

IN THE 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

U.S. PATENT NO. 10,751,029

PETITIONER'S REPLY

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EXHIBIT LIST

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Ex1001	U.S. Patent No. 10,751,029 (“the Patent”)
Ex1002	Declaration of Dr. Rahul Deo
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Ex1004	Prosecution History File of the Patent (Application No. 16/557,261)
Ex1005	U.S. Patent Application Publication No. 2005/0251013 (“Krishnan”)
Ex1006	U.S. Patent Application Publication No. 2019/0076127 (“Aase”)
Ex1007	U.S. Patent No. 10,013,640 (“Angelova”)
Ex1008	International Patent Application Publication No. WO2016/189313 (“Paterson”)
Ex1009	Chen, “Automatic Fetal Ultrasound Standard Plane Detection Using Knowledge Transferred Recurrent Neural Networks,” Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015: 507-514 (November 18, 2015), https://doi.org/10.1007/978-3-319-24553-9_62 (“Chen”)
Ex1010	Wu, “FUIQA: Fetal Ultrasound Image Quality Assessment With Deep Convolutional Networks,” IEEE Transactions on Cybernetics, 47(5):1336-1349 (May 2017), doi: 10.1109/TCYB.2017.2671898 (“Wu”)
Ex1011	First Amended Complaint, <i>University of British Columbia v. Caption Health, Inc.</i> , Case No. 5:24-cv-03200-EKL, Dkt. 46, Dec. 20, 2024.
Ex1012	Itchhaporia, “Artificial Neural Networks: Current Status in Cardiovascular Medicine,” JACC 28(2): 515-521 (August 1996) (“Itchhaporia”)
Ex1013	Chen, “Iterative Multi-domain Regularized Deep Learning for Anatomical Structure Detection and Segmentation from Ultrasound Images,” Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 487-495 (October 2, 2016)
Ex1014	Kong, “Recognizing End-Diastole and End-Systole Frames via Deep Temporal Regression Network,” Medical Image Computing and Computer-Assisted Intervention—MICCAI 2016: 264-272 (2016), DOI:10.1007/978-3-319-46726-9_31

No.	Description
Ex1015	Joint Claim Construction and Prehearing Statement, <i>University of British Columbia v. Caption Health, Inc.</i> , Case No. 5:24-cv-03200-EKL, Dkt. 68, May 30, 2025.
Ex1016	Chen, “Standard plane localization in fetal ultrasound via domain transferred deep neural networks,” <i>IEEE Journal of Biomedical and Health Informatics</i> , 19(5): 1627-1636 (September 2015), DOI:10.1109/JBHI.2015.2425041 (“Chen I”)
Ex1017	Miller et al., “Review of neural network applications in medical imaging and signal processing,” <i>Medical & Biological Engineering & Computing</i> (30):449-464 (September 1992) (“Miller”)
Ex1018	U.S. Patent Application Publication No. 2017/0262982 (“Pagoulatos”)
Ex1019	Reserved
Ex1020	González et al., “Echocardiogram Image Recognition Using Neural Networks in Recent Advances on Hybrid Approaches for Designing Intelligent Systems,” <i>Studies in Computational Intelligence</i> 547:427-435 (March 2014) (“González”)
Ex1021	Donahue et al., “Long-term Recurrent Convolutional Networks for Visual Recognition and Description,” arXiv:1411.4389v1 [cs.CV] (November 2014) (“Donahue”)
Ex1022	Caruana, “Multitask Learning: A Knowledge-Based Source of Inductive Bias,” <i>Proceedings of the 10th International Conference on Machine Learning, ML-93</i> , University of Massachusetts, Amherst, 1993, pp. 41-48.
Ex1023	U.S. Patent No. 5,906,578 (“Rajan”)
Ex1024	U.S. Patent Application Publication No. 2009/0074280 (“Lu”)
Ex1025	U.S. Patent Application Publication No. 2007/0055153 (“Simopoulos”)
Ex1026	Salomon LJ et al. A score-based method for quality control of fetal images at routine second-trimester ultrasound examination. <i>Prenat Diagn.</i> 2008 Sep;28(9):822-7. doi: 10.1002/pd.2016. PMID: 18646244
Ex1027	LeCun et al., “Handwritten Digit Recognition with a Back-Propagation Network,” <i>Neural Computation</i> . 1 (4): 541–551. doi:10.1162/neco.1989.1.4.541. ISSN 0899-7667. S2CID 41312633 (“LeCun”)

No.	Description
Ex1028	A. Bouzerdoun, et al., "Image quality assessment using a neural network approach," Proceedings of the Fourth IEEE International Symposium on Signal Processing and Information Technology, 2004., Rome, Italy, 2004, pp. 330-333, doi: 10.1109/ISSPIT.2004.1433751 ("Bouzerdoun")
Ex1029	A. Krizhevsky, et al., "ImageNet classification with deep convolutional neural networks," Communications of the ACM, Volume 60, Issue 6, pp. 84-90 doi: 10.1145/3065386 (June 2017) ("Krizhevsky")
Ex1030	Declaration of Marla R. Butler in Support of Motion for Admission <i>Pro Hac Vice</i>
Ex1031	Declaration of William E. Manske in Support of Motion for Admission <i>Pro Hac Vice</i>
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Ex1033	Order Granting Plaintiff's Motion for leave to Amend Infringement Contentions, Dkt. 74, July 2, 2025
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Ex1037	Caption Health, Inc. v. University of British Columbia, IPR2025-01066, Paper 13 (October 10, 2025)
Ex1038	UBC's First Supplemental Objections and Response to Defendant's First Set of Interrogatories (Nos. 1-3), March 7, 2025
Ex1039	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
Ex1040	Reserved
Ex1041	Reserved
Ex1042	Lorentzon, M. "Feature Extraction for Image Selection Using Machine Learning," Department of Electrical Engineering, Linköping University, 2017, pp.1-45

