UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

CAPTION HEALTH, INC.,
Petitioner,

v.

UNIVERSITY OF BRITISH COLUMBIA,
Patent Owner.

Case No. IPR2025-01066

Patent No. 11,129,591

PATENT OWNER'S PRELIMINARY RESPONSE

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PATENT OWNER’S EXHIBITS

Exhibit	Description
2001	US 10,751,029
2002	First Amended Complaint and Patent Infringement, dated Dec. 20, 2024, ECF No. 46
2003	Defendants’ First Amended Invalidity Contentions Cover Pleading, dated August 22, 2025
2004	Defendants’ Notice of Motion and Motion to Stay Case Pending *Inter Partes* Review, dated June 27, 2025, ECF No. 72
2005	Order Denying Motion to Stay and Granting Motion to Seal, dated August 6, 2025
2006	DocketNavigator Statistics
2007	Order Setting Initial Case Management Conference and ADR Deadlines, dated May 31, 2024, ECF No. 9
2008	Declaration of Dorianne Salmon in Support of UBC’s Opposition to Defendants’ Motion to Stay Pending *Inter Partes* Review, dated July 11, 2025, ECF No. 77-1
2009	Appendix A to Defendants’ First Amended Invalidity Contentions, dated August 22, 2025
2010	Exhibit E to Infringement Contentions
2011	Defendant GE Healthcare’s Responses to UBC’s Third Set of Requests for Production to Defendant GE Healthcare (Nos. 55-86), dated May 27, 2025
2012	Defendant Caption Health’s Responses to UBC’s Third Set of Requests for Production to Defendant Caption Health (Nos. 30-54), dated May 27, 2025

Exhibit	Description
2013	UBC's Objections and Responses to Defendants' Second Set of Requests for Production of Documents and Things (Nos. 64-113), dated April 21, 2025
2014	Joint Statement regarding Discovery Dispute Over Plaintiff's Amended Infringement Contentions, dated March 19, 2025, ECF No. 58
2015	Plaintiff UBC's Motion for Leave to Amend Infringement Contentions regarding US Patent Nos. 11,129,591 and 10,751,029, dated May 9, 2025, ECF No. 65
2016	Administrative Motion Regarding Case Schedule and Motion to Stay, ECF No. 75
2017	Order Granting Plaintiff's Motion for Leave to Amend Infringement Contentions, dated July 2, 2025, ECF No. 74
2018	Civil Minutes, dated August 6, 2025, ECF No. 81
2019	UBC's list of claim terms, dated April 11, 2025
2020	Defendants' Amended and Supplemented Proposed Claim Terms from U.S. Patent No. 11,129,591 for Construction Pursuant to L.R. 4-1, dated April 11, 2025
2021	Joint Claim Construction and Prehearing Statement Pursuant to Pat. L.R. 4-3, dated May 30, 2025, ECF No. 68
2022	Scheduling Order, dated Aug. 13, 2025, ECF No. 82
2023	US 8,712,157
2024	Emails between R. Rohling and K. Koepsell, dated May 17-25, 2017
2025	A. H. Abdi, et. al., *Automatic quality assessment of apical four-chamber echocardiograms using deep convolutional neural networks*, Medical Imaging 2017: Image Processing, 10133 (Feb. 2017)

Exhibit	Description
2026	A. H. Abdi, et. al., *Automatic Quality Assessment of Echocardiograms Using Convolutional Neural Networks: Feasibility on the Apical Four-Chamber View*, IEEE Transactions on Medical Imaging, Vol. 36, 6:1221-1230 (June 2017)
2027	LinkedIn message from P. Abolmaesumi to S. Cashman, dated Aug. 19, 2021
2028	LinkedIn message from P. Abolmaesumi to H. Hong
2029	Letter from J. Morton to S. Cashman, dated May 5, 2022
2030	Letter from J. Morton to S. Cashman, dated May 24, 2022
2031	Email chain between S. Cashman and J. Morton, dated June 13-27, 2022
2032	Letter from R. Chan to S. Cashman, dated Nov. 11, 2022
2033	GE HealthCare Technologies Inc. Corporate Structure Tree
2034	GE HealthCare Technologies Inc. Corporate Family Report
2035	15/581,004 Notice of References Cited
2036	16/703,360 Notice of References Cited
2037	17/403,390 Notice of References Cited
2038	16/870,633 IDS
2039	16/936,941 Notice of References Cited
2040	16/870,667 IDS
2041	17/192,005 Notice of References Cited
2042	GE Healthcare 10-Q (2023)

