id.* Rather, Krishnan discloses that classification module 108/learning engine 109/knowledge base 110 only support "classification" methods performed by modules 103/104/105, where the classifiers may be "built using neural networks." Ex1005, [0023], [0044]; Sonka, ¶164. To the extent isolated sentences in Krishnan refer to module 102 as employing classification methods, those are clearly errors because Krishnan elsewhere only refers to modules 103/104/105 as the modules that "can implement classification methods." *Id.*, [0023]; §II.D.1; Sonka, ¶164. Indeed, there are other clear typographical errors in Krishnan when referring to the modules, which Dr. Deo admitted during deposition. Ex2051, 54:7-20, 55:20-25; Sonka, ¶164.

Rather than employ neural network techniques, Krishnan 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]; *see* Sonka, ¶165. As noted, Petitioner conceded in the parallel litigation that module 102 employs "non-neural network techniques" (Ex2048, 18), and the Petition elsewhere appears to admit that module 102 does not employ a neural network for learning extracted feature representations. Sonka, ¶165. For example, when summarizing Krishnan, the Petition omits module 102 when discussing modules that may employ "machine learning." Petition, 15 ("modules 103-105 shown in Figure 1 perform their respective functions using machine learning") (citing Ex1005, [0023]); *see also id.* ("[T]he 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."); Sonka, ¶165.

In sum, Krishnan's approach relies on module 102 extracting features according to manual/hand-crafted rules. Sonka, ¶166. These features are thus detected and generated using non-learning-based methods (e.g., segmentation, filtering) that were known in 2005 at the time of Krishnan's filing. *See* Ex1005, Cover; Sonka, ¶166. This would not have conveyed to a POSITA that module 102 could be employed as a neural network for extracting features. Sonka, ¶166.

Petitioner also cannot rely on modules 103/104/105 as neural networks for deriving extracted features from images. *Id.*, ¶167. Modules 103/104/105 do not perform feature extraction and do not receive images. Instead, these modules "would use the set of [extracted] features as an input"—i.e., the features that module 102 extracts using non-neural network techniques are used as inputs to modules 103/104/105 in each of the three alternative embodiments. Ex1005, [0043], step 500 of Fig. 5 ("Input Extracted Feature Data to Classifiers"); Sonka, ¶167.

Thus, when limitations 1(b)/21(b) are properly construed, Krishnan fails to disclose these limitations. Sonka, ¶168.

b. Limitation 30(b)

Turning to limitation 30(b), the agreed construction requires that the corresponding structure performing the claimed function is "a processor and memory operating a neural network." Ex2031, §IV.C; Sonka, ¶169.

Thus, the parties' agreed construction requires that the extracted feature representations be learned using a "processor and memory operating a neural network." Sonka, ¶170.

The Petition is unclear, but Petitioner appears to argue that module 102 may employ a neural network. Petition, 45-46 (identifying module 102 as a "classifier," asserting "classifiers can be 'built using neural networks,'" and asserting "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); Sonka, ¶171.

As discussed above, Petitioner is incorrect, because even in the Figure 5 embodiment employing classification methods, module 102 does not employ a neural network to learn extracted features. §§II.D.1, V.A.1.a; Sonka, ¶172.

Perhaps recognizing that Krishnan does not disclose employing a neural network for feature extraction, Petitioner cites Ex1007 and Ex1014 to argue this was "well-known" prior to the '029 patent's priority date. Petition, 46; Sonka, ¶173. Petitioner, however, asserts anticipation based on Krishnan, and 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]; Sonka, ¶173. 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 2015; published 2018); Ex1014 (publication dated in 2016); Sonka, ¶174. A POSITA would have understood that the "known" methods Krishnan discloses as of 2005 did not employ neural networks for feature extraction. Sonka, ¶174. Thus, Petitioner's arguments as to limitation 30(b) fail as well. Sonka, ¶175.

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. Sonka, ¶176.

c. Additional Extrinsic Evidence Demonstrates That Krishnan's Feature Extraction Step Does Not 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. Sonka, ¶177.

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. *See* §II.A; Ex1029, Abstract; Ex2035-39; Sonka, ¶178. Prior to this, it was known that conventional approaches using manually engineered features were problematic. *See e.g.*, Ex2037, 8 ("[M]ethods [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"); Sonka, ¶¶179-81. Thus, a POSITA would have understood Krishan did not disclose learning extracted feature representations using a neural network. Sonka, ¶182.

2. Petitioner Fails to Show That Krishnan Discloses a "Quality Assessment Value" Under the Construction Petitioner Is Bound by in this IPR (Limitations 1(c)/21(c)/30(c))

Limitations 1(c)/21(c)/30(c) each recite a "quality assessment value." Ex1001, cl.1, 21, 30; Sonka, ¶183. As discussed in §IV.B, Petitioner is bound to apply the construction for this term as "score of diagnostic image quality." *See* Paper 15, 3; Sonka, ¶183.

