

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

U.S. PATENT NO. 11,129,591

Inter Partes Review No.: IPR2025-01066

**PETITION FOR *INTER PARTES* REVIEW OF
U.S. PATENT NO. 11,129,591**

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Patent Trial and Appeal Board
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TABLE OF CONTENTS

I. PRELIMINARY STATEMENT.....	1
II. MANDATORY NOTICES (37 C.F.R. §42.8(A)(1))	4
A. Real Party-in-Interest (37 C.F.R. §42.8(b)(1)).....	4
B. Related Matters (37 C.F.R. §42.8(b)(2)).....	4
C. Lead and Back-up Counsel and Service Information (37 C.F.R. §42.8(b)(3)-(4)).....	4
III. GROUNDS FOR STANDING AND FEES	5
IV. THE PATENT AND PROSECUTION HISTORY	5
A. Background and Specification.....	5
B. Prosecution History	9
V. IDENTIFICATION OF CHALLENGE.....	11
VI. LEVEL OF SKILL IN THE ART.....	11
VII. CLAIM CONSTRUCTION (37 C.F.R. §42.100(b)).....	11
VIII. DETAILED EXPLANATION OF INVALIDITY GROUNDS.....	12
A. Summary of the Prior Art.....	12
1. US2005/0251013 (“Krishnan”).....	12
2. US2016/0247034 (“Lee”)	16
3. US2017/0262982 (“Pagoulatos”).....	19
4. Automatic Fetal Ultrasound Standard Plane Detection (“Chen”)	22
B. Ground A: Krishnan-Lee.....	25
1. Claim 1	25
2. Claim 2: “The system of claim 1 wherein the [first/second] quality assessment value represents an assessment of suitability of the [first/second] at least one echocardiographic image for quantified clinical measurement of anatomical features”	40
3. Claim 3: “The system of claim 1 wherein the at least one processor is configured to: produce signals for causing a representation of the [first/second] quality assessment value to be transmitted to at least one display for causing the at least one display to display the [first/second] quality assessment value in association with the [first/second] at least one	

echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image”	41
4. Claim 4: “The system of claim 1 wherein the at least one processor is configured to: [] apply one or more view categorization functions to the [first/second] at least one echocardiographic image to determine that the [first/second] at least one echocardiographic image falls within the [first/second] view category”	41
5. Claim 5: “The system of claim 1 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.”.....	42
6. Claims 15-19: Method Claims	43
C. Ground B: Krishnan-Lee-Pagoulatos	44
1. Claim 7	44
2. Claim 8: “The system of claim 7 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features”	53
3. Claim 9: “The system of claim 7 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features”	53
4. Claim 11	54
5. Claim 12: “The system of claim 11 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.”	56
6. Claim 13: “The system of claim 11 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was	

taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.”	56
D. Ground C: Krishnan-Lee in view of Chen	56
1. Claims 6 and 20: “wherein each of the sets of assessment parameters includes: a set of common assessment parameters, which are common to each of the sets of assessment parameters; and a set of view category specific assessment parameters, which are unique to the set of assessment parameters.”	56
E. Ground D: Krishnan-Lee-Pagoulatos in view of Chen	61
1. Claims 10 and 14.....	61
IX. CONCLUSION	66

EXHIBIT LIST

No.	Description
Ex1001	U.S. Patent No. 11,129,591 (“the Patent”)
Ex1002	Declaration of Dr. Rahul Deo, M.D., Ph.D.
Ex1003	Curriculum Vitae of Dr. Rahul Deo
Ex1004	Prosecution History File of the Patent (Application No. 16/095,601)
Ex1005	U.S. Patent Application Publication No. 2005/0251013 (“Krishnan”)
Ex1006	U.S. Patent Application Publication No. 2016/0247034 (“Lee”)
Ex1007	U.S. Patent Application Publication No. 2017/0262982 (“Pagoulatos”)
Ex1008	U.S. Provisional Patent Application Publication No. 62/305,980 to Pagoulatos
Ex1009	U.S. Provisional Patent Application Publication No. 62/313,061 to Pagoulatos
Ex1010	Chen et al., “Automatic Fetal Ultrasound Standard Plan Detection Using Knowledge Transferred Recurrent Neural Networks,” Medical Image Computing and Computer-Assisted Intervention, MICCAI 2015, Vol. 9349, pp. 507-514 (November 18, 2015) (“Chen”)
Ex1011	Miller et al., “Review of neural network applications in medical imaging and signal processing,” Medical & Biological Engineering & Computing (30):449-464 (September 1992) (“Miller”)
Ex1012	RESERVED
Ex1013	U.S. Patent No. 5,906,578 (“Rajan”)
Ex1014	U.S. Patent Application Publication No. 2009/0074280 (“Lu”)
Ex1015	U.S. Patent Application Publication No. 2007/0055153 (“Simopoulos”)
Ex1016	González et al., “Echocardiogram Image Recognition Using Neural Networks in Recent Advances on Hybrid Approaches for Designing Intelligent Systems,” Studies in Computational Intelligence 547:427-435 (March 2014) (“González”)
Ex1017	Donahue et al., “Long-term Recurrent Convolutional Networks for Visual Recognition and Description,” arXiv:1411.4389v1 [cs.CV] (November 2014) (“Donahue”)
Ex1018	Caruana, “Multitask Learning: A Knowledge-Based Source of Inductive Bias,” Proceedings of the 10th International Conference on Machine Learning, ML-93, University of Massachusetts, Amherst, 1993, pp. 41-48.

Ex1019	Complaint, <i>University of British Columbia v. Caption Health, Inc., GE Healthcare Technologies Inc.</i> Case No. 3:24-cv-3200-PBS, Dkt. 1, May 28, 2024
Ex1020	Lang RM et al, American Society of Echocardiography's Guidelines and Standards Committee; European Association of Echocardiography. “Recommendations for chamber quantification: a report from the American Society of Echocardiography's Guidelines and Standards Committee and the Chamber Quantification Writing Group, developed in conjunction with the European Association of Echocardiography, a branch of the European Society of Cardiology.” <i>J Am Soc Echocardiogr.</i> 2005 Dec;18(12):1440-63. doi: 10.1016/j.echo.2005.10.005. PMID: 16376782 (“Lang”)
Ex1021	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 (“Salomon”)
Ex1022	LeCun et al., “Backpropagation Applied to Handwritten Zip Code Recognition”. <i>Neural Computation.</i> 1 (4): 541–551. doi:10.1162/neco.1989.1.4.541. ISSN 0899-7667. S2CID 41312633 (“LeCun”)
Ex1023	A. Bouzerdoun, et al., "Image quality assessment using a neural network approach," <i>Proceedings of the Fourth IEEE International Symposium on Signal Processing and Information Technology, 2004.</i> , Rome, Italy, 2004, pp. 330-333, doi: 10.1109/ISSPIT.2004.1433751 (“Bouzerdoun”)
Ex1024	Vignesh, S & Priya, K. & Channappayya, Sumohana. (2015). Face image quality assessment for face selection in surveillance video using convolutional neural networks. 577-581 (“Vignesh”)
Ex1025	Long, Mingsheng & Wang, Jianmin. (2015). Learning Multiple Tasks with Deep Relationship Networks (“Long and Wang”)
Ex1026	S. Hochreiter, J. Schmidhuber, Long short-term memory, <i>Neural Comput.</i> 9 (8) (1997) 1735–1780 (“Hochreiter”)

CLAIMS APPENDIX

Limitation	Claim Language
Claim 1	
[1(pre)]	A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:
[1(a)]	receive signals representing a first at least one echocardiographic image;
[1(b)]	associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;
[1(c)]	determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;
[1(d)]	produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;
[1(e)]	receive signals representing a second at least one echocardiographic image;
[1(f)]	associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;
[1(g)]	determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and
[1(h)]	produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;
[1(i)]	wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment

	values, and wherein the at least one processor is configured to determine the first quality assessment value by:
[1(j)]	determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and
[1(k)]	in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and
[1(l)]	wherein the at least one processor is configured to determine the second quality assessment value by:
[1(m)]	determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and
[1(n)]	in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.
Claim 2	
[2]	The system of claim 1 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.
Claim 3	
[3(pre)]	The system of claim 1 wherein the at least one processor is configured to:
[3(a)]	produce signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and
[3(b)]	produce signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one

	echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.
Claim 4	
[4(pre)]	The system of claim 1 wherein the at least one processor is configured to:
[4(a)]	apply one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and
[4(b)]	apply one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.
Claim 5	
[5]	The system of claim 1 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.
Claim 6	
[6(pre)]	The system of claim 1 wherein each of the sets of assessment parameters includes:
[6(a)]	a set of common assessment parameters, which are common to each of the sets of assessment parameters; and
[6(b)]	a set of view category specific assessment parameters, which are unique to the set of assessment parameters.
Claim 7	
[7(pre)]	The system of claim 1 wherein the at least one processor is configured to train the neural networks by:
[7(a)]	receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;
[7(b)]	receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

[7(c)]	training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.
Claim 8	
[8]	The system of claim 7 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.
Claim 9	
[9]	The system of claim 7 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.
Claim 10	
[10(pre)]	The system of claim 7 wherein each of the sets of neural network parameters includes:
[10(a)]	a set of common neural network parameters, which are common to each of the sets of neural network parameters; and
[10(b)]	a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and
[10(c)]	wherein the at least one processor is configured to, for each echocardiographic training image:
[10(d)]	select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and
[10(e)]	using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.
Claim 11	

[11(pre)]	A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:
[11(a)]	receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;
[11(b)]	receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and
[11(c)]	train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories;
[11(d)]	wherein the at least one processor is further configured to, once the neural networks are trained:
[11(e)]	receive signals representing a first at least one echocardiographic image;
[11(f)]	associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;
[11(g)]	determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;
[11(h)]	produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;
[11(i)]	receive signals representing a second at least one echocardiographic image;
[11(j)]	associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

[11(k)]	determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and
[11(l)]	produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;
[11(m)]	wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:
[11(n)]	determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and
[11(o)]	in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and
[11(p)]	wherein the at least one processor is configured to determine the second quality assessment value by:
[11(q)]	determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and
[11(r)]	in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.
Claim 12	
[12]	The system of claim 11 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.
Claim 13	

[13]	The system of claim 11 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.
Claim 14	
[14(pre)]	The system of claim 11 wherein each of the sets of neural network parameters includes:
[14(a)]	a set of common neural network parameters, which are common to each of the sets of neural network parameters; and
[14(b)]	a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and
[14(c)]	wherein the at least one processor is configured to, for each echocardiographic training image:
[14(d)]	select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and
[14(e)]	using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.
Claim 15	
[15(pre)]	A computer-implemented method of facilitating echocardiographic image analysis, the method comprising:
[15(a)]	receiving signals representing a first at least one echocardiographic image;
[15(b)]	associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;
[15(c)]	determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

[15(d)]	producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;
[15(e)]	receiving signals representing a second at least one echocardiographic image;
[15(f)]	associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;
[15(g)]	determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and
[15(h)]	producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;
[15(i)]	wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein:
[15(j)]	determining the first quality assessment value comprises:
[15(k)]	determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and
[15(l)]	in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters applying a first function based on the first set of assessment parameters to the first at least one echocardiographic image; and
[15(m)]	determining the second quality assessment value comprises:
[15(n)]	determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

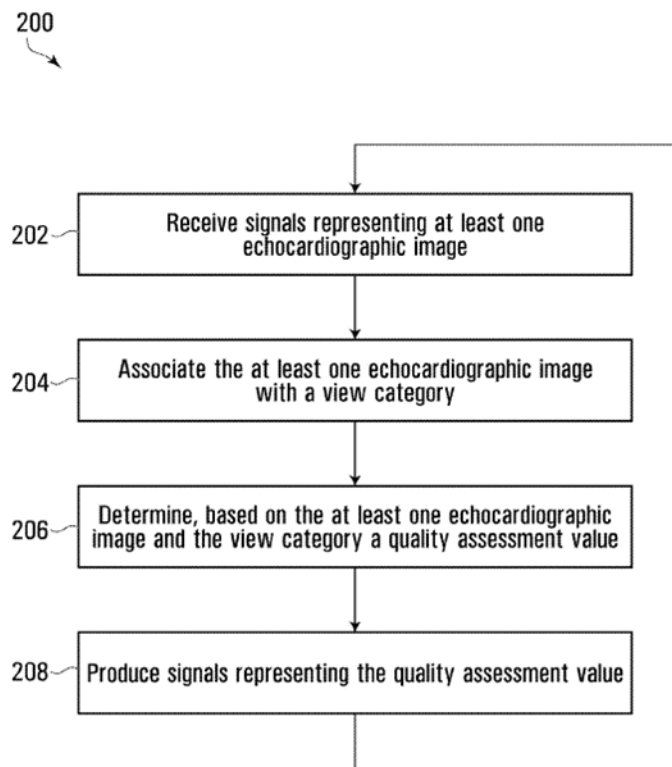
[15(o)]	in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.
Claim 16	
[16]	The method of claim 15 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.
Claim 17	
[17(pre)]	The method of claim 15 wherein:
[17(a)]	producing the signals representing the first quality assessment value comprises producing signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and
[17(b)]	producing the signals representing the second quality assessment value comprises producing signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.
Claim 18	
[18(pre)]	The method of claim 15 wherein:
[18(a)]	associating the first at least one echocardiographic image with the first view category comprises applying one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and
[18(b)]	associating the second at least one echocardiographic image with the second view category comprises applying one or more view categorization functions to the second at least one

	echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.
Claim 19	
[19]	The method of claim 15 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein determining the first quality assessment value comprises determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.
Claim 20	
[20(pre)]	The method of claim 15 wherein each of the sets of assessment parameters includes:
[20(a)]	a set of common assessment parameters, which are common to each of the sets of assessment parameters; and
[20(b)]	a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

I. PRELIMINARY STATEMENT

Petitioner Caption Health, Inc. (“Petitioner”) requests *inter partes* review (“IPR”) of all claims of U.S. Patent No. 11,129,591, entitled *Echocardiographic Image Analysis* (“the Patent,” Ex1001).

The Patent describes a computer-implemented system for facilitating echocardiographic image analysis for image quality assessment. Ex1001, Abstract, 1:15-17. The purported invention is a workflow, shown below, that first associates an echocardiographic image with a standard “view category” and then determines a “quality assessment value” “based on” that view category.



Ex1001, 7:53-8:65, Fig. 3; *see also* Ex1002, ¶¶ 54-63.

The Patent states the obvious—that “the desirable characteristics for each of the different views may differ and so it may be desirable to determine quality assessment values for the echocardiographic images in different ways, depending on what view the echocardiographic images are.” Ex1001, 5:62-66. Accordingly, the Patent directs that “different analyses may be applied to a set of echocardiographic images, depending on which view category [the] set of echocardiographic images falls within.” Ex1001, 8:63-65.

During prosecution, every applied-for claim of the Patent was rejected over U.S. Published Patent Application No. 2005/0251013 to Krishnan et al. (“Krishnan”, Ex1005), which, like the Patent, determines the view category and a quality score for acquired echocardiographic images. Ex1004, pp. 207-252 (May 5, 2021, Office Action). In response to the rejection, the Patent Owner purported to distinguish over Krishnan by amending the applied-for claims to require multiple *view-category-specific* quality assessing neural networks—each defined by a *respective* set of “assessment parameters.” Ex1004, pp. 254-273; *see also* Ex1002, ¶¶ 64-69. Additionally, the Patent Owner amended every claim of the Patent to require the steps of: (i) “determining” which of the sets of assessment parameters (*i.e.*, which neural network) is associated with the same view category as an acquired image; and (ii) “in response to determining” which of the sets of assessment parameters is appropriate, “inputting the ... image into the neural network defined by the ...

assessment parameters” to determine a view-category-specific quality assessment. Ex1004, pp. 254-271. Although Krishnan describes assessing image quality using “one or more classifiers” (Ex1005, [0023], Fig. 5) that may be “neural networks” (*id.*, [0044]), Krishnan does not explicitly describe “determining” which of a plurality of classifiers is associated with the same view category as an acquired image. That step, however, should be obvious to a POSITA in view of Krishnan’s other teachings.