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2043	Businesswire, GE HealthCare to Acquire Caption Health, Expanding Ultrasound to Support New Users Through FDA-Cleared, AI-Powered Image Guidance, Feb. 9, 2023
2044	17/061,578 Notice of References cited
2045	UBC Overview & Facts
2046	’591 Patent Grants Spreadsheet
2047	Ghada Zamzmi, et al., *Harnessing Machine Intelligence in Automatic Echocardiogram Analysis: Current Status, Limitations, and Future Directions* (Apr. 27, 2021)
2048	Robert B. Labs, et al., *Automated assessment of transthoracic echocardiogram image quality using deep neural networks* (2023)
2049	Hsu et al., *Spatiotemporal feature disentanglement for quality surveillance of left ventricular echocardiographic video using ST-R(2 + 1)D-ConvNeXt* (2025)
2050	Sanjeevi G. et al., *Deep learning supported echocardiogram analysis: A comprehensive review* (2024)

I. INTRODUCTION

Patent Owner, University of British Columbia ("UBC" or "Patent Owner") submits this Preliminary Response to the Petition of Caption Health, Inc. ("Caption Health" or "Petitioner") challenging claims 1-20 (the "Challenged Claims") of U.S. Patent No. 11,129,591 (Ex1001, the "'591 Patent").

The '591 Patent was designed to address the longstanding challenge that echocardiograph operators need years of specialized training to capture echocardiographic images properly and assess them. Slight changes in where an ultrasound transducer is placed, or the pressure applied when using the transducer, can result in significant variation in the quality and usability of an image. In most cases, the naked eye cannot ascertain the actual quality and usability of the image. Given the inability to discern the image quality, operators often send inadequate or unusable images to the lab, only to learn later that the procedure must be repeated. As a result, effective echocardiographic analysis can often be significantly delayed, which can delay proper treatment.

The '591 Patent ameliorated these problems by providing view-category-specific neural networks that are configured to receive images and to output quality assessment values in an end-to-end process. Indeed, the challenged independent claims 1, 11, and 15 (and therefore all Challenged Claims) require echocardiographic image analysis systems/methods in which a "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[s] 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." '591 Patent, 1[i], 11[m], 15[i].

Petitioner asserts four grounds of unpatentability against the Challenged Claims.

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

Notably, every ground relies on a combination of Krishnan (Ex1005) and Lee (Ex1006). Further, the Petition relies solely on Krishnan and Lee for independent claims 1 and 15 (including limitations 1[i] and 15[i]). Pet., 32-36 (claim 1), 43-44 (claim 15). For independent claim 11, although Pagoulatos is added to the combination, the Petition again relies solely on Krishnan/Lee as teaching 11[m]. *Id.*, 55 (Ground B: referring back to discussion in §VIII.B.1.f for analysis of limitations

11[m]/[p]); *id.*, 32-36 (Ground A, §VIII.B.1.f: discussing Krishnan and Lee for 1[i]/1[l])).

The Petition is fatally flawed for multiple reasons.

First, regarding limitations 1[i]/11[m]/15[i], Petitioner's Krishnan/Lee combination fails to satisfy 37 C.F.R. §42.104(b)(4). Indeed, the Petition tacitly acknowledges that neither Krishnan's nor Lee's disclosures add up to the disclosure of view-category-specific neural networks, as limitations 1[i]/11[m]/15[i] require. This is not surprising as to Krishnan. During prosecution, the Examiner applied Krishnan in a rejection (Ex1004, 207-19), and the Applicant amended the claims to add certain limitations, including limitation 1[i] (*id.*, 255-56). In the reasons for allowance, the Examiner correctly found that Krishnan does not teach these limitations. *Id.*, 279-80. Petitioner's Krishnan/Lee combination fares no better, as Lee also does not disclose neural networks for assessing image quality—let alone view-category-specific neural networks for assessing image quality.