To establish anticipation, Petitioner cannot mix teachings from distinct embodiments and instead must demonstrate Krishnan discloses an embodiment that anticipates the claims. *See BlephEx, LLC v. Myco Indus., Inc.*, 24 F.4th 1391, 1400-01 (Fed. Cir. 2022) (determining district court did not err in concluding that two figures in same reference depicted separate embodiments and rejecting anticipation argument because "[i]t is not enough that the prior art reference…includes multiple, distinct teachings that the artisan might somehow combine to achieve the claimed invention to show anticipation") (internal quotations and citations omitted); Sonka, ¶184.

For other limitations of claims 1 and 21, Petitioner relies on Krishnan's classifier embodiment. Sonka, ¶185. For example, for limitation 1(d), Petitioner maps to the Figure 5 classifier embodiment. Petition, 30-31 ("Referring to Figure 5, below, Krishnan states: 'In this exemplary embodiment, the feature data extracted from the image dataset would be input to classifiers…to classify the image data (step 501)' for example 'to determine the most likely …view … (step 502).'") (citing Ex1005, [0042]); *id.*, 31 (citing Fig. 5, quoting step 502 ("Determine…Most Likely View…of Image Dataset"), and stating "[t]hus, Krishnan discloses" limitation 1(d)); Sonka, ¶185.

For limitation 21(d), Petitioner points to its analysis of 1(d) without further analysis. Ex1005, 39; Sonka, ¶186.

For claim 30, Petitioner relies on the classifier embodiment of Figure 5 for limitation 30(b) as well at this limitation, 30(c). Ex1005, 45-49; Sonka, ¶187.

There are three alternative embodiments of the quality assessment module 105 in Krishnan (i.e., database querying, template based, and classification methods). Sonka, ¶188. Indeed, Dr. Deo agreed during his deposition that other embodiments of module 105 are "alternatives" to the classifier embodiment. *See* Ex2051, 57:7-58:14; Sonka, ¶188. There is no suggestion in Krishnan that teachings regarding other embodiments apply to the classifier embodiment. Sonka, ¶188. Thus, teachings regarding what the "quality assessment value" may be in Krishnan relating to "alternative" embodiments are irrelevant, and Petitioner must demonstrate that the classifier embodiment produces a "score of diagnostic image quality" for limitations 1(c), 21(c), and 30(c). *Id.*, ¶188.

Petitioner generally relies on Krishnan's quality assessment module 105 for teaching the quality assessment value of limitations 1(c), 21(c), and 30(c). Petition, 26-28 (1(c)), 38-39 (21(c)), 47-48 (30(c)); Sonka, ¶189. Petitioner cites general statements regarding a "level of diagnostic quality," a "range of values," or a "score." Petition, 26-28 (1(c): citing Ex1005, [0020], [0032], [0036]), 39 (21(c): pointing to analysis of 1(c)), 47-48 (30(c): citing Ex1005, [0020], [0021], [0023],

[0043]); Sonka, ¶189. Other than paragraph 43, the disclosures in the cited paragraphs (including a "score") are general teachings that are not necessarily related to the classifier embodiment. Paragraph 43 describes the classifier embodiment and discloses that the quality assessment value may be a "level of quality," but states nothing about a "score." Ex1005, [0043] (referring to a "level of quality"); Sonka, ¶189.

Thus, Petitioner fails to show the quality assessment module 105 produces a "score of diagnostic image quality" when implemented according to the classifier embodiment. Sonka, ¶190. Indeed, as to the classifier embodiment, Dr. Deo opined in his declaration that the output could be a score or could be a binary output, but Krishnan does not necessarily disclose that the output is a score. *See* Ex1002, ¶267 ("The output of such a trained model could either be continuous score (such as a numeric value between 0 and 1 or scaled to be between 0 and 100) or, if a hard threshold is applied to the continuous score, a binary output (0 or 1)."); Sonka, ¶190. Dr. Deo then confirmed during his deposition that Krishnan does not necessarily disclose the quality assessment value in the classifier embodiment is a score. Ex2051, 126:24-127:5; Sonka, ¶190. Although Dr. Deo's opinions were stated as to limitation 12(b), they are general statements regarding Krishnan's classifier embodiment and apply with equal force to these limitations. Sonka, ¶190.

Thus, the Petition fails to show that Krishnan discloses the claimed "quality assessment value" under the construction Petitioner is bound by in this IPR. Sonka, ¶191.

B. Ground B: Krishnan-Chen Does Not Render Obvious Claims 3-8 and 23-26

Petitioner's arguments related to Krishnan-Chen fail. Sonka, ¶192. As an initial matter, because Petitioner failed to show that the base independent claims 1 and 21 are taught by Krishnan as discussed above, Petitioner has also failed to show that any of dependent claims 3-8 and 23-26 are unpatentable over Krishnan in view of Chen for at least this reason. *See* §V.A; Sonka, ¶192. In addition, Petitioner fails to show that Krishnan-Chen renders obvious claims 3-8 and 23-26 for the reasons below. Sonka, ¶192.

1. Petitioner's Proposed Combination Is Unclear and Was Contradicted by Its Expert

Petitioner provides its motivation to combine theory with respect to claims 3 and 4 (Petition, 51-58) and otherwise refers to the same theory for the rest of the claims (Petition, 58-64). *Id.*, ¶193.