Now, for the first time, Petitioner presents the combination of Krishnan with U.S. Published Application 2016/0247034 (“Lee”), which was never considered by the Patent Office. Lee directly rebuts the purported point of novelty argued by the Patent Owner to traverse Krishnan. Lee reflects the knowledge of a POSITA and explicitly teaches that which is obvious—the quality of images in different categories should be evaluated using different assessment parameters. Lee describes selecting, from a plurality of stored classifiers, an appropriate image quality classifier that corresponds to the same category as an acquired image. Ex1006, Abstract, [0009], Fig. 6. Krishnan, in combination with the teachings and express motivations supplied by Lee, renders obvious the claims of the Patent.

For the reasons set forth herein, there is more than a reasonable likelihood that all claims of the Patent are unpatentable. Petitioner respectfully requests institution of a trial and cancellation/invalidation of all claims of the Patent.

II. MANDATORY NOTICES (37 C.F.R. §42.8(A)(1))

A. Real Party-in-Interest (37 C.F.R. §42.8(b)(1))

The real parties-in-interest are Petitioner; Petitioner's parent company, GE HealthCare Technologies Inc.; and Petitioner's insurer, Intellectual Property Insurance Services Corporation ("IPISC").

B. Related Matters (37 C.F.R. §42.8(b)(2))

University of British Columbia ("UBC" or "Patent Owner") has asserted the Patent against Petitioner in *University of British Columbia v. Caption Health, Inc. et al.*, 5-24-cv-3200-EKL (N.D. Cal.) ("CA Litigation"). Ex1019. The earliest date of service is May 28, 2024. *Id.*

UBC has asserted one additional patent against Petitioner in the CA Litigation: U.S. Patent No. 10,751,029.¹ The '029 Patent contains subject matter that overlaps with the subject matter described in the Patent. It is not, however, within the same patent family as the Patent and is not related to the Patent by any priority claim.

C. Lead and Back-up Counsel and Service Information (37 C.F.R. §42.8(b)(3)-(4))

Lead counsel is Jeff Metzcar (No. 52,027) at THOMPSON HINE LLP, 10050

¹ The Complaint (Ex1019) was amended on December 20, 2024 to add U.S. Patent No. 10,751,029.

Innovation Drive, Suite 400, Dayton, OH 45342; Jeff.Metzcar@thompsonhine.com. Backup counsel is David R. Jaglowski (No. 58,514) at THOMPSON HINE LLP, 41 South High Street, Suite 1700, Columbus, Ohio 43215; David.Jaglowski@thompsonhine.com. Supplemental backup counsel are Marla R. Butler (to be admitted *pro hac vice*) and William E. Manske (to be admitted *pro hac vice*) at THOMPSON HINE LLP. Petitioner consents to email service at the following address: IPDocket@ThompsonHine.com.

III. GROUNDS FOR STANDING AND FEES

Petitioner certifies that the Patent is available for IPR and Petitioner is not barred or estopped from requesting review.

The undersigned authorizes the charge of any required fees to Deposit Account No. 20-0809.

IV. THE PATENT AND PROSECUTION HISTORY

The Patent issued on September 28, 2021, from Application No. 16/095,601 (“the ’601 Application”), claiming priority to Provisional Application No. 62/325,779 filed on April 21, 2016. Ex1001, 1.

A. Background and Specification

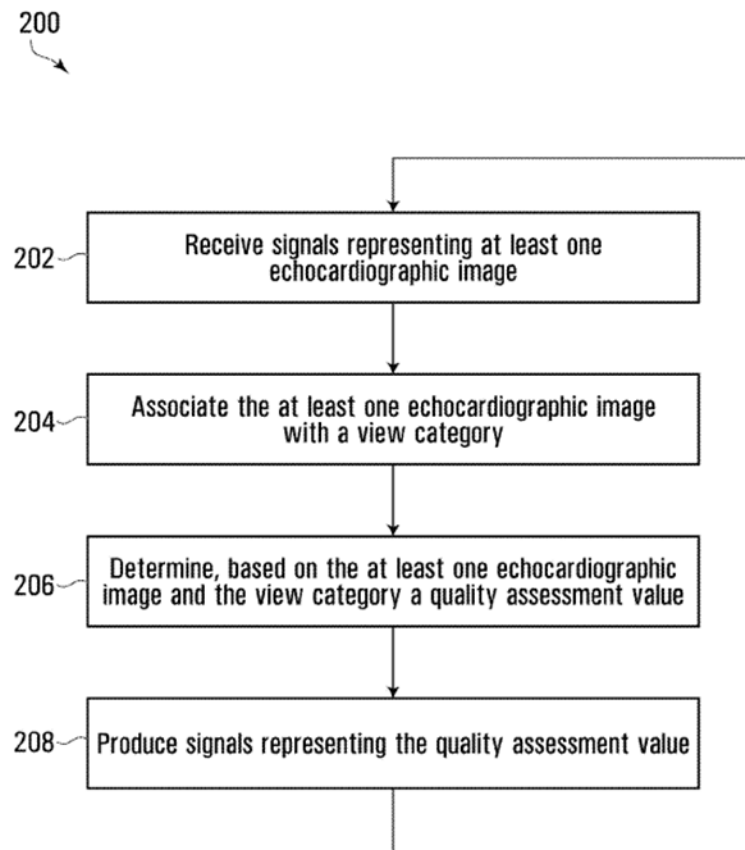
Ultrasound is a commonly used medical imaging modality employed to capture an anatomic representation of diverse organ systems, including the abdomen, the thyroid, skeletal muscle, and the heart. Ex1002, ¶¶ 34-38; Ex1001, 1:23-25; *see also* Ex1002, ¶¶ 6-15, Ex1003. The image observed depends on the location of the

probe on the body, its angle, and the amount of pressure placed on it. Ex1002, ¶ 36. The number of different images that can be generated via ultrasound is infinite. *Id.* This makes (often time-constrained) clinical interpretation challenging. *Id.* Accordingly, radiologists have adopted a series of standardized two-dimensional planes or “views” which highlight critical structures of interest. *Id.*, ¶ 37. For the heart, “standard view categories may include the following 2D echocardiographic imaging plane views: AP2 (apical 2-chamber view), AP3 (apical 3-chamber view), AP4 (apical 4-chamber view), PSAXA (parasternal short axis at aortic valve level view) and PSAXPM (parasternal short axis at papillary muscle level view.” Ex1001, 9:2-7; Ex1002, ¶ 37. These standard views are used to derive specific measurements such as the area or thickness of cardiac chambers. Image quality assessment in ultrasound imaging is typically view-specific and requires the ability to visualize key structures, which differ by view. Ex1002, ¶ 37; Ex1021.

As the Patent explains, “existing echocardiographic systems may be configured to provide feedback regarding general properties of captured images.” Ex1001, 1:29-31. These “feedback” systems were well established in the art as of the purported priority date of the Patent. Ex1002, ¶¶ 39-48. Indeed, as early as 1999, there were systems that used trained neural networks to analyze ultrasound image data and provide real-time feedback to an ultrasound technician during data collection. Ex1002, ¶ 48; Ex1013; *see also* Ex1002, ¶ 46; Ex1022. Other prior art

systems collected three-dimensional echocardiographic data and used neural network classifiers to determine whether desired views of the heart were being collected. Ex1002, ¶ 48; Ex1010; Ex1014; Ex1015; Ex1016.

Against this backdrop, the Patent discloses and claims an echocardiographic image analysis workflow shown in Figure 3 below:



Ex1001, 7:53-8:65, Fig. 3. At block 206, this workflow utilizes multiple neural networks to generate quality assessment values for images from various view categories. *Id.*, 11:27-51. Specifically, to provide a quality assessment for each image that is tailored to the view category of the image, the Patent uses “a plurality

of sets of parameters, each set defining a neural network,” where “each of the sets of parameters may be associated with a view category to indicate that the set of parameters defines a neural network that is to be applied to echocardiographic images which are associated with that view category.” *Id.*, 11:52-59. Thus, “each of the image view categories AP2, AP3, AP4, PSAX_A, and PSAXPM may be associated with a view-category-specific neural network.” *Id.*, 13:48-52.

Figure 8 of the Patent, below, depicts an “exemplary image quality assessment neural network that may be used” (*id.*, 4:15-17), which the Patent characterizes as a “multi-stream network” (*id.*, 12:31-35) that “includes 5 image quality assessment neural networks” (*id.*, 12:10-18). Each of the five image quality assessment neural networks (370, 372, 374, 376, 378) share some common neural network layers with common assessment parameters but also include view-category-specific neural network layers with view-specific assessment parameters. *Id.*, 12:7-21, 12:31-35, 13:5-11, Figs. 9-10.

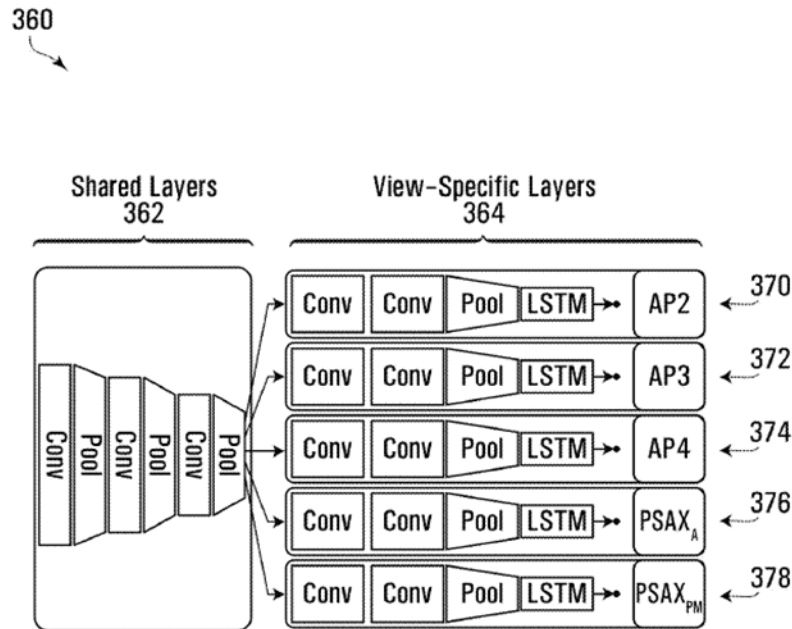


FIG. 8

The Patent suggests that “splitting the neural network 360 into a common portion and view category specific portions may facilitate more efficient training of the neural networks” and “may require fewer learning parameters than would be required if using fully separate neural networks.” *Id.*, 13:53-61.

B. Prosecution History

The Patent was filed on October 22, 2018, claiming a priority filing date of April 21, 2016. In a first Office Action, dated May 5, 2021, the Examiner rejected all claims (1-24) under 35 U.S.C. § 102(a)(1) as being anticipated by Krishnan (Ex1005). Ex1004, pp. 209-219. In response, the Patent Owner amended every independent claim to allegedly distinguish Krishnan. Ex1004, pp. 255-271.

The Patent Owner argued that, as amended, “[t]he claims include determining that a set of assessment parameters is associated with a respective view category and, in response, inputting a corresponding echocardiographic image into a respective neural network to determine the respective quality assessment value of each image.” Ex1004, p. 266. Since “the first and second images are associated with respective first and second view categories ... it is determined that respective first and second sets of assessment parameters are associated with those view categories.” *Id.*, p. 267. Then, “[t]o obtain quality assessment values, the first and second images are input into neural networks defined by the first and second sets of assessment parameters, respectively.” *Id.*

According to the Patent Owner, “Krishnan fails to teach or suggest determining a quality assessment value of an image using a neural network defined by a set of assessment parameters associated with a view category associated with that image.” Ex1004, p. 268.

On August 18, 2021, the Examiner issued a Notice of Allowance stating that the closest prior art, including Krishnan (Ex1005), does not teach or suggest the “determining” functionality, as claimed in each independent claim:

wherein the at least one processor is configured to determine the [first/second] quality assessment value by: determining that a [first/second] set of assessment parameters of the sets of assessment parameters is associated with the [first/second] view category; and in

response to determining that the [first/second] set of assessment parameters is associated with the [first/second] view category, inputting the [first/second] at least one echocardiographic image into the neural network defined by the [first/second] set of assessment parameters;

Ex1004, pp. 274-298. The Examiner did not consider Lee.

V. IDENTIFICATION OF CHALLENGE

Petitioner requests review of all claims of the Patent as follows:

Ground	Prior Art	Basis	Claims Challenged
A	Krishnan in view of Lee (“Krishnan-Lee”)	§103	1-5, 15-19
B	Krishnan-Lee in further view of Pagoulatos (“Krishnan-Lee-Pagoulatos”)	§103	7-9, 11-13
C	Krishnan-Lee in further view of Chen	§103	6, 20
D	Krishnan-Lee-Pagoulatos in further view of Chen	§103	10, 14

VI. LEVEL OF SKILL IN THE ART

The hypothetical person of ordinary skill in the art (“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. Ex1002, ¶¶ 31-33.

VII. CLAIM CONSTRUCTION (37 C.F.R. §42.100(b))

None of the claim terms of the Patent require an express construction for

purposes of this proceeding. Under any reasonable interpretation of the claim terms, the prior art references cited here disclose or teach the elements of the claims.

VIII. DETAILED EXPLANATION OF INVALIDITY GROUNDS

A. Summary of the Prior Art

1. US2005/0251013 (“Krishnan”)

Krishnan is a U.S. patent application published on November 10, 2005. It is prior art to the Patent under 35 U.S.C. §§ 102(a)(1) and 102(a)(2).

Krishnan is directed to “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]. In the primary embodiment, the medical image is an ultrasound image of the heart, and the identified view can be one of the standard views recognized by the American Society of Echocardiography such as, for example, the apical two-chamber view (A2C) or the apical four-chamber view (A4C). Ex1005, [0009], [0019]. “[T]he results of image quality assessment are presented to a user in real-time during image acquisition” so that “the sonographer can determine whether the acquired images are of sufficient diagnostic quality, thereby allowing for changes in image acquisition, if necessary.” Ex1005, [0009].

Referring to Figure 1, which is reproduced below, Krishnan discloses a computer-implemented system 100 that includes an image feature extraction module 102, an anatomy identification module 103, a view identification module 104, an

image quality assessment module 105, a database 106 of previously diagnosed/labeled medical images, and a classification module 108 with a learning engine 109 and “bank of classifiers” 110 that are used by the various modules 102-105 to perform their respective functions. Ex1005, [0016], [0021], [0023], [0043].