Instead of identifying prior art disclosures, the Petition relies on unclear explanations regarding how a POSITA <u>could</u> combine and modify Krishnan's and Lee's disclosures to reach these limitations. Pet. 33 ("A POSITA would understand from these combined disclosures that Krishnan's 'bank of classifiers' <u>could</u> be a plurality of view-category-specific quality assessment classifiers as taught by

Lee.”)[1] (citing Ex1002, ¶¶113-14, 119-20); *id.* (“[T]hese view-category-specific classifiers could each be neural networks instead of view-category-specific templates…”) (emphasis added) (citing Ex1002, ¶119).

Petitioner’s suppositions do not satisfy 37 C.F.R. §42.104(b)(4), which requires that the Petition “specify where each element of the claim is found in the prior art patents or printed publications relied upon.” Accordingly, the Petition should be denied for this reason alone.

Second, even if Krishnan and Lee were somehow combined to form view-category-specific neural networks for assessing image quality, there is no plausible combination that results in view-category-specific neural networks that are configured to receive images—which limitations 1[i]/11[m]/15[i] require. At best, Krishnan suggests inputting extracted features from an image into a neural network and then outputting image quality values. Meanwhile, Lee does not disclose a neural network for assessing image quality at all. But even if it did, Lee—like Krishnan—does not disclose or suggest inputting images into a neural network in an end-to-end process that assesses image quality.

Third, as explained in more detail below, Petitioner has failed to demonstrate that a POSITA would have been motivated to combine Krishnan and Lee with a

[1] All emphases added unless otherwise noted.

reasonable expectation of success/predictable results. To the contrary, there is evidence that a POSITA would not have reasonably expected success or predictable results in implementing view-category-specific neural networks that receive images (not extracted features) as inputs and perform image quality assessment.

Accordingly, for at least these reasons, UBC respectfully submits that the Board should deny institution.

II. BACKGROUND

A. Summary of the '591 Patent

The '591 Patent addresses the problem of "existing echocardiographic systems [that] may be configured to provide feedback regarding general properties of captured images," which "may not assist echocardiographers in capturing high quality echocardiographic images for use in subsequent quantified clinical measurement of anatomical features." Ex1001, 1:29-34. The claimed inventions solved this problem with novel methods and systems formed by training and employing neural networks for assessing the quality of echocardiographic images and providing quantitative analysis to help operators optimize the quality of such images. *See, e.g., id.*, 5:30-45, 6:13-20.

The employed neural networks are trained to assess echocardiographic images of a specific view category. *See, e.g., id.*, 5:62-6:20. As described above, it is typical to capture echocardiographic images from various views or anatomical planes of the heart to allow determination of certain clinical measurements or diagnosis. *See, e.g., id.*, 5:46-51. Because desirable characteristics for each of these various views can differ, there may be different criteria for assessing echocardiographic images based on the view they represent. *See, e.g., id.*, 5:62-67. For example, a quality assessment value for the "AP2" view category may depend on the left ventricle, left atrium, and mitral valve in the image, while a quality assessment value for the "AP3" category may depend on the aortic valve, mitral valve, left atrium, left ventricle, and septum. *See, e.g., id.*, 15:28:39. As the specification explains, the employed neural networks are trained with images and their associated view category information, so that neural network parameters that are eventually used to assess image quality can evaluate quality based on criteria specific to certain view categories. *See, e.g., id.*, 17:60-63, 18:27-35.

Figure 8 shows an example representation of neural networks that may be used for quality assessment.