Petitioner offers unclear and contradictory descriptions for the proposed combination. *Id.*, ¶194. Thus, Petitioner fails to satisfy its burden to set forth a combination with particularity, and the Board should find that Petitioner has not shown these claims are unpatentable. 35 U.S.C. §312(a)(3); *adidas AG v. NIKE, Inc.*, IPR2016-00922, Paper 31, 53 (Feb. 19, 2019) ("[T]he determination by the Board that a Petitioner has failed to explain or justify a ground of unpatentability 'with particularity' is in accord with a determination made by the Board, on the same or similar evidentiary record, that a Petitioner has failed to make its case by a preponderance of the evidence. Stated differently, a lack of clarity or adequate explanation that is present when determining whether to institute trial does not somehow later benefit a Petitioner when examining the merits of the case under the guise of 'preponderance of the evidence.'"); Sonka, ¶194.

Petitioner first proposes to use Chen's neural network architecture to perform feature extraction in the Krishnan and Chen combination. Petition, 52-54 ("Rationale to combine:…Therefore, it would have been natural and obvious to a POSITA to combine the teachings of Krishnan and Chen by <u>using the neural network architecture disclosed in Chen to perform feature extraction</u> as described in Krishnan."), 57-58 ("Rationale to combine: A POSITA would be motivated to combine Krishnan-Chen in the manner proposed (i.e., <u>to use the T-RNN model disclosed in Chen to perform feature extraction and view identification as taught in Krishnan</u>) for the same reasons already explained in Section IX.C.1 above. Ex1002, ¶214."); Sonka, ¶195.

As discussed above, for the base independent claims 1 and 21, Petitioner relies on Krishnan's module 102 for performing feature extraction using "known methods" such as segmentation or filtering to extract features by reference to "known or anticipated image characteristics." *See* §V.A.1; Ex1005, [0034]; Sonka, ¶196. Thus, Petitioner's initial proposed combination is to use Chen's neural network architecture to perform feature extraction in place of Krishnan's automatic feature analysis module 102 (and to remove modules 103-105 as well) without separately analyzing how Chen's wholesale replacement discloses each limitation of claim 1. Sonka, ¶196.

Petitioner then contradicts this proposal and argues that a POSITA would merely "add[]" the neural networks described in Chen to Krishnan's existing classifiers "without modification." Petition, 55 ("A POSITA would also have had a reasonable expectation of success combining Chen with Krishnan. Krishnan already contemplates using a 'bank of classifiers' that perform respective functions. Implementing Chen with Krishnan would merely have involved adding the neural network classifier described in Chen, without modification, to the bank of classifiers described in Krishnan. Ex1002, ¶209."); *id.*, 58 ("And, merely adding Chen's T-RNN to Krishnan's 'bank of classifiers' to perform the same functions already described in Krishnan, would not require any modification of Krishnan or Chen. Ex1002, ¶216."); Sonka, ¶197.

Dr. Deo provides the same arguments. Ex1002, ¶209 ("Chen could therefore be implemented in Krishnan by adding the neural network classifier described in

Chen, with little to no modification to the bank of classifiers described in Krishnan."); *id.*, ¶215 ("A POSITA could merely add Chen's T-RNN to Krishnan's 'bank of classifiers' to perform the same functions already described in Krishnan, which would be a routine change requiring little to [no] experimentation on the part of the POSITA.")[4]; Sonka, ¶198.

The Petition provides no explanation for how wholesale replacement or the alleged addition of Chen's neural network architecture to Krishnan without modification would work. Sonka, ¶199. Dr. Deo was also unable to explain how the proposed combination would work at his deposition, and in fact offered contradictory opinions. *Id.*

For example, Dr. Deo contradicted the "adding" theory from his declaration by instead arguing that module 102, and potentially other modules, would be replaced at his deposition. Ex2051, 107:11-21 (initially stating that the combination requires "no modification" to Krishnan), 108:1-109:19 (subsequently stating that Chen's neural network replaces Krishnan's module 102); 110:16-111:1 (stating the combination would require "little" experimentation); 111:13-22 (stating that the replacement of module 102 is "necessary"); 112:5-113:24 (stating that the

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[4] Dr. Deo clarified that the word "know" should be replaced with "no." *See* Ex2051, 110:1-14.

combination may or may not require module 104 to be replaced); Sonka, ¶200.

At best, Petitioner offers two mutually exclusive paths—the combination can either replace Krishnan's feature extraction module 102 and other modules with Chen's T-RNN neural network or "add" Chen's T-RNN to Krishnan's classifiers 103-105 (with module 102 still in place). Sonka, ¶201. Petitioner, however, never explains with particularity what its combination actually is and how Chen's neural network architecture would successfully be added to Krishnan (with or without modification). *Id.*

2. A Person of Ordinary Skill Would Not Have Been Motivated to Combine Krishnan and Chen and Would Not Have Reasonably Expected a Combination to Succeed

Even if the Petition had clearly articulated how Krishnan and Chen would be combined, a POSITA would not have been motivated to combine them. Sonka, ¶203. Krishnan discloses a conventional system that relies on human-designed/hand-crafted rules to extract features with module 102 using "known segmentation and/or filtering methods." Ex1005, [0034]; Sonka, ¶203. Krishnan's module 102 removes the ability to train on raw images and discover patterns that human-designed rules could not find. Sonka, ¶203. The end-to-end approach in Chen is not compatible with the conventional approach disclosed in Krishnan, which uses a pipeline of serial modules rather than an integrated neural network technique. *Id.* A POSITA seeking to implement a neural network that derives extracted features from images—or that is trained by receiving images as input and outputting quality assessment values and image properties—would not have found Krishnan's fundamentally different approach to be an appropriate starting point. *Id*.