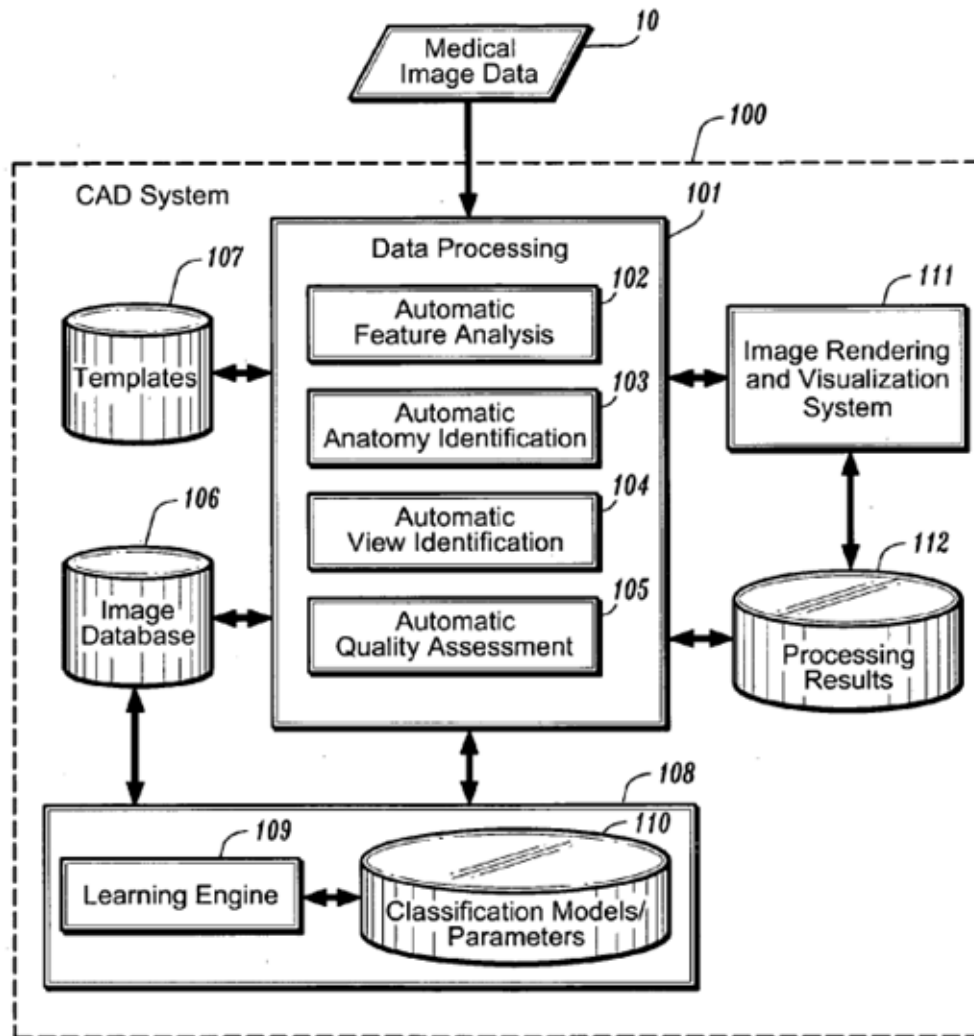


FIG. 1

The system 100 performs the method depicted in Figure 2, below, including the steps

of: (i) obtaining an image dataset including “one or more medical images” (Ex1005, [0033]); (ii) extracting relevant feature data from the image data set using “known segmentation and/or filtering methods” (Ex1005, [0034]); (iii) using the extracted features to automatically identify the anatomy, view and/or quality of the image(s) (Ex1005, [0035]; and (iv) labeling the image(s) according to the anatomy, view, and quality assessment results (Ex1005, [0036]). *See also* Ex1002, ¶¶ 70-74.

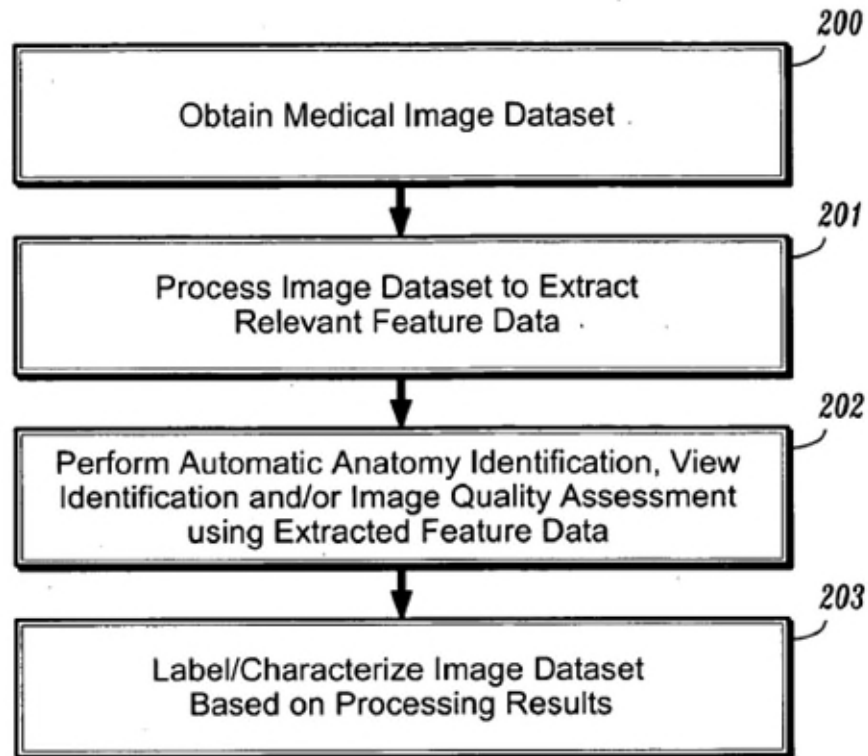


FIG. 2

The image feature extraction module 102 “implements methods for automatically extracting one or more types of features/parameters from input medical image data and combining the extracted features/parameters in a manner

that is suitable for processing by [the other modules (e.g., view identification module 104)].” Ex1005, [0017]. “These features could include any kind of characteristic that could be extracted from the image, such as a particular shape or texture.” Ex1005, [0034]. Additionally, “feature data can be obtained across images, such as motion of a particular point, or the change in a particular feature across images.” *Id.*

The anatomy identification module 103 and view identification module 104 use the extracted “features/parameters” to automatically identify anatomical objects and the view of the acquired image, respectively. Ex1005, [0018]-[0019]. The quality assessment module 105 also “us[es] the extracted features/parameters to assess a level of diagnostic quality of an acquired image data set.” *Id.*, [0020]. Krishnan states that “the results of anatomy and/or view identification may be used for quality assessment.” *Id.*, [0020], [0029] (“The results of anatomy identification and/or view identification can be used to perform automatic image quality assessment...”), Claim 11 (“wherein determining a diagnostic quality of the image data further comprises using results of automatic view identification”).

According to an exemplary embodiment, the various modules 103-105 shown in Figure 1 perform their respective functions using machine learning. Ex1005, [0023]. For example, the various modules 103-105 may be implemented using one or more trained classifiers that have been built by the learning engine 109 using training data such as previously diagnosed/labeled images from the database 106.

Id. As explained by Krishnan, “a classifier design can include a multiplicity of classifiers” and can be “neural networks.” Ex1005, [0044]. “These classifiers would use the set of [extracted] features as an input, and classify the image as belonging to a particular anatomy, view, or level of quality.” *Id.*, [0043]; *see also* Ex.1002, ¶¶ 75-77.

2. US2016/0247034 (“Lee”)

Lee is a U.S. patent application filed on February 22, 2016, and published on August 25, 2016. It is prior art to the Patent under 35 U.S.C. §§ 102(a)(2), 102(d)(2).

Lee is directed to an electronic device, such as a “an ultrasound machine” (Ex1006, [0038]), that determines the quality of images from various image categories using category-specific classifiers (Ex1006, [0009]). The device includes a memory that stores a plurality of classifiers, and a processor configured to “analyze a category of an image of which an image quality evaluation is requested, and determine a classifier corresponding to the category of the image from among the plurality of classifiers.” Ex1006, [0009]. This process is schematically depicted in Figure 6, which is reproduced below. *See also* Ex1002, ¶¶ 70, 78-79.

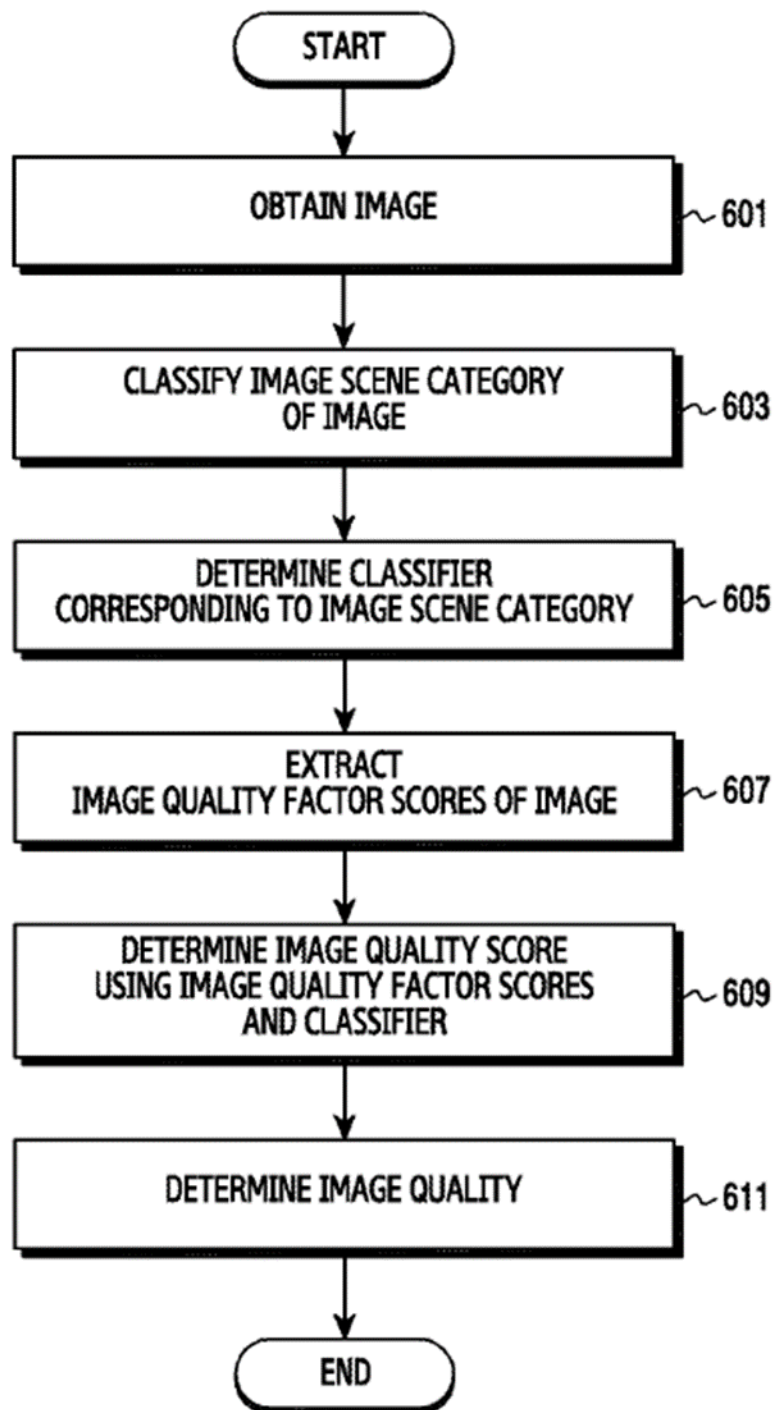


FIG.6

With reference to Figure 5, Lee describes a quality measuring module 485 that

includes a category classifying module 520, a classifier selecting module 530, and an image quality evaluating module 550. Ex1006, [0149]. See also Ex1002, ¶¶ 70, 80-82.

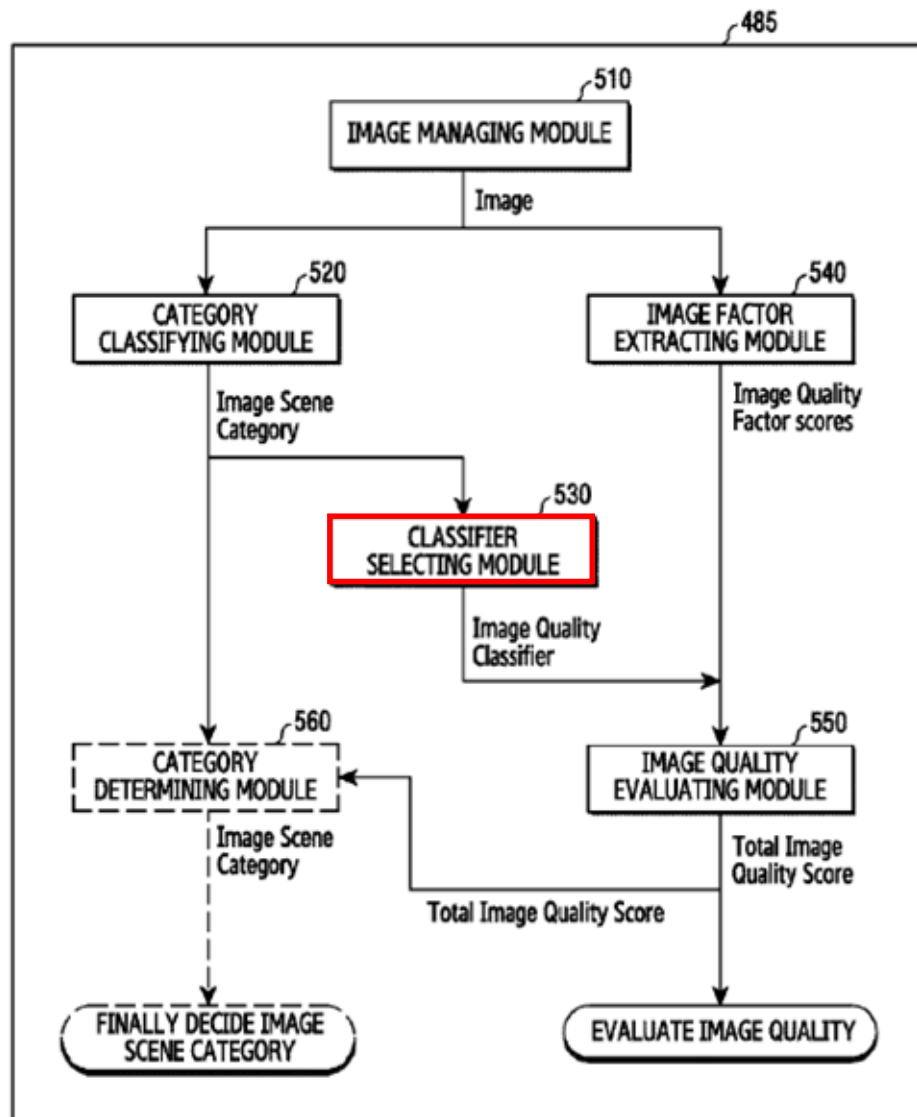


FIG.5

The category classifying module 520 may use “deep learning” to determine a “category or a class” of an image. Ex1006, [0151]. Then, “[t]he classifier selecting

module 530 may select (determine) a classifier (e.g., an image quality classifier) corresponding to the image scene category that is transferred from the category classifying module 520.” Ex1006, [0152].

Lee explains that “when the quality of an image is measured, the quality may be measured from a different perspective view based on an image scene category.” Ex1006, [0153]. Therefore, the selected “classifier may indicate a reference value that is used for differentially measuring quality based on an image scene category of a corresponding image when the classifier measures the quality of the image.” Ex1006, [0152] (emphasis added).

3. US2017/0262982 (“Pagoulatos”)

Pagoulatos is a published U.S. patent application with a priority filing date of March 9, 2016. It is prior art to the Patent under 35 U.S.C. §§ 102(a)(2), 102(d)(2).

Pagoulatos is generally directed to an ultrasound imaging system that uses artificial intelligence, including, for example, trained artificial neural networks, to determine “whether acquired ultrasound images represent a clinically desirable view of one or more organs” (e.g., the heart). Ex1007, [0002], [0035]; *see also* Ex1008, p. 2, 6-7 (1:4-7, 5:23-6:5); Ex1009, p.15, 17, 20 (1:8-10, 3:8-15, 6:4-21). The system includes an ultrasound image recognition module 120, which can implement view-category-specific assessment parameters through a neural network 300 like the one depicted in Figure 3, below. Ex1007, [0016], [0042]-[0044], [0054]; Ex1008,

Fig. 3; *see also* Ex1008, Fig. 3 p. 4, 9, 12-13, 38 (3:6-8, 8:6-26, 11:24-12:19); Ex1009, p. 17, 24, 27, 33, 42 (3:23-25, 10:17-26, 13:9-24, 19:3-14, Fig. 4); *see also* Ex1002, ¶¶ 70, 83-85.