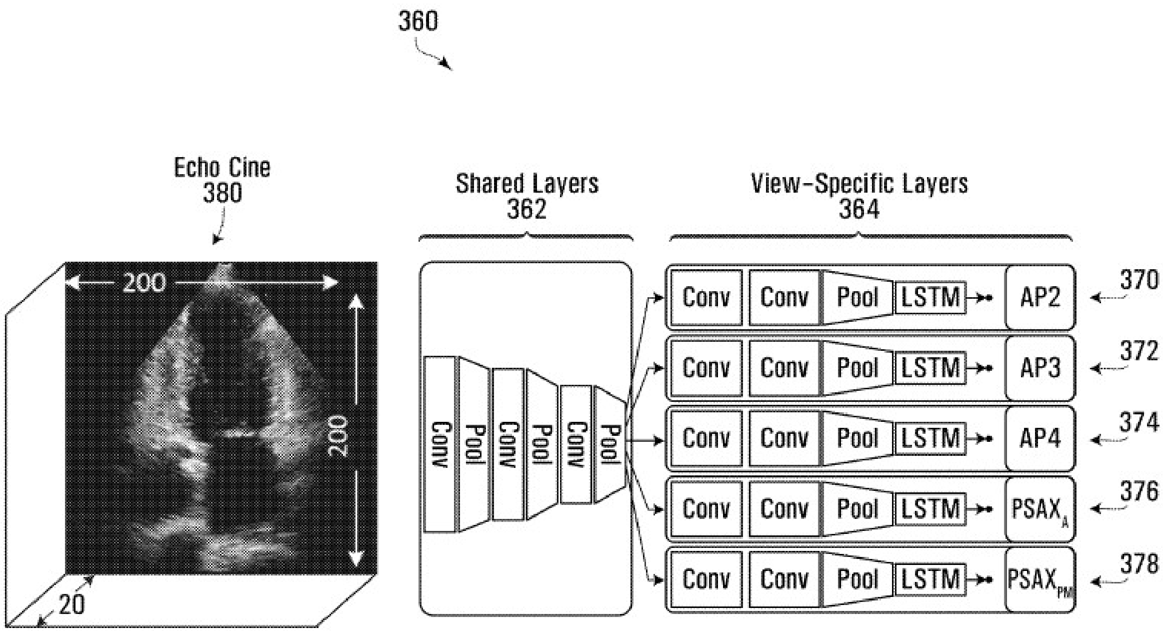

FIG. 8

Id., Fig. 8.

Figure 8 shows a neural network 360 with multiple neural networks within, where "the shared layers 362 and the view category specific layers 370, 372, 374, 376, and 378 may each be considered neural networks[.]" *Id.*, 12:14-18. Each of the view category specific layers includes view category specific parameters defining the corresponding neural network. *See id.*, 13:30-37, Fig. 10.

For context, the language of claim 1 is reproduced below with the language of limitation 1[i] underlined. Claims 11 and 15 include essentially the same underlined language.

> [1pre]. 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] <u>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</u>, 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.

Id., Claim 1.

B. The Alleged Prior Art

1. Krishnan

Krishnan is directed to medical imaging and describes "systems and methods for processing a medical image to automatically identify the anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image." Ex1005, [0002]. Krishnan describes that its systems can be used for processing cardiac ultrasound images, such that the "view" of an image is a standard ultrasound view of the heart (e.g., apical two-chamber view (A2C), apical four-chamber view (A4C), etc.). *See id.*, [0019].

In Figure 4, Krishnan discloses assessing image quality using "template-based methods." *Id.*, [0041].

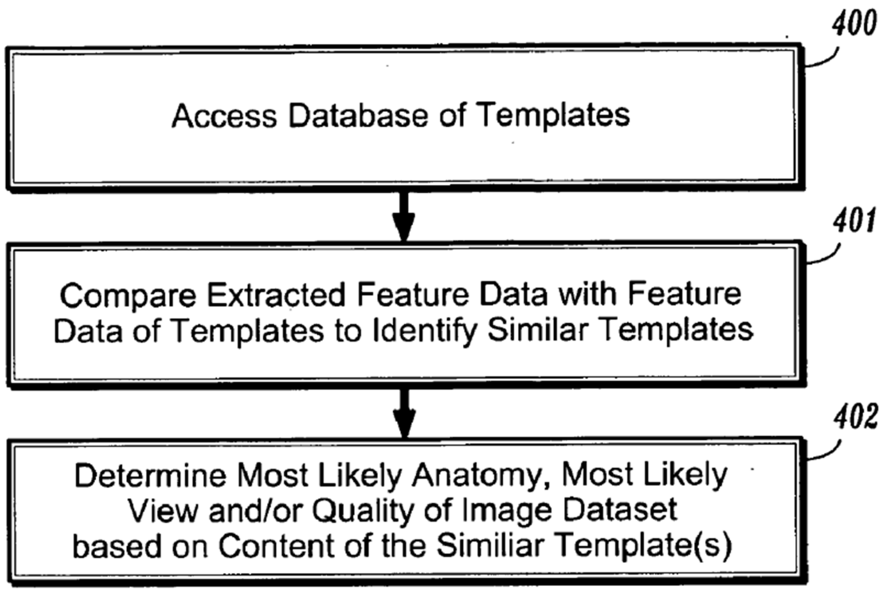

FIG. 4

Id., Fig. 4.