No.	Description
Ex1043	Kumar, G. et al. “A Detailed Review of Feature Extraction in Image Processing Systems” 2014 Fourth International Conference on Advanced Computing and Computational Technologies, pp.5-12.
Ex1044	Oivind Due Trier, et al., “Feature Extraction Methods For Character Recognition – A Survey,” Pattern Recognition 29 (4), pp. 641-662 (1996)
Ex1045	Jain, et al., “Artificial Neural Networks: A Tutorial,” IEEE Computer, Vol. 29 (3), pp. 31-44 (March 1996)
Ex1046	Supplemental Declaration of Dr. Deo
Ex1047	M. Egmont-Petersen, et al., “Image processing with neural networks—a review,” Pattern Recognition 35 (2002), pp. 2279-2301
Ex1048	R. Silverman, “Segmentation of Ultrasonic Images with Neural Networks,” International Journal of Pattern Recognition and Artificial Intelligence, Vol. 5, No. 4, pp. 619-628 (1991)
Ex1049	Lampinen, “Distortion Tolerant Pattern Recognition Based on Self-Organizing Feature Extraction,” IEEE Transactions on Neural Networks, Vol. 6, No. 3, pp. 539-547 (May 1995)
Ex1050	Boskovitz and Guterman, “An Adaptive Neuro-Fuzzy System for Automatic Image Segmentation and Edge Detections,” IEEE Transactions on Fuzzy Systems, Vol. 10, No. 4, pp. 247-262 (April 2022)
Ex1051	S. Becker and M. Plumbley, “Unsupervised Neural Network Learning Procedures For Feature Extraction and Classification,” Journal of Applied Intelligence (6) pp. 185-203 (1996)
Ex1052	J. Mao and A. Jain, “Artificial Neural Networks for Feature Extraction and Multivariate Data Projection,” IEEE Transactions on Neural Networks, Vol. 6, No. 2, pp. 296-317 (1995)
Ex1053	Donahue, et al., “ DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition,” International Conference on Machine Learning (pp. 647-655) PMLR (2014)
Ex1054	June 9, 2022, Director Vidal Guidance Memorandum
Ex1055	July 31, 2025, Director Stewart Guidance Memorandum
Ex1056	Pham et al., “Current Methods in Medical Image Segmentation,” Annu. Rev. Biomed. Eng. 2 (2000): 315-37.

No.	Description
Ex1057	Hasegawa et al., “A Shift-Invariant Neural Network for the Lung Field Segmentation in Chest Radiography,” Journal of VLSI Signal Processing Systems 18.3 (1998): 241-250.
Ex1058	Ning et al., “Toward Automatic Phenotyping of Developing Embryos from Videos,” IEEE Transactions on Image Processing, 2005, 14 (9), pp.1360-1371.
Ex1059	LeCun et al. “Gradient-based learning applied to document recognition,” Proceedings of the IEEE 86.11 (1998): 2278-2324.
Ex1060	Transcript of Dr. Sonka’s Deposition

CLAIMS APPENDIX

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]	he 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]	he 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

The primary prior art reference, Krishnan (Ex1005), discloses—practically *verbatim*—every element of at least claims 1, 2, 21, and 22 of the challenged Patent. Patent Owner (“PO”) has foregone the opportunity to amend its claims and, instead, attempts to save them through claim construction by improperly reading in an unrecited “neural network” limitation. No person of ordinary skill in the art (“POSITA”) would conclude, as PO does, that “extracted feature representations” can only be derived from an image using a neural network (“NN”). Although the Patent describes embodiments that use NNs, neither the Patent nor its prosecution history disavows the myriad other known techniques for deriving extracted features from an image. Instead, the Patent explicitly states that NNs or alternative feature extracting functions can be used.

But regardless, even if the claims did require a feature extracting NN, as PO contends, Krishnan discloses that too. Krishnan repeatedly states that the functions of its data processing module (101), including feature extraction module (102), can be performed using “one or more classifiers,” which Krishnan specifically states may be built from NNs. PO is wrong when it contends that these statements, as applied to the feature extraction module (102), are merely typographical errors. Contrary to PO’s claims, it was well-known before Krishnan’s filing date to extract feature representations from images using NNs—including within the hidden

layers of NN classifiers. Therefore, a POSITA would not dismiss—as merely an obvious error—Krishnan’s disclosure that its feature extraction module (102) can be implemented using a NN.

II. CLAIM CONSTRUCTION

PO proposes to construe “extracted features representations” as “feature representations that are learned using a neural network” for no other reason than the Patent describes embodiments in which NNs perform feature extraction. PO’s expert, Dr. Sonka, admits, however, that “conventional” feature extracting functions do not utilize NNs. Ex2049, ¶74, ¶134; Ex1060, 13:20-14:5.

To justify its construction, PO quotes *GPNE Corp. v. Apple Inc.* for the proposition that “when a patent ‘repeatedly and consistently’ characterizes a claim term in a particular way, it is proper to construe that claim term in accordance with that characterization.” Response, 29 (citing 830 F.3d 1365, 1370-71 (Fed. Cir. 2016)). That vague proposition is certainly not a hard and fast rule of claim construction. Nor does it overrule decades of established precedent that repeatedly warns against restricting the scope of claims to just the disclosed embodiments—even when only a single embodiment is described. *See, e.g., Liebel-Flarsheim Co. v. Medrad, Inc.*, 358 F.3d 898, 906-908 (Fed. Cir. 2004) (summarizing cases in which “there were specific reasons dictating a narrow claim construction beyond the mere fact that the specification disclosed only a single embodiment or

particular structure”). More importantly though, the proposition does not even apply here because the challenged Patent does not consistently characterize “extracted feature representations” as only being derived by NNs.