Even assuming a motivation, the combination certainly would require more than no or little modification and a POSITA would not have had a reasonable expectation of success in combining Krishnan and Chen. Sonka, ¶204. The Petition advances two incompatible theories: (1) using Chen's T-RNN to perform feature extraction and, apparently, replacing modules 102-105; and (2) "adding" Chen's neural network (T-RNN) to Krishnan's bank of classifiers, with module 102 still in place (and potentially modules 103-105 still in place). *Id*.

As to (1), Petitioner cannot reasonably contend that replacing modules 102-105 with Chen's T-RNN would require "little" or "no" modification, because it is a wholesale replacement of Krishnan's sequential pipeline with a new architecture. *Id*., ¶205. Moreover, a wholesale replacement would not satisfy the claim, e.g., because Chen does not disclose outputting any quality assessment value. *Id*.

As to (2), if Chen's T-RNN is "added" to Krishnan's classifiers 103-105 with module 102 still in place, this also would not require little or no modification. *Id*., ¶206. Chen's T-RNN includes J-CNN, which is designed to receive ultrasound image frames, not the extracted features that module 102 outputs. Ex1009, Fig. 2; Ex2052, 13:8-10; Sonka, ¶206. But if Krishnan's module 102 remains, Chen's J-

CNN would instead receive extracted features. A POSITA would not expect reliable or useful results when Chen's J-CNN receives inputs it was not designed to receive. Sonka, ¶206. Indeed, Dr. Deo admitted during his deposition that classification modules 103-105 take extracted features as inputs and that module 102 is distinct because it does not implement classification methods like modules 103-105. *See* Ex2051, 54:22-55:10 (module 103 takes extracted features as input), 56:4-10 (module 104 takes extracted features as input), 56:23-57:4 (module 105 takes extracted features as input), 59:23-60:9 (module 102 is not listed as module that implements classification methods like modules 103-105); Sonka, ¶206. Because module 102 outputs extracted features and not images, Chen's J-CNN would not function as it was designed in Petitioner's combination because it would not receive raw images. Sonka, ¶206. Moreover, the Petition does not explain what role modules 103-105 would serve alongside Chen's T-RNN, which itself includes classification layers. *Id.*

Further, it was known that conventional feature extraction, like that provided by Krishnan's module 102, would not work well on low-contrast ultrasound images. *See* Ex2037, 8; Sonka, ¶207. Therefore, feeding features extracted from ultrasound image into a deep neural network designed for raw images would not have had a reasonable expectation of success. *See id.*

In addition, if module 102 were to be replaced with Chen's feature extracting neural network while keeping Krishnan's modules 103-105 as-is, a POSITA would not have reasonably expected success. Sonka, ¶208. Modules 103-105 were designed to input features that were extracted according to hand-crafted/human designed rules from module 102. Ex1005, [0034]; Sonka, ¶208. Feeding these modules learned features from a neural network would require redesigning and retraining modules 103-105 to accept different inputs. Sonka, ¶208. The Petition does not describe any of the modifications that would be needed and simultaneously asserts that only little or no modification would be required, which is irreconcilable. Petition, 55, 58; Sonka, ¶208.

C. Ground C: Krishnan-Aase Does Not Render Obvious Claims 9/27 and 10/28

Because Petitioner did not establish that the base independent claims 1 and 21 are taught by Krishnan as discussed above, Petitioner has also failed to show that any of dependent claims 9-10 and 27-28 are obvious over Krishnan in view of Aase. *See* §V.A; Sonka, ¶209. But even if the independent claims were shown to be unpatentable, Petitioner has failed to meet its burden to show that these dependent claims would have been obvious. Sonka, ¶209.

For claims 9-10 and 27-28, the Petition proposes a combination of Krishnan and Aase, where Krishnan uses Aase's view-category-specific and quality-assessment-value specific neural networks. Petition, 65 ("Based on the express teachings in Krishnan, it would have been obvious to a POSITA to implement Krishnan using a view-category-specific neural network and a quality-assessment-value-specific neural network as described in Aase."), 66-67 ("Thus, whereas Krishnan extracts features from a set of ultrasound images and inputs the extracted features into a bank of classifiers that perform the function of view identification and quality assessment, Aase explicitly includes a view-category-specific neural network classifier and a quality-assessment-value-specific neural network classifier. Ex1002, ¶¶243-245."), 67 ("Aase makes explicit what Krishnan already discloses or suggests, i.e., a quality-assessment-specific neural network can be used to assess quality, and a view-assignment-specific neural network can be used to identify the view category."), 67-68 ("A POSITA would also have had a reasonable expectation of success since Krishnan and Aase are directed to the same field of endeavor, and Krishnan already expressly describes using a bank or set of neural network classifiers. Implementing Krishnan in a manner that achieves the claimed subject matter <u>would not require any material modification or experimentation</u>. Ex1002, ¶¶247-248."), 69 ("Krishnan-Aase further teaches inputting the extracted features from a set of ultrasound images into separate quality assessment and view identification specific neural network classifiers, as claimed. *See* Section IX.D.1. Thus, Krishnan-Aase teaches all the elements of [10]/[28]. Ex1002, ¶¶249-254."); Sonka, ¶210.