In this embodiment, "a query can be formulated using the feature data extracted from the image dataset and the database of templates would be accessed (step 400) and searched using the query." *Id.*, [0041]. "The extracted feature data comprising the query would be compared to features of the templates to identify similar templates (step 401)." *Id.* "The content of the identified templates would then be used to determine the most likely anatomy or view for the subject image, or to determine the quality of the acquired image (step 402)." *Id.* Krishnan discloses that "templates could be constructed for different cardiac views." *Id.*

Critically, the Figure 4 embodiment does not involve a neural network at all, let alone a neural network that takes images as inputs and outputs quality assessment values.

In Figure 5, Krishnan discloses assessing image quality using “classifiers.” *Id.*, [0042].

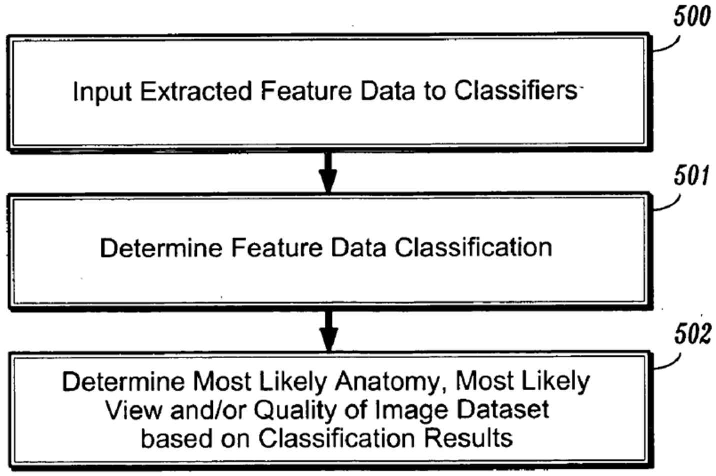

FIG. 5

Id., Fig. 5.

In this embodiment, “feature data extracted from the image dataset would be input to classifiers (step 500) that are trained or designed to process the feature data to classify the image data (step 501).” *Id.*, [0042]. “The classification results would be used to determine the most likely anatomy or view, or assess image quality (step 502).” *Id.* “For example, a bank of classifiers could be constructed to classify the images based on the features extracted.” *Id.*, [0043]. “These classifiers would use the set of features as an input, and classify the image as belonging to a particular anatomy, view, or level or quality.” *Id.* Krishan further discloses that these classifiers could be built “using neural networks.” *Id.*, [0044].

Critically, although the Figure 5 embodiment discloses "classifiers" that may be built "using neural networks," Krishnan does <u>not</u> disclose that these classifiers are view-category specific. Moreover, Krishnan does <u>not</u> disclose that the classifiers take images as input and output quality assessment values—instead, the classifiers take <u>extracted features</u> from the images as inputs and output quality assessment values.

2. Lee

Lee discloses "[a]n electronic device that includes an image quality measuring function and an operation method thereof." Ex1006, Abstract. Lee is focused on determining a scene category (e.g., "mountain, ocean, sky, beach, streets, night view," etc.) of an image and the quality of the image based on that scene category and other image quality factors (e.g., "sharpness, noise, contrast, color accuracy, distortion," etc.). *See id.*, [0152], [0154], [0204]-[0206] (explaining that image quality factors making a night view image versus a sky image high quality are different), Figs. 12A-12B (disclosing "diagrams illustrating examples of an image quality classifier in an electronic device").

Figure 5 of Lee is representative of Lee's process and discloses, *inter alia*, a category classifying module 520, a classifier selecting module 530, an image factor extracting module 540, and an image quality evaluating module 550. *Id.*, [0149].