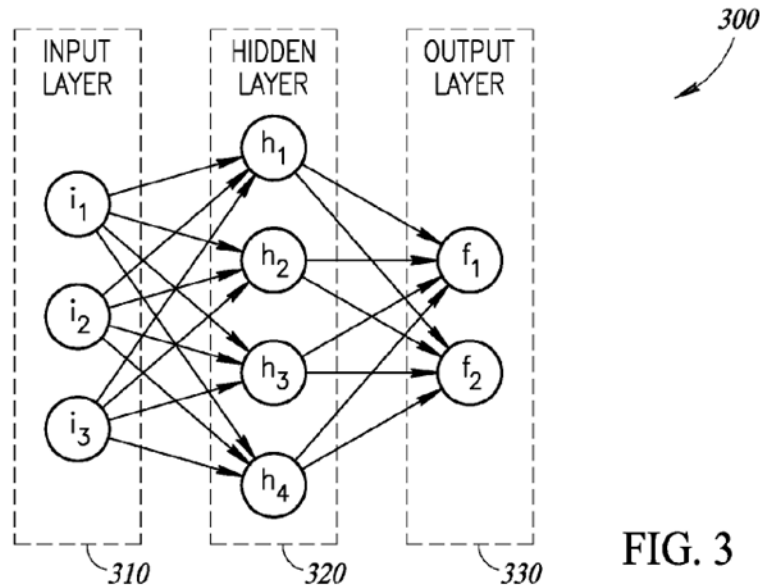


FIG. 3

As depicted in Figure 2, below, Pagoulatos discloses methods and systems for training such neural networks using training images. Ex1007, [0037]-[0038], [0046]-[0047]; *see also* Ex1008, p. 7-8, 10, 37 (6:12-7:12, 9:9-27, Fig. 2); Ex1009, p. 22-23, 28-29, 41 (8:20-9:24, 14:6-15:2, Fig. 3); *see also* Ex1002, ¶¶ 86-87.

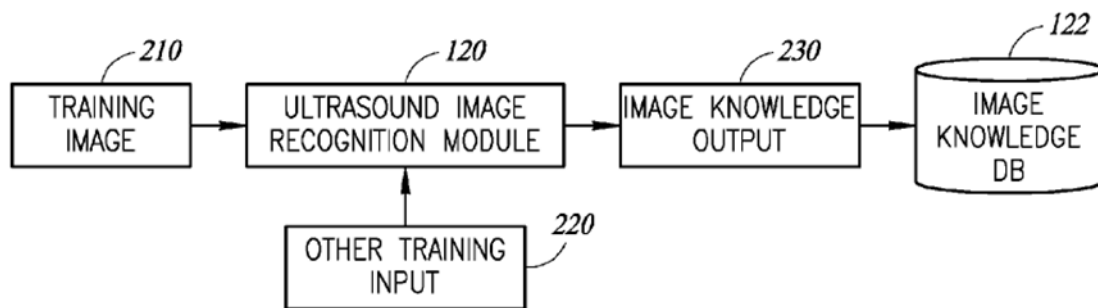


FIG. 2

With reference to Figures 2 and 3 above, Pagoulatos explains: “The neural network 300 may be trained by providing training images 210 to the input layer 310” where “the training images may include ultrasound image information having a wide variety of known characteristics, including, for example, various organ views, various image qualities or characteristics, various imaging angles, and so on.” Ex1007, [0046] (emphasis added); Ex1008, p.10 (9:9-19); Ex1009, p. 28 (14:6-19). “Through training, the neural network 300 may generate and/or modify the hidden layer 320, which represents weighted connections mapping the training images 210 provided at the input layer 310 to known output information at the output layer 330.” *Id.* The “[r]elationships between neurons of the input layer 310, hidden layer 320 and output layer 330, formed through the training process and which may include weight connection relationships” constitute “ultrasound image knowledge 230,” which is stored in an “ultrasound image knowledge database 122.” Ex1007, [0046], [0042]; Ex1008, p.10, 9 (9:9-19, 8:6-14); Ex1009, p. 28, 24 (14:6-19, 10:17-26).

Once the neural network 300 has been sufficiently trained, it can receive non-training images at the input layer 310 and use view-category-specific ultrasound image knowledge stored in database 122 to make determinations about the received images at the output layer 330. Ex1007, [0047]; Ex1008, p. 10 (9:20-27); Ex1009 p. 28-29 (14:20-15:2); Ex1002, ¶ 88. For example, Pagoulatos states that “a user may

select ... a desired view of an organ that is to be imaged” (e.g., a subcostal view of a heart), and the selected view may be communicated to the image recognition module 120 so that “the ultrasound image recognition module 120 may access the appropriate ultrasound image knowledge (e.g., knowledge, rules or regulations associated with a subcostal view of the heart) in the image knowledge database 122 such that received ultrasound images may be compared with, or processed by, knowledge corresponding to the selected view.” Ex1007, [0054]; Ex1008, p. 12-13 (11:24-12:19); Ex1009, p. 33 (19:3-14).

4. Automatic Fetal Ultrasound Standard Plane Detection (“Chen”)

Chen is a conference paper from the 18th International Conference on Medical Image Computing and Computer-Assisted Intervention held in Munich, Germany, on October 5-9, 2015. It was published by Springer International Publishing on November 18, 2015, in Medical Image Computing and Computer-Assisted Intervention, MICCAI 2015, Volume 9349, pp.507-514. Ex1010; *see also* Ex1002, ¶ 89. It is prior art under 35 U.S.C. §102(a)(1).

Chen describes methods for automatically detecting when an acquired image corresponds to a standard fetal ultrasound plane (*i.e.*, view) using trained neural networks. Ex1010, p.507; Ex1002, ¶ 90. Specifically, Chen explores the feasibility of accurately identifying ultrasound images that correspond to the fetal abdominal standard plane (FASP), fetal face axial standard plane (FFASP), and fetal

four-chamber view standard plane (FFVSP) of the heart. Ex1010, p.507. Chen also suggests, however, that the general framework of its teachings “can be easily extended to other US [ultrasound] standard plane or anatomical structure detection problems” such as detection of standard echocardiographic views. *Id.*, p.509.

Pertinent here, Chen teaches the advantages of using convolutional neural network (“CNN”) classifiers trained by “joint learning with knowledge transfer” across multiple domains or tasks. Ex1002, ¶¶ 91-92. Whereas conventional training of a CNN to perform a task (*e.g.*, identify a particular ultrasound standard plane) requires large datasets of labeled (*i.e.*, annotated) images, Chen explains that “[p]revious studies have indicated that the knowledge learned from one domain or task via CNN could benefit the training for another domain or task with limited annotated data.” Ex1010, p.510. Accordingly, Chen proposes “a joint learning model with CNN across multiple detection tasks of US standard planes, as illustrated in Figure 2 (right),” which is reproduced below.

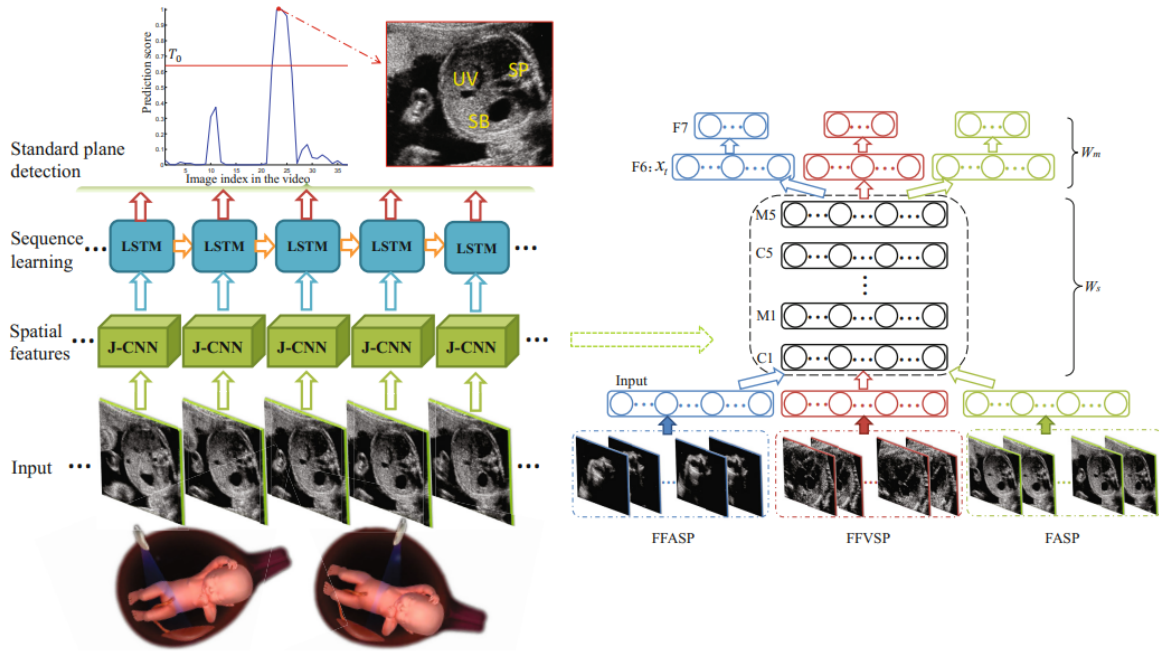


Fig. 2. Left: architecture of the proposed T-RNN; right: the proposed J-CNN.

Referring to the right side of Figure 2 above, Chen states: “In the figure, the matrix W_s denoting the parameters of layers from C1 to M5 is trained from all training samples of the three detection tasks [(i.e., FFASP, FVSP, FASP)] and shared among these tasks.” Ex1010, p.510 (emphasis added). By contrast, “[t]he W_m ($m = 1, 2, 3$ represents the task of FFASP, FVSP and FASP, respectively) denotes the parameters of F6 and F7 layers and is trained individually on each task for the discrimination of different standard planes.” *Id.* (emphasis added). Thus, Chen discloses a multi-stream CNN that contains shared layers with common assessment parameters and view/plane/task specific layers that were individually trained and contain unique, view/plane/task-specific assessment parameters.

Ex1002, ¶ 92.

B. Ground A: Krishnan-Lee

1. Claim 1

Claim 1 is obvious over Krishnan in view of Lee.

- a) **[1(pre)]²: “A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:”**

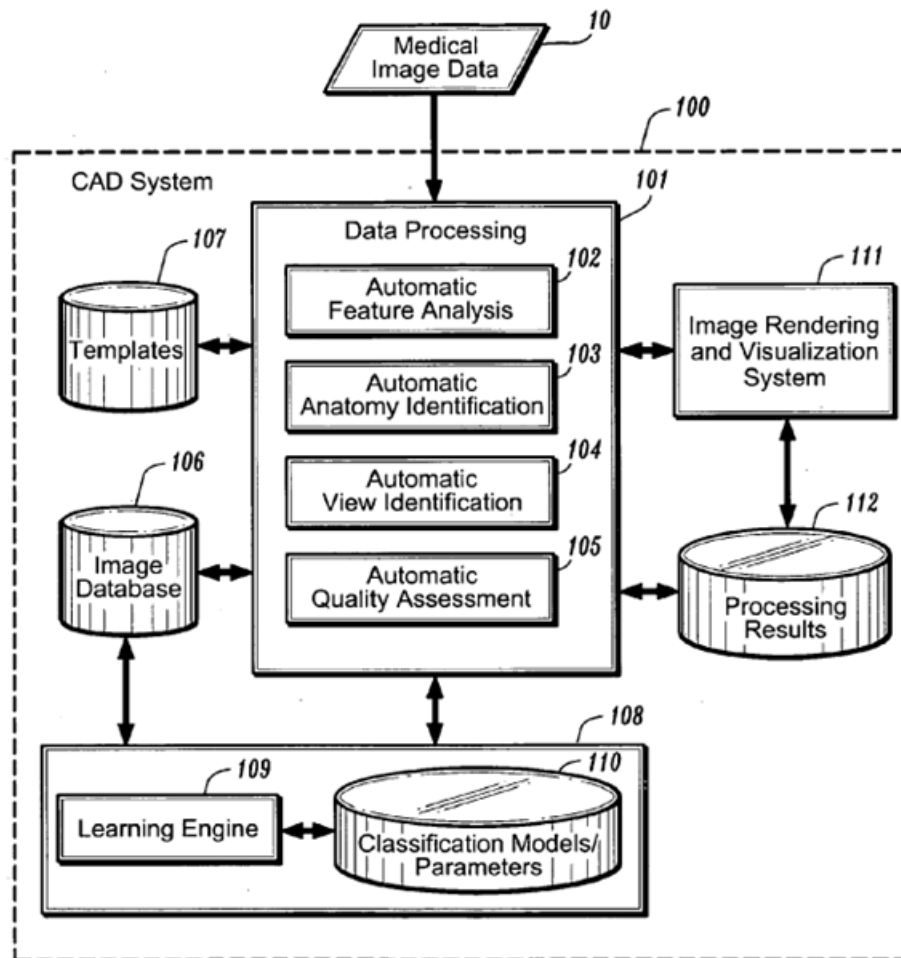
Krishnan discloses [1(pre)]. Ex1005, Abstract, [0005], [0009] (“echocardiography”), [0045], Fig. 1; Ex1002, ¶¶ 96-98. Krishnan discloses “systems and methods” for “processing a medical image to automatically identify the anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image.” Ex1005, Abstract. The “systems and methods” disclosed by Krishnan “may be implemented in various forms of hardware, software, firmware, special purpose processors, or a combination thereof.” Ex1005, [0045].

- b) **[1(a)/(e)]: “receive signals representing a [first/second] at least one echocardiographic image;”**

Krishnan discloses [1(a)/1(e)]. Ex1005, Figs. 1-2, [0009], [0016], [0017], [0032], [0033] (“Image data can be ... multiple views of a beating heart acquired

² The enclosed Claims Appendix includes the full claim language with bracketed reference characters identifying the respective limitations referenced in this Petition.

with a 3D ultrasound probe.”); Ex1002, ¶¶ 99-100. Figure 1 of Krishnan discloses a diagnostic system 100 “for providing automated decision support for medical imaging.” Ex1005, [0016]. The system 100 “comprises a data processing module (101) that implements various methods for analyzing medical image data (10) in one or more imaging modalities (e.g., ultrasound image data, MRI data, nuclear medicine data, etc.) to automatically extract and process relevant information from the medical image.” *Id.*



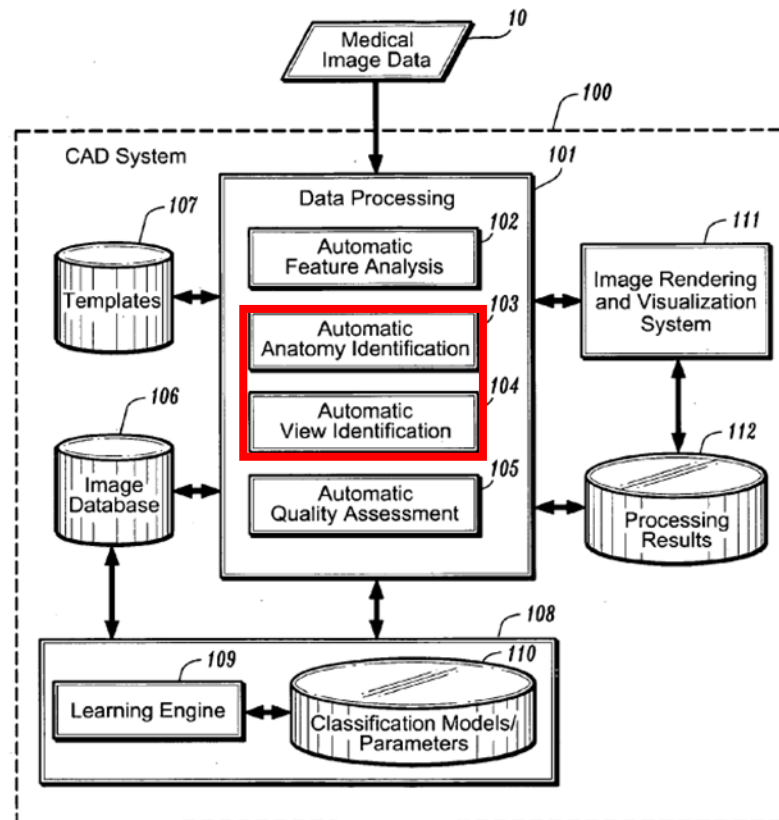
Additionally, Krishnan describes a multi-image workflow. Ex1002, ¶ 99. As

explained in Krishnan, “it is important for the sonographer to acquire, as quickly as possible, diagnostic quality images at multiple views.” Ex1005, [0032] (emphasis added). Accordingly, Krishnan states that the acquired image dataset may be “one or more medical images.” Ex1005, [0033]. For example, during a “stress-echo” examination, “[i]t is important for the sonographer to acquire, as quickly as possible, diagnostic quality images at multiple views” including “up to four (and sometimes more) loops of data for each view, where each loop represents a heart cycle.” *Id.*, [0032] (emphasis added). By providing a quality check, the sonographer can be assured (in real time) “that images are being acquired of diagnostic quality.” *Id.* (emphasis added).