For the same reasons described regarding Krishnan-Chen, a POSITA would not have been motivated to combine Krishnan's conventional system that relies on human-designed/hand-crafted rules to extract features with Aase's neural network approach. §V.B.2.; Sonka, ¶211.

Moreover, this proposed Krishnan-Aase combination is fundamentally flawed. Sonka, ¶212. As is, Aase's feature extraction processing is embedded in the initial layers within the neural networks of its view-assignment-specific neural network (module 160) and quality-assessment-specific neural network (module 170). *See* Ex1006, [0033] ("Each neuron of each layer may perform a processing function and pass the processed ultrasound image information to one of a plurality of neurons of a downstream layer for further processing. As an example, neurons of a first layer may learn to recognize edges of structure in the ultrasound image data. The neurons of a second layer may learn to recognize shapes based on the detected edges from the first layer. The neurons of a third layer may learn positions of the recognized shapes relative to detected landmarks in the ultrasound image data."); *id.*, [0035] ("As an example, neurons of a first layer may learn to recognize a blocked ultrasound transducer aperture, such as by an ultrasound operator finger, a rib of a patient, or any suitable obstruction. The neurons of a second layer may learn to recognize shadows in ultrasound image data caused by a patient's ribs or a breathing lung, among other things. The neurons of a third layer may learn to recognize movement noise caused by the probe 104 transitioning from one image view type to another image view type."); Sonka, ¶212.

However, in Petitioner's proposed combination, Aase's quality-assessment-specific neural network and view-assignment-specific neural network are separated from Aase's feature extraction neural network. *See* Ex2051, 121:8-122:10 (explaining that initial layers of Aase's neural network classifiers do feature extraction for the purpose of view classification and quality assessment); Sonka, ¶213. Rather than receiving specific learned feature representations produced by Aase's own feature extraction layers, Aase's classification neural networks would instead receive outputs from Krishnan's module 102, which produces entirely different hand-crafted features (e.g., edges, boundaries, intensity transitions, etc.). *See* 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[.], using known methods."); Sonka, ¶214

Since Aase's classification neural networks expect specific learned feature representations produced by its own feature extraction layers, a POSITA would not have had a reasonable expectation of success when providing Aase's classification layers hand-crafted extracted features. *See* Ex1006, [0033]-[0034]; Sonka, ¶215. The hand-crafted features that Krishnan's module 102 outputs are an imperfect representation of the overall content of the original image and contain much less information than the original image. Sonka, ¶215. The Petition fails to explain how deep learning with these features would work, and a POSITA would not have expected that using the extracted features instead of images in the Krishnan-Aase combination would work properly. Sonka, ¶215. Additionally, as described above, there would not have been a reasonable expectation of success because it was known that conventional feature extraction, like that provided by Krishnan's module 102, would not work well on low-contrast ultrasound images. *See* §V.B.2; Ex2037, 8; Sonka, ¶215.

Thus, the classification layers would need to be modified to accept Krishnan's hand-crafted features, which the Petition never explains. Sonka, ¶216.

Petitioner also provides no explanation of how Aase's classification neural networks, which are trained end-to-end with Aase's feature extraction neural network, would be trained when Aase's feature extraction neural subnetwork is removed. *Id.*, ¶217. Petitioner completely ignores these fundamental incompatibilities between Krishnan and Aase, and instead incorrectly suggests that the combination would require no material modification or experimentation. *See e.g.*, Petition, 68 ("Implementing Krishnan in a manner that achieves the claimed subject matter would not require any material modification or experimentation.");

Sonka, ¶217.

Petitioner's expert contradicts the proposed combination as well. Dr. Deo's declaration states that the combination "would not require any material modification or experimentation." Ex1002, ¶247; Sonka, ¶218. However, he disavowed the Petition's combination during his deposition by testifying that the combination would require removing Krishnan's modules 102-105 and replacing them with Aase. *See* Ex2051, 116:13-117:15; Sonka, ¶218. Dr. Deo could not explain details about the combination and could only point to paragraphs 245 and 246 of his declaration as purportedly demonstrating this swapping of Krishnan's modules and Aase's neural networks. *See* Ex2051, 118:2-120:5; Sonka, ¶219. However, these paragraphs mention nothing about, let alone explain, how Krishnan's modules 102-105 should be removed and swapped out. Ex1002, ¶¶ 245-46; Sonka, ¶220.

Neither the Petition nor Dr. Deo's declaration includes anything about removing and swapping out Krishnan's modules 102-105 for the proposed Krishnan-Aase combination. Sonka, ¶221. Petitioner also fails to provide any motivation for a wholesale replacement of Krishnan's modules 102-105 with Aase's modules, and there is no motivation for doing so as described regarding Krishan-Chen. §V.B.2; Sonka, ¶221.