As PO and Dr. Sonka admit, many varied techniques—not based on NNs—were known for extracting feature representations from images prior to the filing date of the Patent. *See generally*, Ex1044 (1995) (discussing NNs as an alternative feature extraction technique); Ex1043, “A Detailed Review of Feature Extraction in Imaging Processing Systems” (2014); Ex1042 (2017); Ex1046 (Deo Supplemental Decl.), ¶7. Indeed, that is the basis for PO’s attempt to distinguish Krishnan. The Patent does not provide a special definition of “extracted feature representations”—either explicitly or implicitly—that would exclude any of these techniques. To the contrary, the Patent explicitly leaves open the possibility of extracting features from images by means other than NNs. For example, the specification states:

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.

Ex1001, 6:35-41 (emphasis added). And, most importantly, the specification states:

“In various embodiments, alternative or additional feature extracting functions and/or neural networks may be used to extract features of the input set of ultrasound images.” *Id.* at 11:39-42 (emphasis added). Consequently, the Patent does not disavow known feature extraction techniques or implicitly redefine “extracted feature representation” to mean just those derived by a NN. PO’s construction must be rejected.

Petitioner does not believe construction is required. Nevertheless, as an alternative, the term could be construed merely as: “data representing extracted features.” *See, e.g.*, Ex1001, 8:39-40 (“extracted feature data”), 11:32-39, 12:42-48 (“the features may be in the form of real-valued numbers”).

III. REPLY TO PO’S ARGUMENTS

A. Ground A: Anticipation by Krishnan

1. Krishnan Discloses the Step/Function of “Deriving One or More Extracted Feature Representations” (Limitations 1(b)/21(b)/30(b))

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

Limitations 1(b)/21(b) recite the same computer-implemented step of “derive[/deriving] one or more extracted feature representations from the set of ultrasound images.” Generally, method steps are not restricted to any specific device. *See, e.g., Michaels of Or. Co. v. Clean Gun, LLC*, Case No.: CV-01-1158-ST, 2002 U.S. Dist. LEXIS 20371 at *26 (July 9, 2002, D. Or.) (“If a method claim can be practiced without the specific tools claimed or described in the

specification, then the method claim is not limited to any particular device.”). PO’s proposed construction of “extracted feature representations” improperly restricts the claimed step to just neural network implementations.

Without PO’s overly restrictive claim construction, Krishnan plainly discloses the step of deriving extracted feature representations from a set of ultrasound images. *See, e.g.*, Ex1005, [0017] (“In general, the feature analysis module (102) implements methods for automatically extracting one or more types of features/parameters from input medical image data ...”). But regardless, even under PO’s proposed construction, Krishnan still discloses Limitations 1(b)/21(b).

Krishnan repeatedly and unambiguously states that, in some embodiments, the function of its “feature extraction module (102)” (Ex1005 at [0017]) is performed by one or more NN classifiers. *See* Ex1005, [0044] (“classifiers are built using neural networks, [for] example”), [0023] (“The classifiers are implemented by the various decision support modules (102~105) for performing their respective functions.”), [0021] (“classification system (108) ... can be used ... by one or more of the various automated decision support modules (102~105) ... to perform their respective functions.”) Nevertheless, PO contends that “those are clearly errors because Krishnan elsewhere only refers to modules 103/104/105 as the modules that ‘can employ classification methods.’” Response, 42 (citing only Ex1005, [0023]).

Obviously, a lone description of modules (103-105) implementing classification methods does not also mean, as PO contends, that feature extraction module (102) is not implemented by a classifier. In every instance where Krishnan collectively addresses modules (103-105), including the passage relied on by PO, Krishnan is discussing those modules that process extracted features. See Ex1001, [0017], [0021], [0022], [0023]. These descriptions do not contradict Krishnan's other clear statements that modules (102-105) implement one or more classifiers for performing their respective functions.

As PO points out, Krishnan states: "Feature extraction can implement known segmentation and/or filtering methods for segmenting features of interest or anatomies of interest ... using known methods." Ex1001, [0034]. PO contends that "a POSITA would have understood the 'known' techniques module 102 employs for feature extraction would not have employed neural networks" because "[a]t 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 ... none of which involve neural networks." Response, 19 (citing Sonka, ¶134). PO's claims are demonstrably wrong. See, e.g., "SEGMENTATION OF ULTRASONIC IMAGES WITH NEURAL NETWORKS" (1991), Ex1048, 620-621; Ex1056, 328 (2000) ("ANNs [(i.e., artificial NNs)] ... can be used in a variety of ways for image

segmentation.”); Ex1057 (1998) (describing a convolutional neural network (CNN) for lung segmentation); Ex1058, 3-7 (2005) (describing a CNN for segmenting cell structures).

In 2002, more than 2 years before the filing date of Krishnan, M. Egmont-Petersen *et al.* published a survey of NN image processing applications. Ex1047. First, Egmont-Petersen defined the various steps in the image processing chain, including: “1. Preprocessing/filtering” (i.e., “[o]perations that give as a result a modified image with the same dimensions as the original image”); “2. Data reduction/feature extraction” (i.e., “[a]ny operation that extracts significant components from an image”); “3. Segmentation” (i.e., “[a]ny operation that partitions an image into regions that are coherent with respect to some criterion”); and “4. Object detection and recognition” (i.e., “[d]etermining the position and, possibly, also the orientation ... of specific objects in an image.”) *Id.* at 2. Next, Egmont-Petersen distinguished between the abstraction level of the input data used by each NN application included in the survey, including: “A. Pixel level” (i.e., “[t]he intensities of individual pixels are provided as input to the algorithm”); and “B. Local feature level” (i.e., “[a] set of derived, pixel-based features constitutes the input.” *Id.* Then, in Table 1, which is reproduced below, Egmont-Petersen provided a “taxonomy of image processing algorithms that results from combining the steps of the image processing chain with the abstraction level of the input

data.” *Id.* When added together, Table 1 identifies over 50 NN applications that perform feature extraction and/or segmentation using direct pixel data of images as input.