- c) **[1(b)/(f)]: “associate the [first/second] at least one echocardiographic image with a [first/second] view category of a plurality of predetermined echocardiographic image view categories, [said second view category being different from the first view category];”**

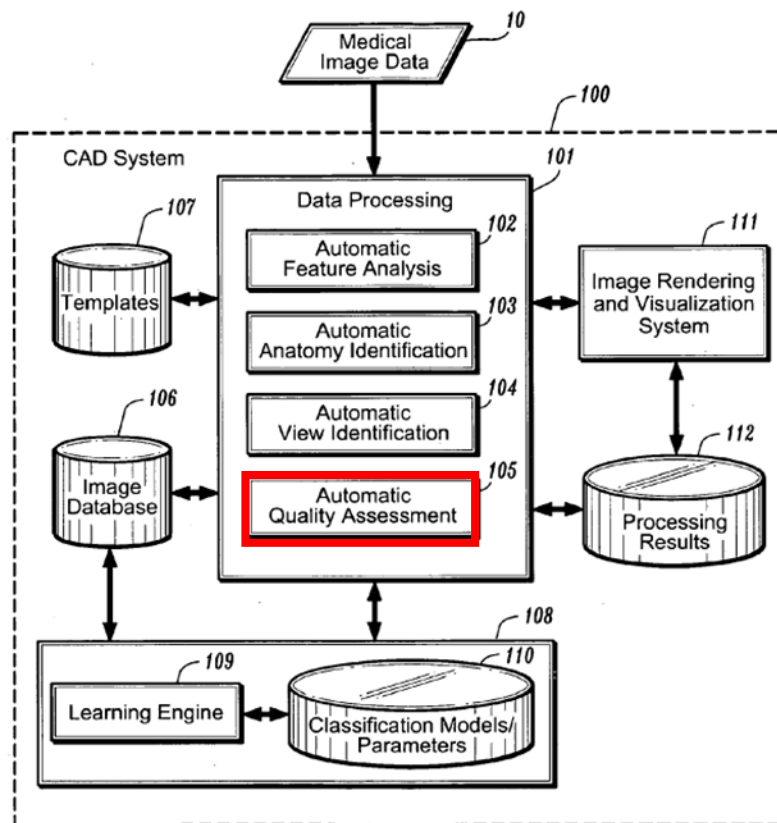
Krishnan discloses [1(b)/(f)]. Ex1005, Fig. 1 (“Automatic View Identification”), Fig. 2 (“Perform Automatic ... View Identification”), [0018], [0019], [0036]; Ex1002, ¶¶ 101-104. Krishnan explains that “the American Society of Echocardiography (ASE) recommends using standard ultrasound views in B-mode to obtain sufficient cardiac image data—the apical two-chamber view (A2C), the apical four-chamber view (A4C), the apical long axis view (ALAX), the parasternal long axis view (PLAX), the parasternal short axis view (PSAX).”

Ex1005, [0019]. Consistent with ASE recommendations, Krishnan “identif[ies] an unknown cardiac image as one of several different ASE standard views. *Id.*, [0019]; Ex1002, ¶ 104; *see also* Ex1020. Specifically, the anatomy identification module 103 and view identification module 104 in Krishnan’s system, highlighted below, use extracted image “features/parameters” to automatically identify anatomical objects and the view of the acquired image, respectively. Ex1005, [0018]-[0019] (“[T]he view identification module (104) ... label[s] a medical image with respect to what view of the anatomy the medical image contains.”).



- d) [1(c)/(g)]: “determine, based on the [first/second] at least one echocardiographic image and the [first/second] view category, a [first/second] quality assessment value representing a view category specific quality assessment of the [first/second] at least one echocardiographic image;”

Krishnan discloses [1(c)/(g)]. Ex1005, Fig. 1, Fig. 2, [0006], [0009], [0019], [0020], [0029], [0036], [0042], [0043]; Ex1002, ¶¶ 105-110. Figure 1 of Krishnan identifies an “automatic quality assessment” module (105), highlighted below. Ex1005, Fig. 1.



After “features/parameters” of one or more medical images are extracted (Ex1005, [0017]), “[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 data set.” Ex1005, [0020]. This workflow is depicted in Figure 2 of Krishnan, annotated below. Ex1005, [0033]-[0036], Fig. 2.

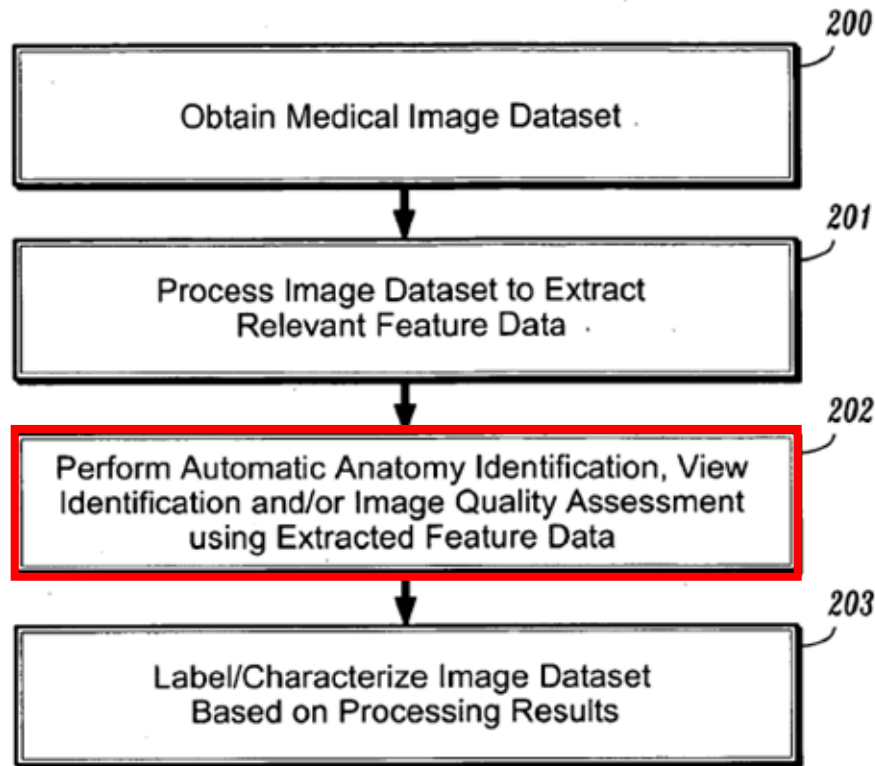


FIG. 2

“[F]or 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].

Krishnan explicitly states that “the results of ... view identification may be used for quality assessment.” Ex1005, [0020], [0029]. For example, Krishnan explains that “templates could be constructed for different cardiac views” and the

content of the input images could be compared to the content of the view-specific templates to determine the quality of the acquired images. Ex1005, [0041]. Similarly, Krishnan states that “view identification and[] image quality assessment are performed using associated classifiers.” Ex1005, [0006] (emphasis added). Thus, Krishnan explicitly discloses using both the image and the view category of the image to determine a view-category-specific quality assessment value of the image. Ex1002, ¶ 110.

- e) **[1(d)/(h)]: “produce signals representing the [first/second] quality assessment value for causing the [first/second] quality assessment value to be associated with the [first/second] at least one echocardiographic image;”**

Krishnan discloses [1(d)/(h)]. Ex1005, [0020], [0032], [0036], claim 30 (“presenting diagnostic quality determination results to a user in real-time”), Fig. 2 (203); Ex1002, ¶¶ 111-112. With reference to Figure 2 of Krishnan, after quality assessment is performed using extracted features from an image dataset, the dataset is labeled based on the quality assessment results. Ex1005, Fig. 2 (203). For example, Krishnan explains that “[t]he image dataset will be labeled ... based on the processing results” and “for image quality assessment, the medical images may include a quality score (within a predefined range).” *Id.*, [0036]. Krishnan also contemplates the implementation of methods “for providing real-time feedback during image acquisition regarding the diagnostic quality of the acquired images.”

Id., [0020], [0032].

- f) **[1(i)/(l)]: “wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and [wherein the at least one processor is configured to determine the [first/second] quality assessment value] by:”**

In response to a rejection over Krishnan, the Patent Owner amended claim 1 to include [1(i)/(l)], [1(j),(m)], and [(1(k))/(n)] and argued “Krishnan fails to teach or suggest determining a quality assessment value of an image using a neural network defined by a set of assessment parameters associated with a view category associated with that image.” Ex1004, pp. 266-268. Additionally, Patent Owner argued that “Krishnan fails to teach or suggest determining quality assessment values for each of two images using two respective neural networks corresponding to the respective view category of each image.” *Id.* But these purportedly novel functions are obvious, as demonstrated by Lee.

Krishnan-Lee discloses, teaches, or suggests [1(i)/(l)], [1(j),(m)], and [(1(k))/(n)]: Lee was not considered by the Examiner. Therefore, the Examiner did not have the benefit of considering Krishnan in view of Lee’s teachings.

As described in Section VIII.A.2 above, Lee describes determining image

quality assessment values using view-category-specific assessment parameters. After first classifying an image as belonging to a particular category, Lee then determines which of a plurality of stored classifiers corresponds to that category and determines an image quality score using that classifier. Ex1006, Figs. 5-6, and 11, [0009], [0152]-[0153], [0169], [0177]. Each classifier is based on different assessment parameters. *Id.*, [0096] (“[T]he image quality may be determined by applying, to the image, a different weight based on the determined image scene classifier.”), [0152]-[0153], [0160]-[0161]. Thus, Lee discloses, as claimed in the Patent, that each of a plurality of image view categories is associated with a respective set of assessment parameters. Ex1002, ¶¶ 78-82, 116.

Krishnan describes determining echocardiographic image quality assessment values using view-category-specific templates (Ex1005, [0041]) or, alternatively (*id.*, [0035]), a “bank of classifiers” (*id.*, [0042]-[0043]). Ex1002, ¶¶ 71-77, 115. “The classifiers can be implemented using machine learning methods” (Ex1005, [0006], [0023]), including “neural networks.” *Id.*, [0042]-[0044].

A POSITA would understand from these combined disclosures that Krishnan’s “bank of classifiers” could be a plurality of view-category-specific quality assessment classifiers as taught by Lee. Ex1002, ¶¶ 113-114, 119-120. Additionally, these view-category-specific classifiers could each be neural networks instead of view-category-specific templates, as expressly described in Krishnan.

Ex1002, ¶ 119. A POSITA would also understand that each of these view-category-specific classifiers would have different assessment parameters for evaluating the quality of images in different view categories “from a different perspective,” as taught by Lee. Ex1002, ¶ 120. Indeed, it is common sense that because the various standard echocardiographic views depict different anatomical structures from different angles, the quality of images associated with respective views should be evaluated differently. *Id.* Furthermore, since neural networks, by necessity, include an input layer and an output layer, and since Krishnan’s quality assessment classifiers output a “quality score” of an echocardiographic image, Krishnan teaches or suggests the multi-layer neural network framework described in [1(i)/(l)], [1(j),(m)], and [(1(k))/(n)]. Ex1002, ¶ 122. Accordingly, the combined disclosures of Krishnan and Lee teach or suggest, as claimed, a plurality of view quality assessment neural networks, each associated with a respective echocardiographic image view category, each having respective assessment parameters, and each configured to output a view-category-specific quality assessment value of one or more received images. Ex1002, ¶¶ 114-122.

Rationale to combine: Lee is analogous art to Krishnan. Both references are directed to the automatic assessment of the quality of images in different view categories using machine learning. Ex1002, ¶¶ 117-118; *see, e.g.*, Ex1005, [0002], [0009]; Ex1006, [0009], [0038], [0168]. And both references contemplate

application of their teachings to a variety of medical imaging devices, including ultrasound machines. *See* Ex1006 [0038]; Ex1005, [0016].

A POSITA would have found it obvious, and been motivated, to implement Krishnan using multiple view-category-specific neural networks based on the express teachings in Lee. Ex1002, ¶¶ 123-126. The use of neural networks for image quality assessment was well known as early as 2004. Ex1002, ¶¶ 47-48, 118. As deep convolutional networks became the dominant architecture for computer vision, neural networks were proposed for use in quality assessment tasks such as selecting the best quality image in a set for submitting to a facial recognition system. Ex1002, ¶¶ 47-48, 118; *see also* Ex1024. There are numerous prior art examples of neural networks deployed for image quality assessment. Ex1002, ¶ 49-51; Ex1017; Ex1023, Ex1026.

As detailed above, Krishnan explains that echocardiographic images are categorized according to standard views and states that the identification of these views can be used to assess the quality of the echocardiographic images. Ex1005, [0019], [0026], [0042]-[0043]; Ex1002, ¶ 124. Indeed, Krishnan already describes template-based embodiments in which the quality of an image is determined by comparing its contents to the contents of view-category-specific templates. Ex1005, [0041]. Krishnan also states, however, that “classifiers” can be used to assess the quality of images, and that these “classifiers” “can be implemented using machine

learning methods, model-based methods, or any combination of machine learning and mode-based methods” (Ex1005, [0006]), including “neural networks” (id., [0044]).

Lee expressly teaches what should be common sense, *i.e.*, that the quality of images in different categories should be assessed using different assessment parameters. Ex1002, ¶ 125. In ultrasound medical imaging, distinct standardized planes exist to enable visualization and quantification of different anatomic structures. *Id.* It follows, then, that image quality would depend on which structures in the image are required for successful analysis, and therefore no single set of assessment parameters would be sufficient to analyze all images. *Id.* Accordingly, Lee describes selecting an appropriate “classifier” for evaluating an image after first determining the category of the image. Ex1006, [0009], [0152]-[0153]. When this teaching is applied to Krishnan—particularly the embodiment in which Krishnan’s quality assessment classifier is based on a neural network—a POSITA would have been motivated to use respective view-specific neural networks to assess the quality of echocardiographic images in the respective view categories. Ex1002, ¶ 125. Additionally, a POSITA would have had a reasonable expectation of success practicing Krishnan in this manner since Krishnan already contemplates having a “bank of classifiers” and expressly allows for variability of implementation and configuration. Ex1002, ¶ 121; Ex1005, [0045].

Alternatively, it would have been obvious to a POSITA to combine the teachings of Krishnan and Lee because such combination would merely amount to applying known work from the field of automatic image processing (Lee) to an echocardiographic image use case (Krishnan) to yield predictable results. Ex1002, ¶ 126. Whereas Krishnan is directed to assessing the quality of images provided from different view categories, a POSITA would know from the teachings in Lee that different assessment parameters can be used to assess the quality of images in different categories. *Id.* Thus, it would have been within the ordinary skill and knowledge of a POSITA practicing Krishnan to evaluate the quality of echocardiographic images using neural network classifiers to use a plurality of view-category-specific neural networks. Ex1002, ¶ 126.

g) [1(j)/(m)]: “determining that a [first/second] set of assessment parameters of the sets of assessment parameters is associated with the [first/second] view category; and;”

Lee discloses [1(j)/(m)]. Ex1006, Fig. 5, (530), Fig. 6 (“Determine Classifier Corresponding to Image Scene Category 605”), Fig. 11 (“Determine Classifier that Matches Image Scene Category 1103”), [0009], [0011], [0152], [0177]; Ex1002, ¶¶ 127-128. Lee expressly discloses a computer-implemented system having a processor configured to “determine a classifier corresponding to the category of [an] image from among a plurality of classifiers.” Ex1006, [0009]. Lee discloses a “classifier selecting module 530” that “may change an image quality classifier to

correspond to an image scene category, and thereby chang[e] a perspective of measurement.” *Id.*, [0153]. Lee further states that “the classifier selecting module 530[] may be configured to select a classifier corresponding to the image scene category from among various image quality classifiers stored in advance in the memory.” *Id.*, [0177].