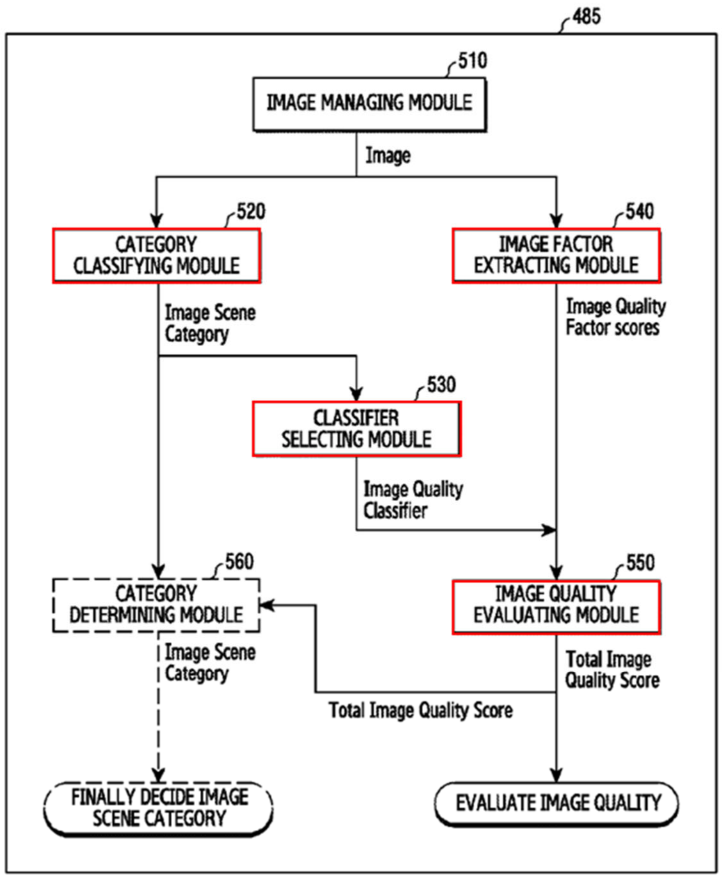

FIG.5

Id., Fig. 5.[2]

Lee discloses that "category classifying module 520 may classify an image scene category of [an] image…" *Id.*, [0151]. This category classification may use "deep learning." *Id.* Notably, to the extent the "deep learning" involves a neural network, it is for classifying the images into categories—not assessing image

[2] Figures annotated in color unless otherwise noted.

quality. Thus, this is not relevant to the Challenged Claims' requirement of view-category specific neural networks for outputting quality assessment values.

Lee then discloses that a "[quality] 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 [a] category classifying module 520." *Id.*, [0152]. "For example, the classifier selecting module 530 may select a classifier corresponding to the transferred image scene category of the image (e.g., mountain, ocean, sky, beach, streets, night view, or the like), out of image quality classifiers stored in advance." *Id.*

Following this, the image quality evaluating module uses outputs from the image factor extracting module 540 (e.g., sharpness, blur, etc.) together with the image quality classifier to extract a total image quality score.

> The image factor extracting module 540 may extract image quality factor scores with respect to the image based on at least some of an image or image information that is transferred from the image managing module 510. For example, the image factor extracting module 540 may extract an image quality factor such as sharpness, noise, contrast, color accuracy, distortion, blur, or the like of the image, measure the extracted image quality factor, and determine a score of each image quality factor.

Id., [00154].

> The image quality evaluating module 550 (e.g., a total image quality evaluator) may extract a total image quality score with respect to the image using the image quality factor scores transferred from the image factor extracting module 540 and the image quality classifier transferred from the classifier selecting module 530.

Id., [0160].

Notably, Petitioner does not assert that Lee's "image quality classifiers" or Lee's "image quality evaluating module" employ neural networks for evaluating image quality.

III. LEVEL OF ORDINARY SKILL

The Petition proposes that a POSITA "would include a person with an advanced degree in Computer Engineering, Computer Science, Physics, or other field related to computer imaging, and at least 1 year of research experience training machine learning models to analyze ultrasound data." Pet., 11.