Table 1
The image processing tasks categorised into a two-dimensional taxonomy^a

	Preprocessing	Compression/ feature extract	Segmentation	Recognition	Image understanding	Optimisation
Pixel	26	25	39	51	3	5
Feature	4	2	19	38	2	3
Structure			2	6		5
Object						1
Object set				2	2	
Scene						

^aEach cell contains the number of applications in our survey where neural networks accomplish a specific task in the image processing chain.

With respect to “feature extraction” generally, Egmont-Petersen states: “Among the ANNs that have been trained to perform feature extraction, feed-forward ANNs have been used in most of the reviewed applications.” *Id.* at 6 of 23. Additionally, Egmont-Petersen states: “Most of the ANNs trained for feature extraction obtain pixel data as input.” *Id.* Thus, contrary to PO’s claims, a POSITA would be aware of the concept of extracting features from images using NNs prior to Krishnan. Ex1046, ¶10; *see also*, “Artificial Neural Networks for Feature Extraction and Multivariate Data Projection,” Ex1052, 296 (1995) (“Recently, a large number of artificial neural networks and learning algorithms have been proposed for feature extraction....”); “Unsupervised Neural Network Learning Procedures For Feature Extraction and Classification,” Ex1051, 1 (“In this article, we review unsupervised neural network learning procedures which can

be applied to the task of preprocessing raw data to extract useful features for subsequent classification.”).

With respect to “segmentation,” which Krishnan specifically calls out for the implementation of feature extraction, Egmont-Peterson states: “Many ANN approaches have been presented that segment images directly from pixel or voxel data.” Ex1047, 6. Additionally, Egmont-Peterson explains: “Segmentation is the portioning of an image into parts that are coherent according to some criterion. When considered a classification task, the purpose of segmentation is to assign labels to individual pixels or voxels.” *Id.* (emphasis added). This description is completely consistent with Krishnan’s disclosure that feature extraction/segmentation can be performed using a trained NN “classifier.” To a POSITA, segmentation by NN is a classification task that involves classifying/labeling each pixel of an image as belonging to one anatomical structure or another. *See, e.g.,* Ex1050, 248 (“the image segmentation problem may be regarded as a classification problem”); Ex1046, ¶10.

Regardless of whether Krishnan contains other typographical errors, Krishnan’s inclusion of the feature extraction module (102) within the list of modules that implement NN classifiers is not an error. But even if it was, as PO contends, the error would not be apparent and obvious to a POSITA. Before Krishnan, and certainly long before the priority date of the Patent, it was known to

extract feature representations directly from images using NNs—including by image segmentation, which is a pixel-by-pixel NN classification task. Thus, Krishnan is prior art for all that it states. *See In re Garfinkel*, 437 F.2d 1005, 1008 (C.C.P.A. 1971) (crediting a prior art disclosure despite an alleged error “since the error, if it exists, is not apparent or obvious from reading the publication.”).

For all the reasons above, Krishnan discloses Limitations 1(b)/21(b).

b) Limitation 30(b)

PO disputes that Krishnan discloses Limitation 30(b) for the same reason PO disputes that Krishnan discloses Limitations 1(b)/21(b), stating again that “[a] POSITA would have understood that the ‘known’ methods Krishnan discloses as of 2005 did not employ neural networks for feature extraction.” Response, 45. PO is plainly wrong for the same reasons explained in the preceding Section.

Contrary to PO’s claims, a POSITA at the time of Krishnan’s disclosure would be aware of NNs for performing feature extraction from images—including NN classifiers in which feature extraction occurs within the hidden layers of the NN. *See, e.g.*, Ex1027 (LeCun 1990), 396 (“the learning network is directly fed with images, rather than feature vectors”), 400 (“The network has four hidden layers.... Layers H1 and H3 are ... feature extractors....”; Ex1045, 42-43 (“The feature extraction implicitly takes place within the intermediate stages (hidden layers) of the ANN. A nice property of this scheme is that feature extraction and

classification are integrated and trained simultaneously to produce optimal classification results.”) (“A typical example of this integrated feature extraction-classification scheme is the network developed by Le Cun et al.”); Ex1044, 657 (stating of LeCun’s NN: “Note that the feature extractors are not hand-crafted or ad-hoc selected rules, but are trained on a large set of training samples.”); Ex1049, 539 (“Our approach is to likewise divide the object recognition problem to separate feature extraction and classification tasks, but to use only neural networks for both. The total system is then a multilayer collection of neural modules.”). As already detailed, Krishnan states that its feature extraction module (102) can implement one or more NN classifiers to perform its function. That disclosure is not an obvious error that would be summarily disregarded by a POSITA. Thus, Krishnan discloses the claimed “means for deriving one or more extracted feature representations” in Limitation 30(b).

2. Krishnan Discloses the Step/Function of Determining a “Quality Assessment Value” (Limitations 1(c)/21(c)/30(c))

PO’s Response improperly lumps together the method steps recited in Limitations 1(c)/21(c) with the means-plus-function element in Limitation 30(c), arguing that Petitioner must specifically show that Krishnan’s NN “classifier embodiment” satisfies each of these limitations. Response, 47-49. Petitioner addresses the claims separately.