- h) **[1(k)/(n)]: “in response to determining that the [first/second] set of assessment parameters is associated with the [first/second] view category, inputting the [first/second] at least one echocardiographic image into the neural network defined by the [first/second] set of assessment parameters.”**

Krishnan-Lee discloses [1(k)/(n)]. As explained in Section VIII.B.1.g, above, Lee discloses a “classifier selecting module” that may “select and provide an image quality classifier that is appropriate” for a given image. Ex1006, [0153], Fig. 5 (530); *see also* Ex1002, ¶¶ 129-131. As depicted in Figure 5 of Lee, below, the image is then input into “the image quality evaluating module,” and the “image quality evaluating module” may “extract a total image quality score with respect to the image using ... the image quality classifier.” *Id.*, [0160].

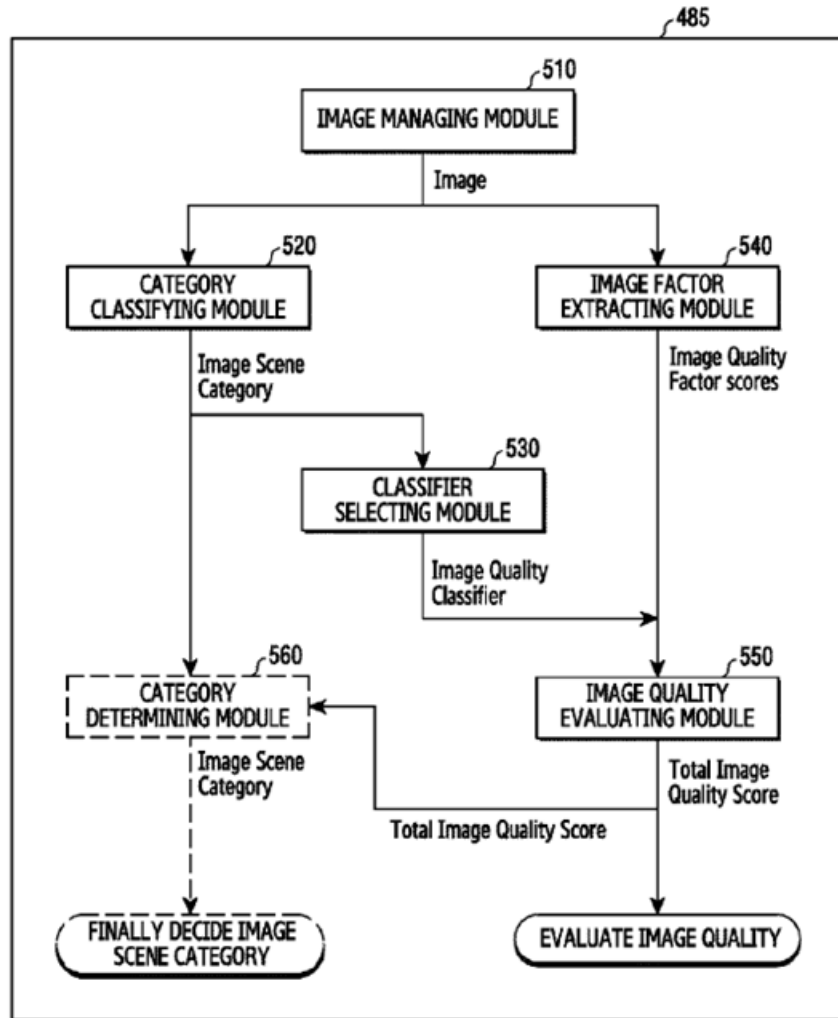


FIG.5

As is also explained in Section VIII.B.1.f, above, Krishnan-Lee discloses, teaches, or suggests that the image quality classifier may be a neural network having view-category-specific assessment parameters. Ex1005, [0042], [0043]; Ex1002, ¶ 125.

Accordingly, Krishnan-Lee discloses, teaches, or suggests all the limitations of claim 1 and renders it obvious. Ex1002, ¶¶ 96-131.

2. **Claim 2: “The system of claim 1 wherein the [first/second] quality assessment value represents an assessment of suitability of the [first/second] at least one echocardiographic image for quantified clinical measurement of anatomical features”**

Claim 2 depends from claim 1, which is rendered obvious by Krishnan-Lee. *See* Section VIII.B.1. Krishnan also discloses the limitations of claim 2. Ex1005, [0020], [0029]-[0030], [0036] (“[F]or image quality assessment, the medical images may include a quality score (within a predefined range) that provides an indication a diagnostic quality level of the medical images.”); Ex1002, ¶¶ 132-134.

A POSITA would recognize that one (of several) indications of diagnostic quality may be the images’ suitability for “clinical measurement of anatomical features.” Ex1002, ¶ 134. In fact, one common application of medical images is measurement of anatomic structures and comparison to normal values for the population. *Id.*; *see also* Ex1020. For example, the thickness of the left ventricle, a heart chamber, is used to diagnose a disease known as left ventricular hypertrophy. Specific standardized ultrasound views (e.g., PLAX) are used for this diagnosis. *Id.* One measure of PLAX quality is thus whether a user can visualize and make accurate measurements of the left ventricular so that medical diagnoses can be made. *Id.*

3. **Claim 3: “The system of claim 1 wherein the at least one processor is configured to: produce signals for causing a representation of the [first/second] quality assessment value to be transmitted to at least one display for causing the at least one display to display the [first/second] quality assessment value in association with the [first/second] at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image”**

Claim 3 depends from claim 1, which is rendered obvious by Krishnan-Lee.

See Section VIII.B.1. Krishnan also discloses the limitations of claim 3. Ex1005, [0020] (“[M]ethods can be implemented for providing real-time feedback during image acquisition regarding the diagnostic quality of the acquired images, allowing for changes in the image acquisition.”), [0032] (“feedback can be provided back to the operator of the imaging device in real time”), [0036]; Ex1002, ¶¶ 135-138. Krishnan expressly discloses an “image rendering and visualization system (111),” shown in Figure 1, that processes, generates, and displays “2D and/or 3D images on a computer monitor.” Ex1005, [0025].

4. **Claim 4: “The system of claim 1 wherein the at least one processor is configured to: [] apply one or more view categorization functions to the [first/second] at least one echocardiographic image to determine that the [first/second] at least one echocardiographic image falls within the [first/second] view category”**

Claim 4 depends from claim 1, which is rendered obvious by Krishnan-Lee.

See Section VIII.B.1. Krishnan and Lee also both disclose the limitations of claim 4. Krishnan discloses a “view identification module” that “implements methods ...

to automatically identify the view of an acquired image.” Ex1005, [0019], Fig. 1 (“Automatic View Identification 104”), Fig. 2 (“Perform Automatic ... View Identification”), [0006] (“[A]utomated ... view identification and/or image quality assessment are performed using associated classifiers The classifiers can be implemented using machine learning methods, model-based methods, or any combination of machine learning and model-based methods.”). The automatic identification methods could include “database querying methods (*id.*, [0021]), “template-based methods” (*id.*, [0022]), or “principle (machine) learning” methods (*id.*, [0023]); Ex1002, ¶¶ 139-142. Lee discloses a “category classifying module 520” that may define a “category or class” of an image using, for example, “deep learning.” Ex1006, [0151], [0168], [0176] (“classify the image through various algorithms”), Fig. 5 (520); Ex1002, ¶ 143.

5. **Claim 5: “The system of claim 1 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.”**

Claim 5 depends from claim 1, which is rendered obvious by Krishnan-Lee. See Section VIII.B.1. Krishnan also discloses the limitations of claim 5. Ex1005, [0017], [0032], [0033]. Krishnan states that the acquired image dataset may be “one or more medical images.” Ex1005, [0033]. For example, during a “stress-echo”

examination, “[i]t is important for the sonographer to acquire, as quickly as possible, diagnostic quality images at multiple views” including “up to four (and sometimes more) loops of data for each view, where each loop represents a heart cycle.” *Id.*, [0032] (emphasis added). Krishnan teaches that its “automatic image quality assessment” can provide “feedback ... to the operator of the imaging device in real time” and can “automatically select the images of the highest quality” from the loops of images. *Id.* These teachings disclose the limitations of claim 5. Ex1002, ¶¶ 144-145.

6. Claims 15-19: Method Claims

Claim 15 recites a “a computer-implemented method of facilitating echocardiographic image analysis” that is substantively identical to the “computer-implemented system for facilitating echocardiographic image analysis” recited in claim 1, addressed above. Whereas claim 1 (the system claim) recites a “processor” configured to perform various functions, claim 15 (the method claim) recites a series of steps performing the same functions identified in claim 1. Similarly, dependent claims 16-19 are substantively identical to dependent claims 2-5 discussed above. For the reasons discussed above and the additional reasons in the table below, Krishnan-Lee renders method claims 15-19 obvious. Ex1002, ¶¶ 146-147.

Limitation	Reasoning {referenced limitation}
[15(pre)]	See Section VIII.B.1.a {[1(pre)]}
[15(a)/(e)]	See Section VIII.B.1.b {[1(a)/(e)]}
[15(b)/(f)]	See Section VIII.B.1.c {[1(b)/(f)]}
[15(c)/(g)]	See Section VIII.B.1.d {[1(c)/(g)]}
[15(d)/(h)]	See Section VIII.B.1.e {[1(d)/(h)]}
[15(i)/(l)]	See Section VIII.B.1.f {[1(i)/(l)]}
[15(j)/(m)]	See Section VIII.B.1.g {[1(j)/(m)]}
[15(k)/(n)]	See Section VIII.B.1.h {[1(k)/(n)]}
[16]	See Section VIII.B.2 {[2]}
[17]	See Section VIII.B.3 {[3]}
[18]	See Section VIII.B.4 {[4]}
[19]	See Section VIII.B.5 {[5]}

C. Ground B: Krishnan-Lee-Pagoulatos

1. Claim 7

Claim 7 depends from claim 1, which is rendered obvious by Krishnan-Lee. See Section VIII.B.1. Claim 7 adds limitations relating to neural network “training” and is rendered obvious by Krishnan-Lee in further view of Pagoulatos.

Rationale to combine: Krishnan, Lee, and Pagoulatos are analogous art. Each is directed to automatically assessing the quality of images using machine learning. Ex1005, [0002], [0009]; Ex1006, [0009], [0038], [0168]; Ex1007, [0002]; Ex1008, p. 2 (1:4-7); Ex1009, p.15, 17 (1:8-10, 3:8-15); *see also* Ex1002, ¶¶ 118, 152.

As already explained in Section VIII.B.1.f above, a POSITA would be motivated to combine Krishnan and Lee based on Lee’s express teaching that different assessment parameters/classifiers should be used to assess the quality of images from different categories differently. Additionally, a POSITA would be

motivated to combine Pagoulatos with Krishnan because, whereas Krishnan *generally* discloses a “learning engine (109) ... for training/building one or more classifiers” to assess echocardiographic images (Ex1005, [0023]), Pagoulatos describes *in detail* techniques for training neural network classifiers to assess echocardiographic images. Ex1007, [0037]-[0038], [0040]-[0042], [0046]-[0047], Figs. 2, 8); Ex1008, p. 7-10, 37 (6:12-7:12, 7:17-8:14, 9:9-27, Fig. 2); Ex1009, p. 22-24, 28-29, 41 (8:20-9:24, 10:1-26, 14:6-15:2, Fig. 3); Ex1002, ¶¶ 148-151. For example, Pagoulatos describes an iterative training process (Ex1007, [0040]) using training images having a wide variety of known characteristics, and mapping—through a back-propagation learning algorithm (*id.*, [0041])—the training images provided to the input layer of a neural network to known information produced at the output layer of the neural network (*id.*, [0046]). *See also* Ex1008, p. 8-9 (7:17--8:5), p. 10 (9:9-19); Ex1009, p. 24 (10:1-16), p. 28 (14:6-19); Ex1002, ¶ 151. The advantage of this process, according to Pagoulatos, is that the trained neural network classifier “may learn to modify its behavior” and “alter the manner in which it makes determinations with respect to new input, such as, for example, ultrasound image information received from [an] ultrasound device.” Ex1007, [0043]; Ex1008, p. 9 (8:15-18); Ex1009, p. 27 (13:9-16).

Applying the neural network training technique described in Pagoulatos to the neural network classifiers disclosed in Krishnan would merely have amounted to

applying a known technique to known device to yield predictable results. Ex1002, ¶¶ 152. A POSITA would have been motivated to implement training methods described in Pagoulatos with Krishnan based on the advantages described in Pagoulatos. *Id.* Additionally, a POSITA would have had a reasonable expectation of success in doing so, since Pagoulatos explicitly describes its disclosed technique as “a common method of training artificial neural networks.” Ex1007, [0041]; Ex1008, p. 8-9 (7:23-8:5); Ex1009, p. 24 (10:6-16); Ex1002, ¶¶ 152.

Krishnan-Lee-Pagoulatos discloses, teaches, or suggests claim 7: As detailed below, the combination of Krishnan-Lee-Pagoulatos, discloses, teaches, or suggests every element of claim 7.

a) [7(pre)]: “The system of claim 1 wherein the at least one processor is configured to train the neural networks by:”

The Patent describes “training” neural networks using a “plurality of echocardiographic training images” and “associated expert quality assessment values to determine sets of neural network parameters defining the neural networks.” Ex1001, 2:2-11, Figs. 14, 16. As a general matter, the “training” framework disclosed in the Patent—use of pre-analyzed images to train neural network parameters—is the standard method already known in the art. Ex1011, p.450 (“For a network to be trained ... a ‘training’ data set of example inputs and their corresponding desired outputs is required.... During learning the example inputs are

presented to the network and the resultant and desired outputs are compared.”); Ex1002, ¶¶ 153-155. Regardless, the “training” workflow discussed and claimed in the Patent is taught by Krishnan-Lee-Pagoulatos. Ex1002, ¶¶ 153-155.

Krishnan discloses that its quality assessment module 105 may be implemented using one or more “trained” classifiers that may be built from “neural networks.” Ex1005, [0023], [0042]-[0044]. Additionally, Krishnan discloses a “learning engine (109) [that] includes methods for training/building one or more classifiers using training data that is learned from ... previously diagnosed/labeled cases.” *Id.*, [0023], [0045] (“special purpose processors”), Fig. 1 (“Learning Engine 109”) (“Classification Models/Parameters 110”).

Pagoulatos likewise discloses a processor configured to train one or more neural networks. Ex1007, Abstract, [0036]-[0037], [0040], [0044], [0046]-[0047]; Ex1008, p. 7-10 (6:6-22, 7:17-22, 8:19-26, 9:9-27); Ex1009, p. 21-24, 27-29 (7:4-17, 8:20-9:4, 10:1-5, 13:17-24, 14:6-15:2). Pagoulatos discloses an “ultrasound image recognition module 120” that can implement artificial neural networks (*id.*, [0044]), and states that [t]he ultrasound image recognition module 120 may include, or otherwise be executed by, a computer processor configured to perform the various functions and operations described herein” (*id.* [0036], including “an iterative training process” (*id.*, [0040]). *See also* Ex1008, p. 9 (8:19-26), p. 7 (6:6-11), p. 8 (7:17-22); Ex1009, p. 27 (13:17-24), p. 21 (7:4-17), p. 24 (10:1-5).

- b) [7(a)]: “receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories; and”**

Pagoulatos discloses, and Krishnan teaches or suggests, [7(a)]. Krishnan’s learning engine (109) utilizes a “database (106) of previously diagnosed/labeled medical images.” Ex1005, [0023]. Because the images in this database are used as “training data” to “to train classifiers for performing” automated view identification, a POSITA would understand the “training data” as including images associated with one of the plurality of predetermined echocardiographic image view categories. Ex1005, [0007]; *see also id.* Ex1005, Fig. 1 (“Learning Engine 109”) (“Classification Models/Parameters 110”); Ex1002, ¶¶ 156-157.

Pagoulatos further discloses [7(a)]. Ex1007, [0025] (“trained using a large number of ultrasound images representing known or clinically determined views”), [0037], [0046]; Ex1008, p. 6-7, 10 (5:23-6:5, 6:12-22, 9:9-19); Ex1009, p. 18-19, 22-23, 28 (4:17-5:3, 8:20-9:4, 14:6-19); Ex1002, ¶ 158. For example, Pagoulatos describes training “based on training images” that “may include a variety of ultrasound image information associated with known views of an organ, such as the heart.” Ex1007, [0037]; Ex1008, p. 7 (6:12-22); Ex1009, p. 22-23 (8:20-9:4). Additionally, Pagoulatos explains that an example “neural network 300 may be trained by providing training images 210 to the input layer 310” where “the training

images may include ultrasound image information having a wide variety of known characteristics, including, for example, various organ views.” Ex1007, [0046]; Ex1008, p.10 (9:9-19); Ex1009, p. 28 (14:6-19).