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

For purposes of this Preliminary Response only, Patent Owner has applied Petitioner's formulation of a POSITA (to the extent the analysis depends on it). Regardless, Patent Owner's analysis would not change if the Board were to make slight modifications to the definition (including by adopting Patent Owner's alternative).

Patent Owner reserves the right to further address the formulation of a POSITA if trial is instituted.

IV. CLAIM CONSTRUCTION

Petitioner states that "[n]one of the claim terms of the Patent require an express construction for purposes of this proceeding." Pet. 11-12. For purposes of this Preliminary Response, Patent Owner also does not believe any specific construction is required but reserves the right to propose constructions in any future papers.

V. PETITIONER HAS NOT DEMONSTRATED A REASONABLE LIKELIHOOD OF PREVAILING AS TO ANY CHALLENGED CLAIM

A. All Grounds: Krishnan and Lee, Alone or in Combination, Fail to Render Obvious 1[i], 11[m], and 15[i]

Limitations 1[i], 11[m] and 15[i] each recite a "plurality" of "view categories" that are "associated with a respective set of [neural network] assessment parameters." Ex1001, Claim 1, 11, 15. Moreover, each set of neural network assessment parameters define[s] "a neural network…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." *Id.*

In other words, these limitations require (1) view-category specific neural networks that (2) receive images as inputs and output quality assessment values.

Petitioner relies solely on Krishnan and Lee to teach these limitations. However, as explained in detail below, Petitioner's combination fails to satisfy 37 C.F.R. §42.104(b)(4). And regardless, there is no plausible combination of Krishnan and Lee that renders obvious 1[i], 11[m] and 15[i].

1. 1[i]/11[m]/15[i]: The Petition Fails to Satisfy 37 C.F.R. §42.104(b)(4)

37 C.F.R. §42.104(b)(4) requires that a petition "specify where each element of the claim is found in the prior art patents or printed publications relied upon." Here, for limitations 1[i]/11[m]/15[i], the Petition relies on disclosures that do not add up to the claim limitations, and supposition about how a POSITA *could* combine those disclosures and modify them to reach the limitations. Pet., 32-37, 43-44, 55-56. Such gap-filling does not meet the requirements of §42.104(b)(4).

More specifically, Petitioner fails to explain how its combination of Krishnan and Lee results in view-category specific neural networks for assessing image quality. As to Krishnan, the Petition argues that it teaches "determining echocardiographic image quality assessment values using view-category-specific templates." Pet. 33 (citing Ex1005, [0041]). But these "templates" for assessing image quality are not neural networks, and Petitioner does not argue that they are. Indeed, Krishnan's Paragraph 41 describes its Figure 4 embodiment. Figure 4 discusses formulating a query using extracted feature data and searching templates created from known cases to determine a view and quality. Ex1005, [0041], Fig. 4. Although Petitioner points to Krishnan, Paragraph 35, to argue that Figures 4 and 5 can be alternatives (Pet. 33), Petitioner never explains how Figure 4, as one alternative, meets any limitation of claim 1. *See id.*, 33-37.

In sum, Petitioner does not explain how Krishnan's template comparison disclosed in Figure 4 relates to neural networks at all, much less teaches view-category-specific neural networks as limitations 1[i], 11[m], and 15[i] require.

Petitioner next points to Krishnan's "bank of classifiers" in its Figure 5 embodiment. Pet. 33 (citing Ex1005, [0042]-[0043]). Petitioner argues that Krishnan's classifiers can be implemented using machine learning methods including neural networks. *Id.* (citing Ex1005, [0006], [0023], [0042]-[0044]). Petitioner also cites the testimony of its expert, Dr. Deo. But in the cited testimony, Dr. Deo either provides an overview of Krishnan without analysis of how the cited disclosures meet any particular claim limitations (*id.* (citing Ex1002, ¶¶71-77)), or—in the context of 1[i]—simply quotes the same portions of Krishnan cited in the Petition without further explanation (*id.* (citing Ex1002, ¶115)). Such reliance on conclusory testimony is deficient. *See Xerox Corp. v. Bytemark, Inc.*, IPR2022-