Challenged claim 1 recites a method. As previously explained, the steps of

the method are not limited to the use of NN classifiers. Krishnan discloses the same method in Krishnan's FIG. 2, as well as a computer-implemented system for performing that method in FIG. 1. The Petition, therefore, appropriately cites Krishnan's FIGS. 1 and 2, and descriptions thereof, to satisfy all the limitations of claim 1, including 1(c). See Petition, 21-34. Although the Petition also briefly cites Krishnan's FIG. 5 when addressing Limitation 1(d), that citation is cumulative of other citations to more general descriptions of FIGS. 1 and 2. Regardless, Petitioner did not "mix teachings from distinct embodiments" in Krishnan, as PO implies. Therefore, PO's suggestion that Petitioner must cite directly to Krishnan's classifier embodiment to satisfy Limitation 1(c) has no merit.

Challenged claim 21 is directed to a system but recites, at Limitation 21(c), the same step as Limitation 1(c). PO again wrongly suggests that Petitioner's analysis of claim 21 should be limited to Krishnan's classifier embodiment. The step recited in Limitation 21(c) is not restricted to any device besides a "processor" that is configured to perform the step. Therefore, the Petition, when addressing Limitation 21(c), states that "Krishnan discloses a computer-implemented method ... where steps of the method are carried out by a data processor (101)." Petition, 38. Additionally, the Petition refers back to the analysis of Limitation 1(c), which, as already explained, relies on general descriptions of Krishnan's disclosed method

in FIG. 2. Thus, the Petition completely maps claim 21 to Krishnan without the need to rely specifically on Krishnan's classifier embodiment.

With respect to Limitation 30(c), which is drafted in means-plus-function format, the Petition cites to the analysis of Limitation 21(c), which incorporates the analysis of Limitation 1(c), to support the uncontested proposition that Krishnan discloses the function recited in 30(c). Petition, 47. The Petition also cites to Krishnan's classifier embodiments, which can be "built using neural networks," as satisfying the described "means" for performing the recited function. PO's sole response is to argue that Krishnan's "general statements" and "general teachings" regarding the determination of a quality assessment value "are not necessarily related to the classifier embodiment." *Id.* at 48-49. PO is wrong.

Krishnan states that "[t]he quality assessment module (105) implements methods for using the extracted features/parameters to assess a level of diagnostic quality of an acquired image" and can also implement methods for "determining a quality measure within a predefined range of values." EX1005, [0020]. This description corresponds, almost *verbatim*, to both the claim language, "quality assessment value," and the claim construction to which PO claims Petitioner is bound (i.e., "score of diagnostic image quality"). Krishnan then states: "The classifiers are implemented by the various decision support modules (102~105) for performing their respective functions." EX1005, [0023] (emphasis added). Thus,

Krishnan explicitly states that its “classifier embodiment” performs the function of module (105), which is the same function recited in Limitation 30(c).

Likewise, while discussing the method depicted in FIG. 2, which includes automatic image quality assessment (step 202), Krishnan states that “for image quality assessment, the medical images may include a quality score (within a predefined range) that provides an indication [of] a diagnostic quality level of the medical images.” *Id.*, [0036] (emphasis added). This disclosure broadly applies to each embodiment for performing step (202), including the “classifier embodiment,” because Krishnan also states that the “[m]ethods for automatic ... quality assessment (step 202) ... can be implemented using one or more techniques including a database query approach (e.g., FIG. 3), a template processing approach (e.g., FIG. 4) and/or classification (e.g., FIG. 5).” EX1005, [0035] (emphasis added).

Contrary to PO’s claim, Krishnan discloses that each of the approaches in FIGS. 3, 4, and 5 produces a score of diagnostic quality as described with respect to FIG. 2. If not each, then which? The descriptions of FIGs 3/4/5 in paragraphs [0037]/[0041]/[0042], respectively, do not distinguish the quality assessment results of one approach from the other. Thus, Krishnan’s “general statements” and “general teachings” regarding the step of quality assessment in FIG. 2 are intended to apply equally to the subsequently disclosed embodiments for implementing that

step—not some undisclosed embodiment or some subset of the disclosed embodiments that is not identified.

Nor, as PO claims, does Dr. Deo admit that Krishnan’s classifier embodiment does not produce a quality assessment score. Response, 49 (citing Ex1002, ¶267). While addressing the concept of training a NN classifier, Dr. Deo merely explained that “[t]he output of such a trained model could either be [a] continuous score ... or, if a hard threshold is applied to the continuous score, a binary output (0 or 1).” Ex1002, ¶267 (emphasis added). In both scenarios the classifier produces a continuous quality assessment score. In the second scenario, a downstream thresholding operation converts the continuous score to a binary score, *i.e.*, 0 (below the threshold) or 1 (above the threshold). Both scenarios satisfy the “quality assessment value” limitation.

For these reasons, Krishnan’s classifier embodiments, which are implemented by one or more NNs, disclose Limitation 30(c).

B. Ground B: Obviousness based on Krishnan-Chen

Dependent claims 3-8 and 23-26 introduce additional details regarding the feature extraction function, including, for example, the use of a convolutional NN (claim 6) and a recurrent NN (claim 8). These routine implementation details should not add patentable weight to the claims already shown to be anticipated by Krishnan.

The feature extraction scheme described in the Patent is essentially identical to the feature extraction scheme disclosed in Chen (Ex1009) three years earlier. FIG. 4 of the Patent and the left side of Fig. 2 of Chen are reproduced below, one above the other, with annotations highlighting their corresponding convolutional NNs (red) that feed into their corresponding recurrent NNs (blue). Indeed, the only difference between the Patent and Chen appears to be that the Patent tacks on an additional quality assessment classifier (alongside the view classifier) after feature extraction.