- c) **[7(b)]: “receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and.”**

Krishnan teaches or suggests, and Pagoulatos discloses, [7(b)]. As explained in the preceding section, Krishnan discloses “training/building one or more classifiers using training data ... of previously diagnosed/labeled cases”) Ex1005, [0023], [0043]; Ex1002, ¶¶ 159-160. Because the training images are used to train classifiers to perform view identification and determine image quality, a POSITA would understand that the training images would be labelled according to view category and quality. Ex1002, ¶ 160. This is confirmed by Krishnan’s explanation of a “database querying method” in which the view identification and quality assessment modules (104, 105) can “search for similar labeled cases” in a database of “labeled/diagnosed medical images” to “identify the particular ... view, or help identify the quality of the image.” Ex1005, [0021]. Ex1002, ¶ 160.

Pagoulatos likewise discloses training one or more classifiers, including a neural network, using training image data that is labelled with

view-category-specific quality assessments. Ex1002, ¶ 161. Pagoulatos states that its classifiers “may be trained using a large number of ultrasound images representing known or clinically determined views” (Ex1007, [0025]), for example, “ultrasound images which have been pre-determined (e.g., by a physician) as adequately showing a clinically desirable ... view of a heart” (*id.*, [0037] (emphasis added)). *See also* Ex1008, p. 6-7 (5:23-6:5), p. 7 (6:12-22); Ex1009, p. 18-19 (4:17-5:3), p. 22-23 (8:20-9:4). Additionally, Pagoulatos states that “the training images may include ... information having a wide variety of known characteristics, including, for example, various organ views, various image qualities or characteristics, various imaging angles, and so on.” Ex1007, [0046] (emphasis added); Ex1008, p.10 (9:9-19); Ex1009, p. 28 (14:6-19).

d) [7(c)]: “training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks”

Krishnan-Lee-Pagoulatos discloses [7(c)]. Ex1007, [0037], [0040]-[0041], [0046], Fig. 2; Ex1008, p.7-10 (6:12-22, 7:17-8:5, 9:9-19); Ex1009, p. 22-24, 28 (8:20-9:4, 10:1-16, 14:6-19); Ex1002, ¶¶ 162-166. As discussed in Section VIII.B.1, above, Krishnan-Lee discloses, teaches, or suggests the use of multiple view-category-specific neural networks (e.g., a “bank of classifiers”)—the desired output of which are quality assessment values. Pagoulatos discloses the training of

such neural networks as described in [7(c)].

Pagoulatos states that a “neural network 300 may be trained by providing training images 210 to the input layer 310.” Ex1007, [0046]; Ex1008, p.10 (9:9-19); Ex1009, p. 28 (14:6-19). As previously discussed, Pagoulatos also explains that the training images can include a variety of information including “known characteristics” such as “various image qualities.” Ex1007, [0037], [0046]; Ex1008, p. 7, 10 (6:12-22, 9:9-19); Ex1009, p. 22-23, 28 (8:20-9:4, 14:6-19). In the case of quality assessment neural networks, like those described in Krishnan, where the desired outputs of the neural networks are predicted quality scores, a POSITA would understand that the training images would be labeled with pre-determined quality values, and an object of training would be to minimize the error between the output predictions and the input labels. Ex1002, ¶ 163. Pagoulatos teaches that through an “iterative training process” the parameters of the neural network are updated “until performance of the network is satisfactory.” Ex1007, [0040]-[0041]; Ex1008, p. 8-9 (7:17-8:5); Ex1009, p. 24 (10:1-16). Once trained, “the neural network 300 may make determinations about the received ultrasound image information at the output layer 330.” Ex1007, [0047]; Ex1008, p. 10 (9:20-27); Ex1009, p. 28-29 (14:20-15:2).

With reference to Figures 2 and 3, below, Pagoulatos explains that “through training, the neural network 300 may generate and/or modify the hidden layer 320,

which represents weighted connections mapping the training images 210 provided at the input layer 310 to known output information at the output layer 330.” Ex1007, [0046]; Ex1008, p.10, 37-38 (9:9-19, Figs. 2-3); Ex1009, p. 28, 41-42 (14:6-19, Figs. 3-4).

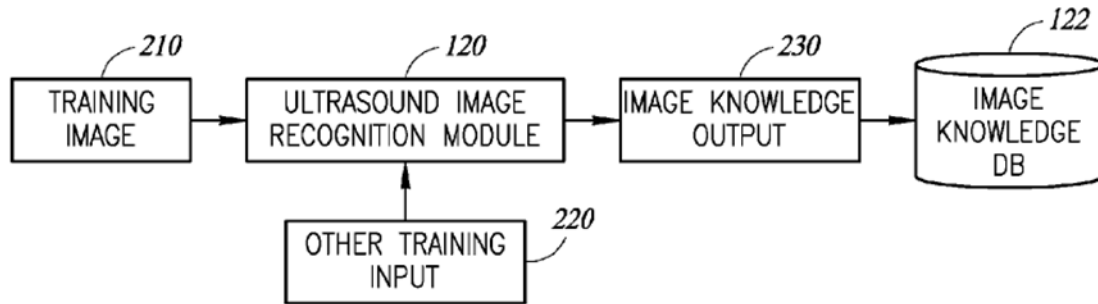


FIG. 2

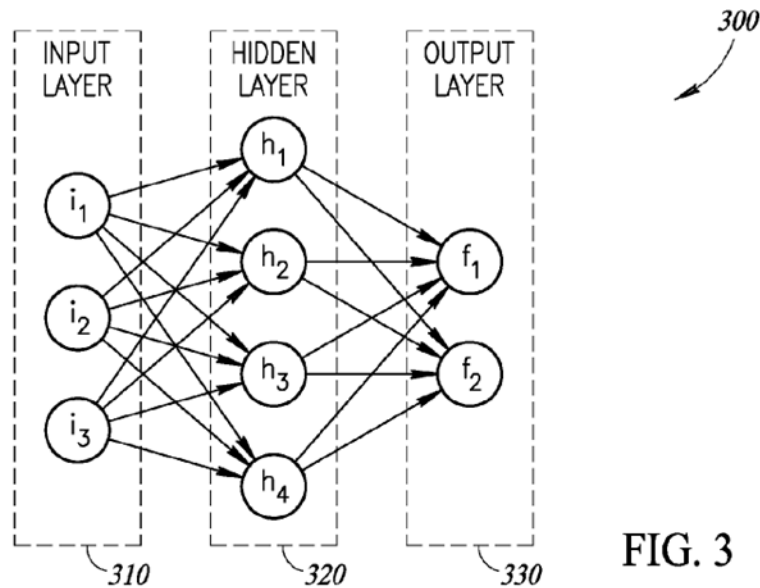


FIG. 3

The “[r]elationships between neurons of the input layer 310, hidden layer 320 and output layer 330, formed through the training process and which may include weight connection relationships” constitute “ultrasound image knowledge 230,” which is

stored in an “ultrasound image knowledge database 122.” Ex1007, [0046], [0042]; Ex1008, p.10, 9 (9:9-19, 8:6-14); Ex1009, p. 28, 24 (14:6-19, 10:17-26). Thus, Krishnan-Lee-Pagoulatos teaches the use of training image data to determine neural network parameters as recited in [7(c)]. Ex1002, ¶¶ 162-166.

2. Claim 8: “The system of claim 7 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features”

Claim 8 depends from claim 7, which is rendered obvious by Krishnan-Lee-Pagoulatos. See Section VIII.C.1. Krishnan also discloses the limitations of claim 8. Ex1005, [0020] (“diagnostic quality”), [0029]-[0030] (“determine the existence, if any, of foreshortening”), [0036] (“[F]or image quality assessment, the medical images may include a quality score (within a predefined range) that provides an indication a diagnostic quality level of the medical images.”); Ex1002, ¶¶ 167-169.

3. Claim 9: “The system of claim 7 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features”

Claim 9 depends from claim 7, which is rendered obvious by Krishnan-Lee-Pagoulatos. See Section VIII.C.1. Krishnan and Pagoulatos also disclose or suggest the limitations of claim 9. Ex1002, ¶¶ 170-172. Krishnan teaches

that its image quality classifiers may be built/trained using “previously diagnosed/labeled cases” (Ex1005, [0023], where the “image quality assessment... may include a quality score ... that provides an indication [of] a diagnostic quality level of the medical images” (*id.*, [0036])). Similarly, Pagoulatos states that “the training images ... may be ultrasound images which have been pre-determined (e.g., by a physician) as adequately showing a clinically desirable ... view of the heart” (Ex1007, [0037]) and “the training images may include ultrasound image information having a wide variety of known characteristics, including, for example, ... various image qualities ..., various imaging angles, and so on (*id.*, [0046])). *See also* Ex1008, p. 7 (6:12-22), p. 10 (9:9-19); Ex1009, p. 22-23 (8:20-9:4), p. 28 (14:6-19).

4. Claim 11

Claim 11 is obvious over Krishnan-Lee-Pagoulatos.

a) [11(pre), 11(a), 11(b)]:

The preamble and elements (a)-(b) of Claim 11 are substantively identical to Claim 7 of the Patent, which is discussed above. For the reasons discussed above and the additional reasons in the table below, Krishnan-Lee-Pagoulatos discloses or teaches these claim elements. Ex1002, ¶ 173.

Limitation	Reasoning {referenced limitation}
[11(pre)]	<i>See</i> Section VIII.C.1.a) {[7(pre)]}
[11(a)]	<i>See</i> Section VIII.C.1.b) {[7(a)]}
[11(b)]	<i>See</i> Section VIII.C.1.c) {[7(b)]}

b) [11(c)]: “at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories”

For the same reasons previously explained with respect to claim 1 in Section VIII.B.1.f) above, Krishnan-Lee discloses, teaches, or suggests, a plurality of view-category-specific neural networks (i.e., “bank of classifiers”) having different view-category-specific parameters (e.g., weights and biases). Ex1002, ¶¶ 113-126, 174-175. Because each of the neural network classifiers taught by Krishnan-Lee is specific to one of a plurality of predetermined view categories, at least a “portion of each neural network” is also associated with view category, as claimed. *Id.*

c) [11(d)-(r)]

Element 11(d) begins a recitation of functions that occur “once the neural networks are trained.” This post-training functionality—recited in elements (e)-(j) of claim 11—is substantively identical to the functionality set forth in claim 1 of the Patent, which is discussed above. Ex1002, ¶¶ 99-128, 176. For the reasons discussed above and the additional reasons in the table below, Krishnan-Lee-Pagoulatos discloses or teaches these claim elements. *Id.*

Limitation	Reasoning {referenced limitation}
[11(e)/(i)]	See Section VIII.B.1.b) {[1(a)/(e)]}
[11(f)/(j)]	See Section VIII.B.1.c) {[1(b)/(f)]}
[11(g)/(k)]	See Section VIII.B.1.d) {[1(c)/(g)]}
[11(h)/(l)]	See Section VIII.B.1.e) {[1(d)/(h)]}
[11(m)/(p)]	See Section VIII.B.1.f) {[1(i)/(l)]}

[11(n)/(q)]	See Section VIII.B.1.g) {[1(j)/(m)]}
[11 (o)/(r)]	See Section VIII.B.1.h) {[1(k)/(n)]}

5. **Claim 12: “The system of claim 11 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.”**

Claim 12 depends from claim 11, which is rendered obvious by Krishnan-Lee-Pagoulatos. See Section VIII.B.9. Krishnan also discloses the limitations of claim 12, which is substantively identical to claim 8. See Section VIII.C.2. Ex1002, ¶¶ 177-179.

6. **Claim 13: “The system of claim 11 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.”**

Claim 13 depends from claim 11, which is rendered obvious by Krishnan-Lee-Pagoulatos. See Section VIII.B.9. Krishnan and Pagoulatos also teach the limitations of claim 12, which is substantively identical to claim 9. See Section VIII.C.3. Ex1002, ¶¶ 180-182.

D. Ground C: Krishnan-Lee in view of Chen

1. **Claims 6 and 20: “wherein each of the sets of assessment parameters includes: a set of common assessment parameters, which are common to each of the sets of assessment parameters; and a set of view category specific assessment parameters, which are unique to the set of assessment parameters.”**

Claims 6 and 20 are identical except they depend from system claim 1 and method claim 15, respectively. Claims 1 and 15 are both rendered obvious by Krishnan-Lee. *See* Sections VIII.B.1 and VIII.B.6. Claims 6 and 20 are rendered obvious by Krishnan-Lee in further view of Chen. *See* Ex1002, ¶¶ 183-194.

Figure 8 of the Patent, below, is “a representation of an exemplary image quality assessment neural network that may be used” in the contemplated system. Ex1001, 4:15-17; Ex1002, ¶ 185.

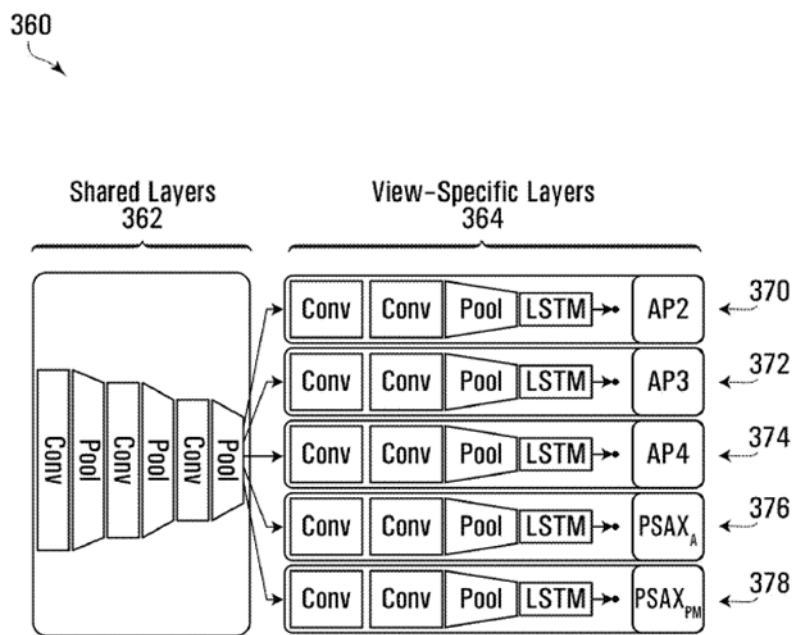


FIG. 8

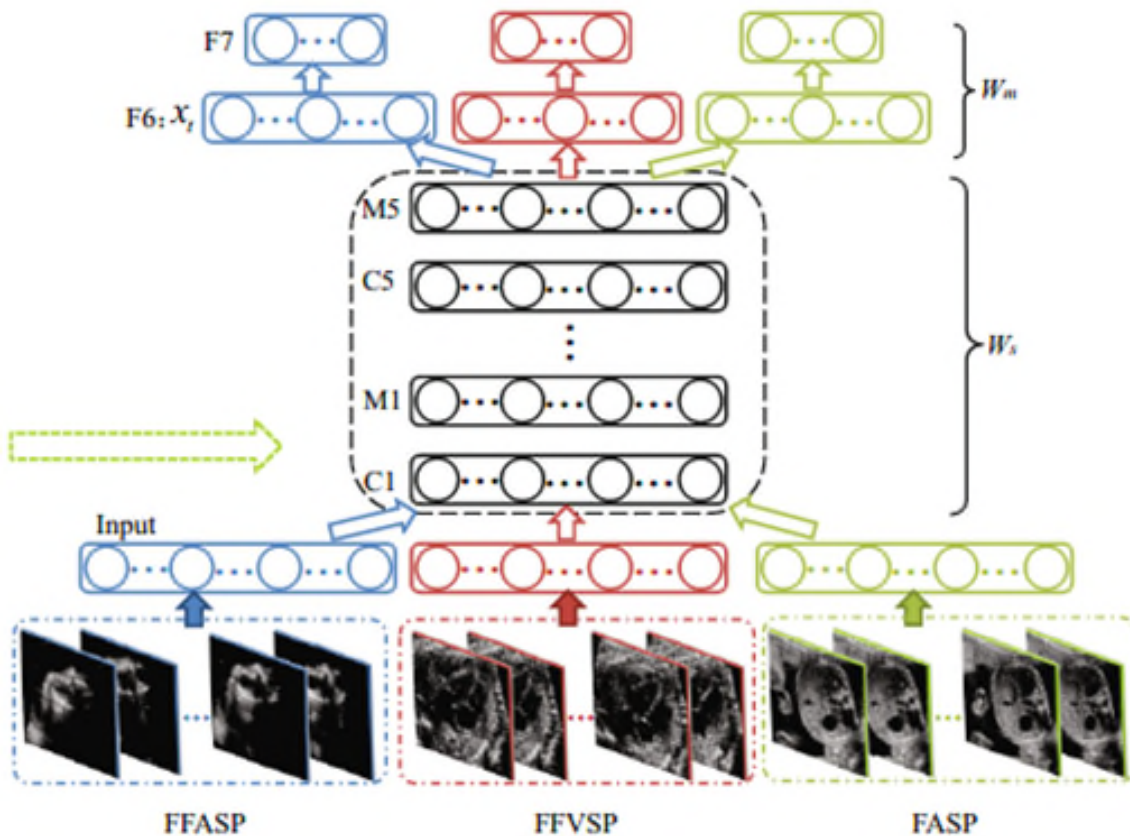
Referring to Figure 8, the Patent states: “the neural network shown at 360 includes 5 image quality assessment neural networks, each including the same shared layers 362 but including a different set of view category specific layers 370, 372, 374, 376,

and 378.” Ex1001, 12:10-14. A “[common] set of parameters defining the shared layers 362 ... is shown at 320 in FIG. 9.” Ex1001, 13:13-20, Figs. 8, 9; Ex1002, ¶ 186. A “[unique] set of parameters defining the set of view category specific layers 374 ... is shown at 40 in FIG. 10.” Ex1001, 13:26-37, Figs. 8, 9, 10; Ex1002, ¶ 187.