D. Ground D: Krishnan-Chen-Wu Does Not Render Obvious Claims 12-20

1. Petitioner Fails to Articulate a Proposed Combination of Krishnan, Chen, and Wu, Let Alone a Motivation to Combine With a Reasonable Expectation of Success (Claims 12-20)

For this ground, Petitioner relies on a combination of Krishnan in view of Chen and Wu. Petition, 69-87; Sonka, ¶222. Even worse than Grounds B or C, for Ground D, Petitioner and Dr. Deo have not even attempted to describe a particular combination. Sonka, ¶222.

With respect to rationale to combine and reasonable expectation of success, the Petition relies on general statements in 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. Sonka, ¶223. 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"); Sonka, ¶224.

However, the Petition fails to explain with any particularity how either of the training frameworks of Chen and Wu would be modified to work with Krishnan's implementation. Petition, 72-73; Sonka, ¶225. 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); Sonka, ¶225.

Indeed, for the same reasons described regarding Krishnan-Chen, a POSITA would not have been motivated to combine Krishnan's conventional system that relies on human-designed/hand-crafted rules to extract features with Chen's and Wu's neural network approaches. §V.B.2.; Sonka, ¶226.

Dr. Deo's declaration does not make up for the Petition's deficiencies. Sonka, ¶227. 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. *Id.* For example, Dr.

Deo first states that "it would have been intuitive to a POSITA to use recurrent neural networks—like those disclosed 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; Sonka, ¶227. Dr. Deo then lists excerpts from Chen and Wu regarding techniques for training and then repeats his assertions regarding motivation to combine. *See* Ex1002 ("a POSITA would have been further motivated to implement the training methods described in Chen and Wu"); Sonka, ¶227.

With respect to reasonable expectation of success, the only support that Dr. Deo provides is the same general statements in Chen and Wu cited in the Petition, which state that their implementations can be extended or generalized to other contexts. *See* Ex1002, ¶262; Sonka, ¶228. However, like the Petition, Dr. Deo fails to specifically explain how either of their frameworks would be modified to work with other implementations. *See id*.

The Petition then jumps from general motivation (Krishnan contemplates neural networks, Chen/Wu teach architectures/training) to claim-by-claim mapping without describing the actual combination. Petition, 71-73; Sonka, ¶229.

Dr. Deo could not explain the combination during his deposition either. In fact, he repeatedly contradicted himself during the deposition and effectively admitted that he had not proposed an actual combination. *See* Ex2051, 122:23-123:3

(stating that Krishnan's module 102 is removed from the combination); *id.*, 123:4-15 (stating that Krishnan's module 102 is swapped out and modules 103-105 are optional); Ex2052, 23:5-20 (stating that it was "never [his] intention" to swap modules); *id.*, 24:5-9 (stating that Krishnan's modules are a "scaffold" to which other references provide modern implementations); Sonka, ¶230.

Accordingly, the Petition fails to satisfy the particularity requirement of 35 U.S.C. §312(a)(3). Sonka, ¶231. Further, Petitioner has failed to demonstrate why a POSITA would have been motivated to combine the references with a reasonable expectation of success. *Id.*

2. Krishnan (or Krishnan-Chen-Wu) Fails to Disclose or Teach a Neural Network That Uses a Set of Ultrasound Training Images as an Input (Limitation 12(d))

In addition to the general deficiency as to claims 12-20 discussed above, Petitioner has failed to show that the combination discloses limitation 12(d). Sonka, ¶232. And because Petitioner has failed to show that limitation 12(d) is disclosed, Petitioner has failed to show that claim 12 and dependent claims 13-20 are unpatentable. *Id.*

Limitation 12(d) recites "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." Sonka, ¶233. In other words, this limitation requires inputting training images into a neural network to train the network. *Id*.

Petitioner relies on Krishnan in view of Chen and Wu for claim 12. Petition, 69-79; Sonka, ¶234. However, for limitation 12(d), the Petition cites neither Chen nor Wu and instead relies solely on Krishnan. Petition, 78-79; Sonka, ¶234.

For 12(d), the Petition argues that "Krishnan trains one or more neural network classifiers." Petition, 78 (citing Ex1005, [0023], [0044]); Sonka, ¶235. The Petition further 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.'" Petition, 78 (citing Ex1002, ¶273; Ex1018, [0037], [0040]-[0041]); Sonka, ¶235.

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. Sonka, ¶236. Instead, Petitioner cites Ex1018 ("Pagoulatos"), which is a patent application filed/published in 2017 that is not part of Petitioner's proposed obviousness ground and cannot be relied upon to supply a missing limitation. *See* 37 C.F.R. §42.104(b)(4); Sonka, ¶237.

Even if Petitioner could rely on Pagoulatos, its disclosures are irrelevant because Krishnan's actual disclosures foreclose any argument that Krishnan discloses a neural network that uses a set of ultrasound training images as input. Sonka, ¶238. As explained regarding Ground A, Krishnan does not disclose neural network "classifiers" that take ultrasound training images as inputs (for either image analysis or training purposes). *See* §V.A.1.; Sonka, ¶238.