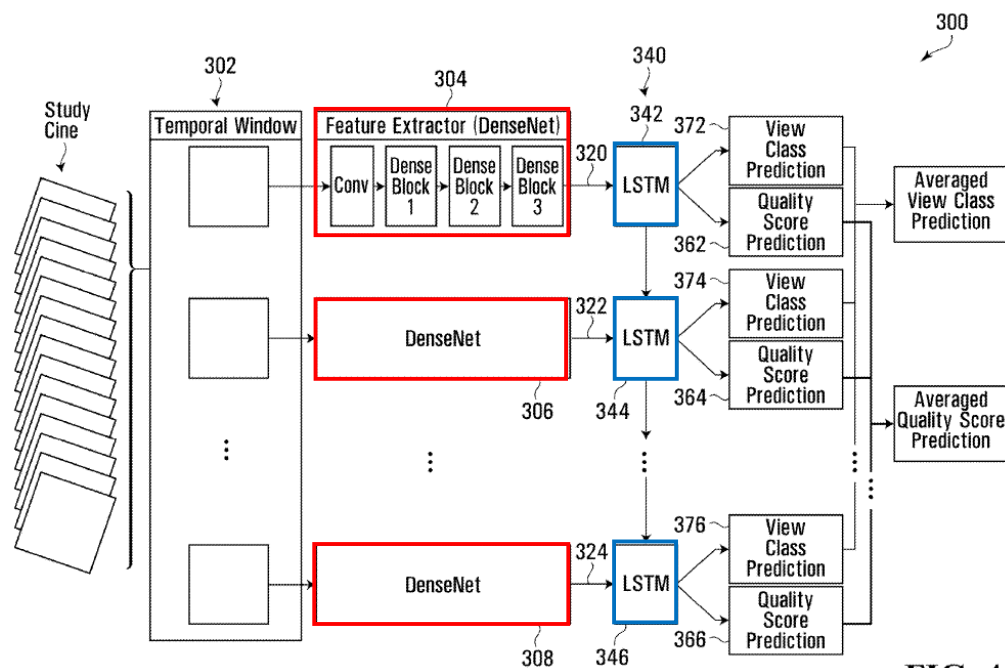


FIG. 4

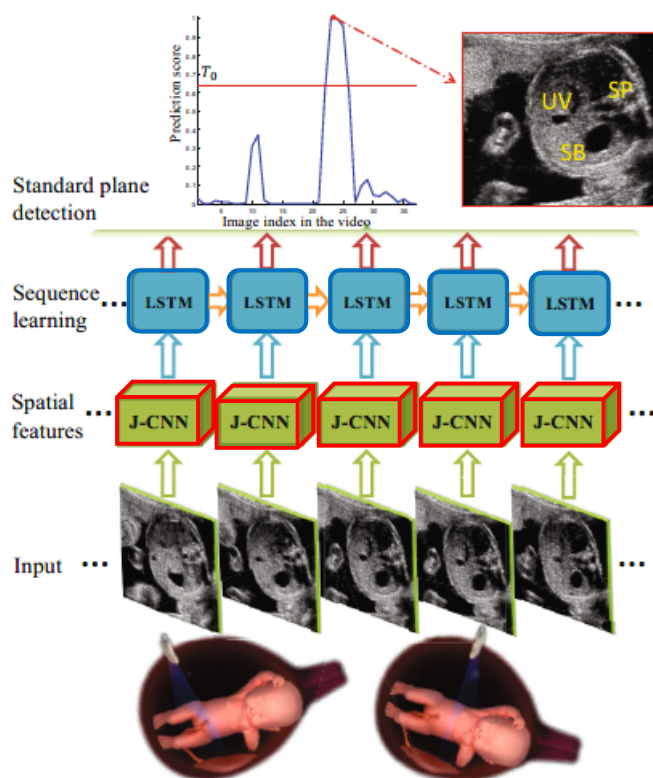


Fig. 2

Contrary to PO's mischaracterizations, the combination of Krishnan-Chen presented in the Petition is straightforward. Since Krishnan describes a modular system, including a feature extraction module (102), Petitioner simply proposes to perform Krishnan's feature extraction function using Chen's feature extracting NN. This combination is stated clearly in the Petition: "using the neural network architecture disclosed in Chen to perform feature extraction as described in Krishnan." Petition, 54.

Krishnan's view identification module (104) and quality assessment module (105), which are implemented by a bank of classifiers that take the extracted features as input (Ex1005, [0043]), remain in the proposed combination. This too is stated clearly in the Petition: "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." *Id.*, 55. Thus, Chen, which is a feature extracting NN and view classifier, is simply added to Krishnan's existing bank of classifiers. This possibility is specifically contemplated by Krishnan, which states that "a classifier design can include a multiplicity of classifiers ... run in parallel" (Ex1005, [0044]), and "[t]hese classifiers would use the set of features as an input, and classify the image as belonging to a particular ... view or level of quality" (*id.*, [0043]).

PO attempts to create confusion by manufacturing strawman arguments that

were not presented in the Petition. First, PO contends that Petitioner proposes to completely replace all of Krishnan's functional modules (102-105) with just Chen's NN. *See*, Response, 52 ("in place of Krishnan's automatic feature analysis module 102 (and to remove modules 103-105 as well)"), 53 ("wholesale replacement"), 54 ("replace Krishnan's feature extraction module 102 and other modules"), 55 ("replacing modules 102-105"). That is plainly not the case since the Petition explicitly proposes "adding" the NN of Chen to Krishnan's existing "bank of classifiers." Petition, 55, 58. Second, PO contends that Petitioner proposes to feed extracted features, rather than images, from Krishnan's feature extraction module (102) into Chen's NN. Response, 55-56. That too is plainly not the case since the Petition explicitly proposes "using the neural network architecture disclosed in Chen to perform [the] feature extraction." Petition, 54, 57.