Multi-stream neural network structures, like the one depicted in Figure 8 of the Patent, comprising common (shared) layers with common parameters and category-specific layers with unique parameters were known in the art as of the priority date of the Patent. Ex1002, ¶¶ 49-53, 188. Indeed, Caruana (Ex1018) described this approach, termed multi-task learning, as early as 1993. Ex1002, ¶ 188. Subsequent applications of multi-task learning have been seen in computer vision including for image classification. *Id.*; *see also* Ex1025 (Long and Wang). Chen is another example, with specific application to ultrasound image analysis. Ex1010, p.507; Ex1002, ¶ 90.

Chen discloses [6]/[20]: Chen describes a joint learning framework that produces a multi-stream convolutional neural network (J-CNN) with shared layers that were trained jointly, followed by branching layers that were individually trained. Ex1010, pp.507, 509-510; Ex1002, ¶¶ 189-191. The purpose of jointly training early layers, Chen teaches, is “to address the insufficiency issue of limited training data” (Ex1010, Abstract), “which reduces the overfitting problem caused by the inadequacy of training data” (*id.*, p.509).

Referring to the right side of Figure 2, which is enlarged below, Chen’s multi-stream J-CNN contains 3 sets of assessment parameters, each with a “set of common [neural network assessment] parameters, which are common to each of the sets of neural network parameters” and “a set of view category specific [neural network assessment] parameters, which are unique to the set of neural network parameters,” as claimed in the Patent. Ex1002, ¶¶ 190-191.



In the figure above, “the matrix W_s denoting the parameters of layers from C1 to M5 is trained from all training samples of the three detection tasks [(i.e., FFASP, FFVSP, FASP)] and shared among these tasks.” Ex1010, p.510 (emphasis added). These

layers contain the “common assessment parameters.” Ex1002, ¶ 191. By contrast, “[t]he W_m ($m = 1, 2, 3$ represents the task of FFASP, FFVSP and FASP, respectively) denotes the parameters of F6 and F7 layers and is trained individually on each task for the discrimination of different standard planes.” *Id.* (emphasis added). These view category-specific layers contain unique assessment parameters. Ex1002, ¶ 191.

Rationale to combine: Krishnan, Lee, and Chen are analogous art. All are directed to the automatic quality assessment of images associated with different view categories using trained neural networks. Ex1010, p.507; Ex1005, [0002], [0009], [0019], [0044]; Ex1006, [0009], [0038], [0168].

A POSITA would have been motivated to improve Krishnan-Lee based on the express teachings and suggestions in Chen. Ex1002, ¶¶ 192-194. Whereas Krishnan-Lee teaches, suggests, and renders obvious the use of multiple view-category-specific neural network classifiers having different assessment parameters for each view-category, Chen teaches the advantages of combining such separate neural networks into a neural network having common layers and separate task-specific layers. Ex1002, ¶ 193. Specifically, Chen teaches that by combining separate task-specific neural networks in a manner that they share some commonly trained layers, the problems of insufficient training data and overfitting can be reduced. Ex1010, pp.507, 509 (“joint learning ... across multi-tasks ... reduces the overfitting problem caused by the inadequacy of training data”); Ex1002, ¶ 193. This

same rationale is parroted in the later-filed Patent, which states that “splitting the neural network 360 into a common portion and view category specific portions may facilitate more efficient training” and “may result in requiring fewer learning parameters than would be required if using fully separate neural networks.” Ex1001, 13:53-59. Again, this is the standard description of how multi-task learning is used in training neural networks, and the concomitant benefits of the structure were known in the art as of 2015. Ex1002, ¶ 193.

To achieve the benefits explicitly described in Chen, a POSITA would have been motivated to structure the separate view-category-specific “bank of classifiers” taught by Krishnan-Lee to have a structure like that depicted in Figure 8 of the Patent with common and view-specific layers/assessment parameters. Ex1002, ¶ 194.

Additionally, a POSITA would have had a reasonable expectation of success combining Krishnan-Lee with Chen since the combinations merely involve the implementation of a specific neural network architecture, and Krishnan is open to any machine learning classifier and/or neural network. Ex1005, [0006], [0023], [0042]-[0044]; Ex1002, ¶ 194. Indeed, Chen contemplates that its proposed neural network framework “can be easily extended to other ... anatomical structure detection problems.” Ex1010, p.509.

E. Ground D: Krishnan-Lee-Pagoulatos in view of Chen

1. Claims 10 and 14

Dependent Claims 10 and 14 are substantively the same but depend from claims 7 and 11, respectively. Claims 7 and 11 are each rendered obvious by Krishnan-Lee-Pagoulatos. *See* Sections VIII.C.1 and VIII.C.4. As discussed below, Chen discloses all the additional limitations of claims 10 and 14. Additionally, it would have been obvious to a POSITA to combine the teachings of Chen with Krishnan-Lee-Pagoulatos for the same reasons already explained in Section VIII.D above. Ex1002, ¶¶ 192-194, 195-197. The mere addition of Pagoulatos to Krishnan-Lee does not alter or diminish the motivation to combine Chen with Krishnan-Lee as Pagoulatos is not inconsistent, or in conflict, with Chen. Ex1002, ¶ 197. Accordingly, Claims 10 and 14 are rendered obvious by Krishnan-Lee-Pagoulatos in view of Chen. *Id.*

a) [10(pre)]/[14(pre)]-[10(a)]/[14(a)]-[10(b)]/[14(b)]

[10(pre)]/[14(pre)], [10(a)]/[14(a)], and [10(b)]/[14(b)] are substantively identical to the elements of claims 6 and 20, which are addressed above in Section VIII.D.1. Whereas claims 6 and 20 recite “sets of assessment parameters,” claims 10 and 14 recite “sets of neural network parameters.” However, each “set of assessment parameters” recited in claims 6 and 20 is defined as “being a set of neural network parameters” in underlying independent claims 1 and 15, respectively. Accordingly, elements [10(pre)]/[14(pre)], [10(a)]/[14(a)], and [10(b)]/[14(b)] are disclosed by Chen for the same reasons provided in Section VIII.D.1. Ex1002, ¶¶

183-191, 196.

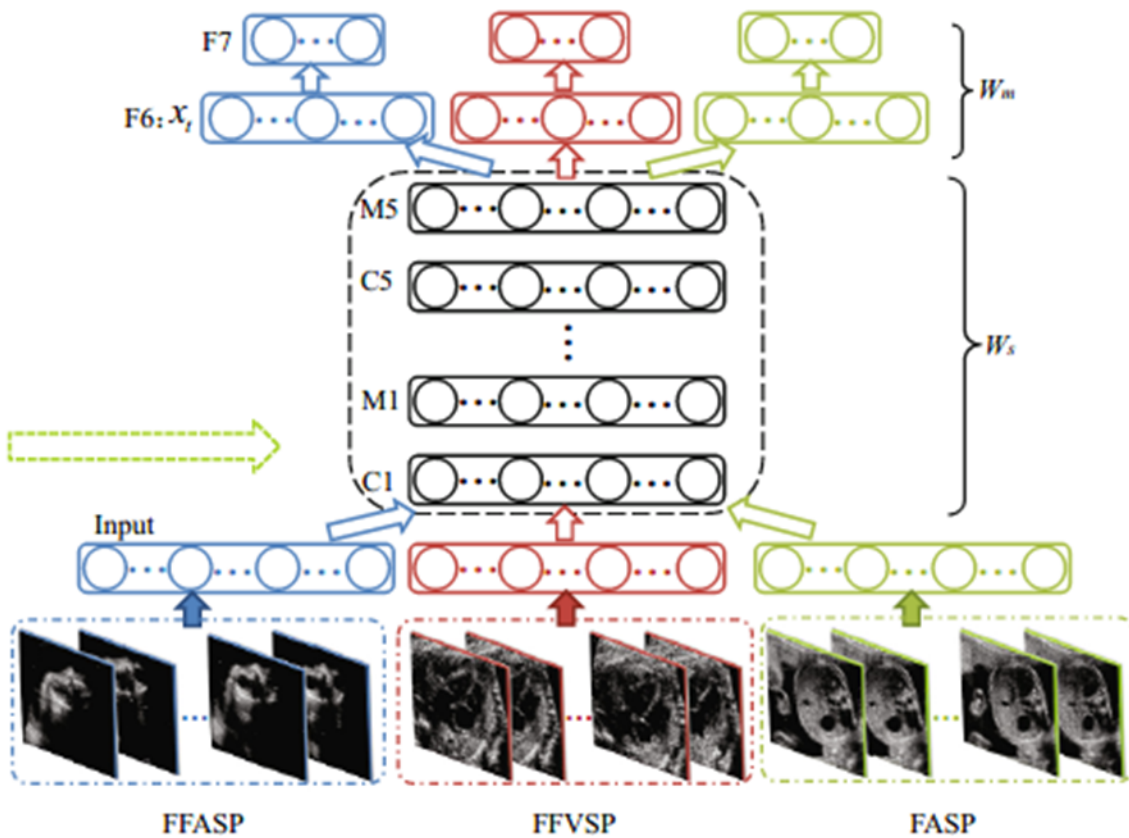
- b) **[10(c)]/[14(c)]: “wherein the at least one processor is configured to, for each echocardiographic training image:”**

[10(c)]/[14(c)] merely recite that the at least one processor of the underlying claims (i.e., 1 and 11, respectively) is configured to perform the functions described in the subsequent claim elements. Since Chen discloses a computer-implemented artificial neural network training technique that performs the functions described in the subsequent claim elements, Chen discloses [10(c)]/[14(c)]. Ex1002, ¶ 198. And Krishnan already explains that its systems and methods “may be implemented in various forms of hardware, software, firmware, special purpose processors, or a combination thereof.” Ex1005, [0045]; *see also* Ex1005, [0005], [0009], Fig. 1.

- c) **[10(d)]/[14(d)]: “select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and:”**

Chen discloses [10(d)]/[14(d)]. Ex1010, pp.510, 512, Fig. 2 (right); Ex1002, ¶¶ 199-200. As explained in Section VIII.A.4 above, Chen discloses a neural network training technique in which ultrasound images that are labeled by view category are used to train both view-category-specific neural network layers and common neural network layers that are used to assess each view category. *See also* Ex1002, ¶¶ 199-200. Chen states that “[f]or training the ... classifier under the

framework of J-CNN [(i.e., joint learning CNN)], training samples of [each standard view] FASP, FFASP, and FFVSP were generated” and “[t]hey were manually annotated [(i.e., labelled)] by an experienced obstetrician.” Ex1010, p.512. With reference to the J-CNN depicted in Figure 2, below, Chen further teaches that the parameters (W_s) of the common layers from C1 to M5 are “trained from all training samples of the three detection tasks and shared among the tasks.” Ex1010, p.510. By contrast, the parameters (W_m) of the view-category-specific layers (F6 and F7) are “trained individually on each task for the discrimination of different standard planes ([i.e., views]).” Ex1010, p.510 (emphasis added).



In order to train the view-category-specific layers having view-category-specific parameters “individually,” the view-category-specific network/layer/parameters would need to be “selected” as claimed in 10(d)]/[14(d)]. Ex1002, ¶ 200. Accordingly, Chen discloses [10(d)]/[14(d)].

- d) **[10(e)]/[14(e)]: “using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.”**

Chen discloses [10(e)]/[14(e)] for the same reasons already explained in the preceding Section. Ex1010, pp.510, 512; Ex1002, ¶¶ 199-201. Alternatively, Chen in combination with Krishnan renders obvious [10(e)]/[14(e)]. Ex1002, ¶¶ 201-203.

Chen teaches that labelled training images for each view category are used to train both common neural network layers, as well as view-category-specific neural network layers that are associated with the same view category as the respective training images. Ex1002, ¶ 202. The training image is used as the training input, and the training label is used as the desired output. Ex1010, p.510 (describing loss function for training); Ex1002, ¶ 202. To the extent Chen does not explicitly describe that an expert quality assessment value is the desired output of training, Chen in combination with Krishnan renders this limitation obvious since the purpose of

Krishnan's neural network classifier is explicitly to predict a diagnostic quality score based on previously labelled cases. Ex1005, [0020], [0032], [0036], claim 30 ("presenting diagnostic quality determination results to a user in real-time"), Fig. 2 (203); Ex1002, ¶ 202.

IX. CONCLUSION

For the foregoing reasons, claims 1-20 of the Patent are invalid.

* * *

Date: May 28, 2025

By: /David R. Jaglowski/
David R. Jaglowski
Registration No. 58,514
THOMPSON HINE LLP
41 South High Street, Suite 1700
Columbus, Ohio 43215

Jeffrey C. Metzcar
Registration No. 52,027
THOMPSON HINE LLP
10050 Innovation Drive, Suite 400
Dayton, OH 45342

Marla R. Butler
THOMPSON HINE LLP
Two Alliance Center
3560 Lenox Road, NE., Suite 1600
Atlanta, GA 30326-4266

William E. Manske
THOMPSON HINE LLP
800 Nicollet Avenue, Suite 2925
Minneapolis, MN 55402

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 11,466 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.

Date: May 28, 2025

/ David R. Jaglowski /
David R. Jaglowski
Registration No. 58,514
THOMPSON HINE LLP
41 South High Street, Suite 1700
Columbus, Ohio 43215

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 Petition for *Inter Partes* Review in connection with U.S. Patent No. 11,129,591 and supporting evidence was served on May 28, 2025, via FEDERAL EXPRESS on the following counsel of record for Patent Owner, University of British Columbia:

157691 - Kolitch Romano Dascenzo Gates LLC
621 SW Morrison St., Suite 1100
Portland, OR
UNITED STATES

Courtesy copies were also served via electronic mail on Patent Owner's counsel of record in a related district court litigation:

Ramsey M. Al-Salam
Moeka Takagi
Dorianne Salmon
PERKINS COIE LLP
1201 Third Avenue, Suite 4900
Seattle, Washington 98101-3099
RAlsalam@perkinscoie.com
MTakagi@perkinscoie.com
DSalmon@perkinscoie.com

Date: May 28, 2025

/ Andrew C. Himebaugh /
Andrew C. Himebaugh
THOMPSON HINE LLP
20 N. Clark Street, Suite 3200
Chicago, Illinois 60602