Instead, only Krishnan's modules 103-105 may employ classification methods in the Figure 5 embodiment, and those modules receive extracted features as input. Ex1005, [0042] ("[F]eature 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.*, [0043] ("For example, a bank of classifiers could be constructed to classify the images based on the features extracted…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."); Sonka, ¶239.

Module 102 does not employ classification methods or classifiers that may be built with neural networks. Instead, module 102 extracts features from images using non-neural network techniques such as segmentation or filtering, and it provides those extracted features as inputs to modules 103-105. *See* Ex1005, [0034]; Sonka, ¶240. As described above, there would not have been a reasonable expectation of success because it was known that conventional feature extraction, like that provided by Krishnan's module 102, would not work well on low-contrast ultrasound images. *See* §V.B.2; Ex2037, 8; Sonka, ¶240.

Moreover, Petitioner cannot rely on Chen or Wu to teach limitation 12(d) when it did not analyze either reference for this limitation. 35 U.S.C. §312(a)(3); 37 C.F.R. §42.104(b)(4); Sonka, ¶241. But even if the Board were to reconstruct a combination, any version that uses Chen or Wu for feature extraction while retaining Krishnan's separate classifiers 103-105 would not be expected to succeed without modification—which Petitioner does not explain—because modules 103-105 are not designed to provide classification feedback to the feature extractor. Sonka, ¶241. Thus, Petitioner has not shown that Chen's/Wu's neural networks could learn how to extract features. *Id*.

Otherwise, this would be a wholesale replacement of Krishnan with Chen and Wu, which the Petition fails to explain at all and moreover would destroy Krishnan's modular architecture. *Id*., ¶242.

Thus, the Petition fails to demonstrate that the proposed combination of Krishnan, Chen, and Wu discloses a neural network that uses a set of ultrasound images as an input as limitation 12(d) requires. Sonka, ¶243.

3. Petitioner's Krishnan-Chen-Wu Combination for Claims 14-20 Suffers From Additional Deficiencies

For the reasons above, Petitioner has not shown that the Krishnan-Chen-Wu combination renders obvious claim 12. Sonka, ¶244. As a result, Petitioner has not shown that dependent claims 13-20—which depend from claim 12—are unpatentable. *Id.*

Moreover, there are additional deficiencies as to Petitioner's analysis of dependent claims 14-20. *Id.*, ¶245. For claims 14-15, which ultimately depend from claim 12, Petitioner proposes that "Krishnan discloses the 'feature extracting neural network.'" Petition, 80 (claim 14); *id.*, 81 (claim 15); Sonka, ¶246. But as explained above, Krishnan's module 102—which extracts features—is not a neural network. Sonka, ¶246.

Dr. Deo confirmed during his deposition that Krishnan's module 102 is the alleged feature extracting neural network, but Dr. Deo then contradicted himself and argued he was also relying on Chen and Wu without explicitly citing them. Ex2052, 4:14-9:7; Sonka, ¶247. Petitioner, however, does not cite disclosures in Chen or Wu for these claims. Petition, 79-81; Sonka, ¶247. Thus, Krishnan-Chen-Wu has not been shown to teach these claims. Sonka, ¶247. But even if a combination were reconstructed based on the teachings of Chen and Wu, such a combination would not work for the same reason as described regarding claim 12. *Id.*

With respect to claims 16-20, Petitioner has failed to explain what the proposed combination is or how the teachings of one reference would be applied to the other. *Id.*, ¶248.

All of these claims require a "feature extracting neural network." Petition, 81-

83 (cl.16); *id*., 83-84 (cl.17); *id*., 84 (cl.18); *id*., 84-87 (cl.19); *id*., 87 (cl.20); Sonka, ¶249. The Petition's combinations are unclear as to what the "feature extracting neural network" is and thus fail to meet Petitioner's burden. Petition, 81-87; Sonka, ¶249. Further, there is no statement anywhere in Dr. Deo's declaration about how Krishnan would be modified to incorporate the teachings of Chen and Wu. *See* Ex1002, 134-160; Sonka, ¶249.

Dr. Deo's contradictory testimony only exacerbates the deficiencies. Sonka, ¶250. For example, Dr. Deo testified regarding claim 16 that he was not relying on Chen's neural network to extract features in the combination, and then Dr. Deo contradicted himself and stated that Chen was "a possible embodiment" of Krishnan's feature extraction without taking a position. Ex2052, 13:4-7 (stating that he was not relying on Chen's J-CNN as the claimed feature extracting neural network); *id*., 13:15-14:6 (testifying that "Chen is a possible embodiment" of Krishnan's feature extraction functions); Sonka, ¶250.

Further, as to claim 19, Dr. Deo testified that Krishnan's module 102 would instead be implemented as Chen's neural network without explaining how the combination would work. Ex2052, 19:9-16 (stating that Chen is implemented as Krishnan's module 102); Sonka, ¶251.