Under the proposed combination, feature extraction is performed using Chen's NN architecture, and those extracted features are fed to one or more NN classifiers implementing Krishnan's other functional modules. PO's argument against the technical compatibility of this combination has no merit. PO claims that Krishnan's modules (103-105) can only accept hand-crafted features, not features output by a NN (like Chen's). The premise of PO's position, which is wrong, is that Krishnan's feature extraction module (102) is never implemented as a NN. To the contrary, Krishnan is clear: "The classifiers are implemented by the

various decision support modules (102~105) for performing their respective functions” (Ex1005, [0023]) and the “classifiers are built using neural networks” (*id.*, [0044]). Thus, Krishnan is no different than the Patent, which is no different than Chen—i.e., all disclose a neural (sub)network that accepts images and extracts features that are then fed into one or more additional neural (sub)networks to perform classification tasks.

Contrary to PO’s claim, a POSITA could easily modularize a NN—like Chen—to feed extracted features into another functional module. Ex1046, ¶21-25. Even the Patent refers to its own feature extracting NNs as “feature extraction module[s].” Ex1001, 17:67-18-1.

C. Ground C: Obviousness based on Krishnan-Aase

PO challenges the combination of Krishnan-Aase based on purported unfeasibility of inserting the NNs described in Aase into the modular workflow described in Krishnan. PO misunderstands the combination. The Petition, as written, does not even propose swapping out parts of Krishnan for parts of Aase. Indeed, even PO’s Response acknowledges that “[n]either 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.” Response, 62.

As presented in the Petition, Ground C is a “teaching” combination, meaning that Aase supplies the teaching—not new NN components—to implement

Krishnan's NN classifiers in a manner that satisfies all the limitations of the challenged claims. That is what the Petition means by "implement Krishnan using a view-category-specific neural network and a quality-assessment-specific neural network, as in Aase." Petition, 67 (emphasis added).

As previously described in Ground A, Krishnan discloses a view identification module and a quality assessment module that are implemented by one or more NN classifiers for performing their respective functions. Aase teaches, by example, that Krishnan's one or more NN classifiers can be implemented as dedicated, function-specific neural networks since Aase uses a "view-assignment-specific neural network" (module 160) and a "quality-assessment-specific neural network" (module 170). EX1006, [0032]-[0035]. Rather than grafting the NNs from Aase into Krishnan, as PO contends, Ground C merely proposes that a POSITA, informed by (i) Krishnan's disclosure of "one or more" NN classifiers and (ii) Aase's disclosure of dedicated view-identification and quality-assessment NN classifiers, would find it obvious to implement Krishnan's system using dedicated NNs. That is why the Petition states "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." Petition, 67.

In response to deposition questioning, Petitioner's expert, Dr. Deo, also testified regarding a combination in which Aase's NNs replaced all of Krishnan's modules (102-105). Candidly, however, that combination was not the intended basis of Ground C in the Petition. Indeed, PO's counsel understood this and repeatedly challenged Dr. Deo during his deposition to show where such a combination was described. Deo Dep., Ex2051, 117:16-17, 118:2-5, 118:17-21.

Regardless, PO's attack on compatibility has no merit with respect to this combination either. As before, PO manufactures a strawman argument that is not presented in the Petition or by Dr. Deo during his deposition. PO contends that "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" such that "Aase's classification neural networks would instead receive outputs from Krishnan's module 102, which produces entirely different hand-crafted features." Response, 60. That is plainly wrong. Dr. Deo repeatedly explained during his deposition that, in the version of Krishnan-Aase he was describing, each of Krishnan's modules (102-105), including the feature extraction module, would be replaced by the neural networks of Aase, which perform the function of feature extraction within their initial internal neural network layers. Ex2051, 116:7-15, 117:4-15, 120:1-5, 121:8-18, 123:2-3. That eliminates PO's incompatibility argument, which is based on a configuration that

no one proposed.

It also bears emphasizing here that PO's opposition to Ground C includes admissions from which the inescapable conclusion is that Aase, like Krishnan, also anticipates at least independent claims 1/21/30. Although Petitioner subjectively selected Krishnan as the strongest anticipatory reference because Krishnan uses the same "extracted feature" terminology as the Patent, PO now admits that "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)." Response, 59. This is identical to the Patent.

D. Ground D: Obviousness based on Krishnan-Chen-Wu

1. Ground D is properly identified.

Ground D is based on the combination of Krishnan-Chen-Wu, which renders the Patent's "training claims" obvious in view of a POSITA's general knowledge of NN training. In the introduction to Ground D, the Petition first provides evidence that the NN training technique employed by the Patent is standard. Petition, 70 (citing Ex1012, Ex1017, Ex1018). Therefore, the Petition states, "once it is determined that Krishnan discloses neural network classifiers that perform the same functions recited in the claims (i.e., quality assessment and view category assignment for a set of ultrasound images), the training claims are also

rendered obvious because a POSITA would already know how to train such networks using well-known, standard methods.” *Id.* (emphasis added).

In the introduction to independent claim 12, which is the broadest of the training claims, the Petition further explains why it would have been obvious to use the NN classifiers described in Chen and Wu within Krishnan’s contemplated bank of classifiers to perform the same functions taught by Krishnan. *Id.* 71. It would also be obvious, therefore, to train those NNs in the manner already taught by Chen and Wu. *Id.*, 72. Both use labeled images as the training input and the labels as the desired output.

In the portion of the Petition that addresses the training claims element-by-element, the Petition cites either Krishnan/Chen/Wu as disclosing, or Krishnan in view of the knowledge of a POSITA as teaching or suggesting, each respective element. Therefore, Petitioner respectfully submits that the basis of Ground D is sufficiently identified.

2. Limitation 12(d).

To satisfy Limitations 12(b) and 12(c), the Petition cites to the NN training described in Wu and Chen, respectively. Petition, 75-77. To satisfy 12(d), the Petition refers back to 12(b)/12(c), stating “[a] POSITA would understand how neural networks are typically trained ... as discussed above with respect to ... [12(b)], and [12(c)].” *Id.*, 78.

Additionally, the Petition states that “Krishnan teaches or suggests [12(d)]” in view of the knowledge of a POSITA. Petition, 70, 78. Evidence of that knowledge is provided by Dr. Deo’s declaration (Ex1002, ¶256-257), which is corroborated in the Petition by at least Pagoulatos (Ex1018). Petition, 78. PO, without even attempting to rebut the general knowledge of a POSITA, argues that Petitioner cannot rely on the teachings in Pagoulatos because Pagoulatos is not part of Petitioner’s proposed obviousness ground. *Id.*

The present case is identical to *Koninklijke Philips N.V. v Google LLC*, 948 F.3d 1330 (Fed. Cir. 2020). In that case, the Petitioner, Google, alleged that although the prior art reference, SMIL 1.0, did not disclose every element of the claimed invention, the differences between the claimed invention and SMIL 1.0 were such that the claimed invention would have been obvious to a POSITA because a POSITA would have known about the technique of “pipelining” as evidenced by expert testimony and confirmed by another prior art reference, Hua. *Id.* at 1337-38. Hua, however, was not presented as a combination with SMIL 1.0. *Id.* at 1334. The patent owner, Philips, argued that Google was required to make Hua part of the combination because 35 U.S.C. §311(b) prohibits the use of general knowledge to supply a missing claim element in an IPR. *Id.* The Federal Circuit disagreed. *Id.* at 1337. The Federal Circuit affirmed the Board’s finding of unpatentability stating: “[H]ere the Board relied on expert evidence, which was

corroborated by Hua, in concluding that pipelining was not only in the prior art, but also within the general knowledge of a skilled artisan.” *Id.* at 1338. More recently, the Federal Circuit has repeated that “general knowledge can be used to supply a missing claim limitation” and cited, with approval, “our decision in *Koninklijke*, where we held that it is permissible for ‘general knowledge to supply a missing claim limitation in an [IPR].’” *Shockwave Med., Inc. v. Cardiovascular Sys.*, 142 F.4th 1371, 1378-79 (Fed. Cir. 2025).

Ultimately, Krishnan (supplemented by Chen/Wu/general knowledge) renders the Patent’s training claims obvious because Krishnan’s NN classifier embodiment is no different than the principal embodiment depicted in FIG. 4 of the Patent. FIG. 4 shows feature extracting neural networks (304/306/308/342/344/346)—also referred to as “feature extraction module[s]”—feeding into quality assessment neural networks (362/364/366) and view identification neural networks (372/374/376). Ex1001, 2:51-53, 6:35-64, 17:67-18:1, 18:9-10. Krishnan likewise discloses a feature extraction module (102) that feeds into a view identification module (104) and a quality assessment module (105), where Krishnan states that each of the modules (102-105) can be implemented by one or more NN classifiers. Even if the express teachings of Chen and Wu are ignored with respect to 12(d), the general knowledge of a POSITA supplies the unstated, but standard, detail of how to train such a neural network

scheme using training images as input and the training labels as the desired outputs. Nothing about the Patent’s training technique is new or patentable once it becomes clear that the NN being trained is disclosed in Petitioner’s references.

3. The controlling guidance from the Office permits the use of “general knowledge” in this Petition.

On June 9, 2022, then Director Vidal issued definitive guidance stating that “the Board should not deny a petition in which an applicant points to general knowledge ... to satisfy a claim limitation.” Ex1054, 6. Subsequently, on July 31, 2025, Director Stewart issued new guidance superseding Director Vidal’s 2022 Memorandum and stating that “general knowledge” may no longer be used to supply a missing claim limitation. Ex1055, 1. However, Director Stewart also explicitly stated: “This Memorandum will apply to any petition for IPR filed on or after September 1, 2025.” *Id.*, 3. The drafting of the present Petition was substantially completed before Director Stewart’s guidance issued and was filed before September 1, 2025, on August 15, 2025. Accordingly, Director Vidal’s 2022 Memorandum—citing the Federal Circuit’s *Koninklijke* decision—is the controlling guidance applicable to this Petition.

IV. SECONDARY CONSIDERATIONS

PO’s perfunctory claim of nonobviousness based on secondary considerations is completely unsupported. PO provides no evidence that the claimed invention has been implemented or commercialized in any way that even

could fulfill an “unmet need”—if an unmet need had been proven. Nor has PO cited any authority for its claim that mere citations to the Patent in patents belonging to others are evidence that the Patent is recognized as “pioneering.” Even assuming that the Patent has been cited by other applicants in IDSs, these disclosures are neither praise nor admissions of novelty/nonobviousness. Obviously, the motivation, i.e., duty, to disclose potentially relevant prior art has nothing to do with industry recognition or praise for the Patent.

* * *

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CERTIFICATION UNDER 37 C.F.R. § 42.24(D)

Pursuant to 37 C.F.R. §42.24(a)(1)(i), I certify that this paper includes 5,574 words. In accordance with 37 C.F.R. §42.24(a)(1), this word count does not include a count of the words in a table of contents, a table of authorities, mandatory notices under §42.8, a certificate of service or word count, or appendix of exhibits or claim listing. Furthermore, in accordance with 37 C.F.R. §42.24(d), this word count is the word count of the word-processing system used to prepare the paper.

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CERTIFICATE OF SERVICE

Pursuant to 37 C.F.R. §§42.6 and 42.105, the undersigned hereby certifies that a true and correct copy of the Petitioner's Reply in connection with IPR2025-1422 and supporting evidence was served on August 18, 2026, upon agreement of the parties, via electronic mail on the following counsel of record for Patent Owner, University of British Columbia:

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