VI. PETITIONER'S EXPERT DR. DEO OFFERS CONCLUSORY AND CONTRADICTORY OPINIONS THAT PRECLUDE A FINDING THAT ANY CHALLENGED CLAIM IS UNPATENTABLE

"Expert testimony that does not disclose the underlying facts or data on which the opinion is based is entitled to little or no weight." 37 C.F.R. § 42.65(a). Here, there is a pervasive problem with Dr. Deo's conclusory and contradictory expert testimony. Sonka, ¶252. The record is replete with examples where Dr. Deo's declaration does not explain the basis for the positions in the declaration (or the Petition) and where Dr. Deo's deposition testimony contradicts both (1) the opinions in his declaration; and (2) other deposition testimony regarding the same issue. *Id.*, ¶¶252-254.

For example, Dr. Deo disavowed the conclusory theory from his declaration that Krishnan needed no modification in the proposed combination of Krishnan and Chen by instead arguing at his deposition that Krishnan's module 102, and potentially other modules, would need to be replaced. *See* §V.B.1; Ex2051, 107:11-21 (initially stating that the combination requires "no modification" to Krishnan), 108:1-109:19 (subsequently stating that Chen's neural network replaces Krishnan's module 102), 110:16-111:1 (stating the combination would require "little" experimentation), 111:13-22 (stating that the replacement of module 102 is "necessary"), 112:5-113:24 (stating that the combination may or may not require module 104 to be replaced); Sonka, ¶252.

In another instance, Dr. Deo made contradictory statements regarding the combination of Krishnan and Chen that were not articulated in the Petition. *See* §V.B.1; Ex2051, 122:23-123:3 (stating that Krishnan's module 102 is removed from the combination), 123:4-15 (stating that Krishnan's module 102 is swapped out and modules 103-105 are optional); Ex2052, 23:5-20 (stating that it was "never [his] intention" to swap modules), 24:5-9 (stating that Krishnan's modules are a "scaffold" to which other references provide modern implementations); Sonka, ¶253.

Dr. Deo's testimony is internally inconsistent on material issues and, on obviousness issues, repeatedly contradicts his declaration (while in certain places disclaims the existence of a concrete proposed combination at all). Sonka, ¶254. Dr. Deo's testimony cannot be relied upon to meet Petitioner's burden to demonstrate the unpatentability of any challenged claim. *Interactive Commc'ns Int'l, Inc. v. Blackhawk Network Inc.*, IPR2024-00465, Paper 40, 3-4 (Oct. 9, 2025) (Director Squires) ("The Board abused its discretion by improperly crediting expert testimony that has multiple material contradictions and that the Board found lacked credibility at least in certain respects…Because the Board rested its finding of a reason to combine on Mr. Hutton's contradictory testimony and that testimony was central to Petitioner's analysis that an ordinarily skilled artisan would have had a reason to combine the disclosures of Szrek and Llach, the Board's finding of unpatentability on the Szrek-based grounds is vacated…The Petition also raises other grounds that rely on Mr. Hutton's testimony that the Board's Decision did not reach. *See* Decision 51. Having determined that Mr. Hutton is not credible as to multiple material aspects of his testimony, it would be inappropriate in this instance to rely on this testimony for the other grounds."); *see also Finesse Wireless LLC v. AT&T Mobility LLC*, 156 F.4th 1221, 1227 (Fed. Cir. 2025) ("When the party with the burden of proof, . . . rests its case on an expert's self-contradictory testimony, we may conclude the evidence is insufficient to satisfy that standard."); *N.L.R.B. v. Pittsburgh S.S. Co.*, 337 U.S. 656, 659 (1949) ("[I]n the determination of litigated facts, the testimony of one who has been found unreliable as to one issue may properly be accorded little weight as to the next."); Sonka, ¶¶252-254.

VII. SECONDARY CONSIDERATIONS

Secondary considerations of nonobviousness further support that grounds B, C, and D do not demonstrate that the challenged claims are unpatentable. Sonka, ¶255.

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. *Id.*, ¶256. 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. *See* §II.A; Sonka, ¶256. For example, there was a long known issue with conventional methods, like those described in Krishnan, not working well on low-contrast ultrasound images. *See, e.g.*, Ex2037, 8; Sonka, ¶256. The ’029 patent’s end-to-end learning system fulfilled this unmet need. Sonka, ¶256.

That the ’029 patent overcame these challenges is evidenced by the recognition of others in the field that the ’029 patent was pioneering with respect to its deep learning approach for deriving task-specific training-set-optimal features from ultrasound images. *Id.*, ¶257. 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); Sonka, ¶257.

Such widespread citation by industry leaders indicates that a POSITA would have recognized the ’029 patent as disclosing a novel and nonobvious contribution as of its 2018 priority date—specifically, its deep-learning approach for automatically deriving task-specific feature representations from ultrasound images, rather than relying on the hand-crafted feature extraction techniques that dominated the field previously. Sonka, ¶258. 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. *Id.*

VIII. CONCLUSION

For all the above reasons, Petitioner has not met its burden of demonstrating the unpatentability of any challenged claim. Sonka, ¶260. Accordingly, UBC requests the Board confirm the patentability of claims 1-30. *Id.*

Respectfully submitted,

Dated: May 8, 2026

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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 Response to the Petition for *inter partes* review totals 13,956 words, 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.

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 RESPONSE and accompanying exhibits by email to the electronic service addresses for Petitioner on the date indicated below:

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