00624, Paper 9, 16 (Aug. 24, 2022) (designated precedential Feb. 10, 2023) (citing *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 421 (2007)) (finding reliance on conclusory and unsupported declaration testimony to be "particularly problematic" where it attempts to "supply a limitation missing from the prior art"); *see also DSS Tech. Mgmt., Inc. v. Apple Inc.*, 885 F.3d 1367, 1374-75 (Fed. Cir. 2018) (holding as inadequate the petitioner's reliance on expert testimony that was "conclusory" and "unspecific" for a limitation that was not "unusually simple," related to technology that was "not 'particularly straightforward,'" and "play[ed] a major role in the subject matter claimed"); *Arendi S.A.R.L. v. Apple Inc.*, 832 F.3d 1355, 1366 (Fed. Cir. 2016) (finding that a missing claim limitation cannot be determined obvious based on "conclusory statements and unspecific expert testimony").

Thus, as with Figure 4, Petitioner has failed to explain how Krishnan discloses that the "classifiers" of Figure 5 are view-category-specific neural networks, as limitations 1[i], 11[m], and 15[i] require.

As to Lee, Petitioner argues that it teaches determining a classifier to use based on the category of the image. Pet. 32-33. But Petitioner does not assert that Lee teaches that its classifiers for determining image quality are neural networks—and indeed, Lee does not. *See id.*, 36 (relying on Krishnan for a classifier based on a neural network). Instead, Petitioner concludes that "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." *Id.*, 33 (citing Ex1002, ¶¶78-82, 116).

Petitioner's contentions regarding Lee, however, do not add up to the claim limitations, because even if the "assessment parameters" in Lee are view category specific, Petitioner does not contend that they define a neural network as limitations 1[i], 11[m], and 15[i] require.

In sum, Petitioner plainly concedes that there is no teaching in either Krishnan or Lee of view-category-specific neural networks for assessing image quality. Instead, Petitioner and its expert speculate about what the combination of teachings from Krishnan and Lee "could" teach. Pet. 33 ("A POSITA would understand from these combined disclosures that Krishnan's 'bank of classifiers' <u>could</u> be a plurality of view-category-specific quality assessment classifiers as taught by Lee.") (citing Ex1002, ¶¶113-14, 119-20); *id.* ("[T]hese view-category-specific classifiers <u>could</u> each be neural networks instead of view-category-specific templates…") (citing Ex1002, ¶119).

Petitioner says the combination of teachings from Krishnan and Lee *could* meet these limitations if gaps were filled, but Petitioner has not provided supporting evidence entitled to any weight that shows a reasonable likelihood of filling those gaps. This does not meet Petitioner's burden under 37 C.F.R. §42.104(b)(4).

2. 1[i]/11[m]/15[i]: Krishnan and Lee, Alone or in Combination, Fail to Disclose View-Category-Specific Neural Networks That Receive Images and Output Quality Assessment Values

The Krishnan/Lee combination fails to disclose limitations 1[i], 11[m], and 15[i] for an additional reason. These limitations not only require view-category specific neural networks, but also require that the view-category specific neural networks have an "input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values." Ex1001, Claims 1, 11, 15.

Even if the Krishnan/Lee combination rendered obvious view-category-specific neural networks for outputting quality assessment values (it does not), the Krishnan/Lee combination does not disclose that such alleged networks "receive one or more echocardiographic images." As to Krishnan, Figure 4 (templates) does not use a neural network at all, and Figure 5 (classifiers) involves inputting extracted feature data from an image into a neural network. Ex1005, [0042] (disclosing that "feature data extracted from the image dataset would be input to classifiers (step 500) that are trained or designed to process the feature data to classify the image data (step 501)"); *id.*, [0043] ("For example, a bank of classifiers could be constructed to classify the images based on the features extracted."); *id.*("These classifiers would use the set of features as an input, and classify the image as belonging to a particular anatomy, view, or level or quality."). Moreover, inputting images into Krishnan's purported neural network would not have been obvious because Krishnan does not disclose learning-based feature extraction. *See* §V.C.

Thus, at best, Krishnan discloses that extracted features are input into a neural network—not images as 1[i], 11[m], and 15[i] require.

As to Lee, it discloses "deep learning" for classifying images into categories, but it does not disclose the use of neural networks for image quality assessment. Even if it did, Lee's "image quality evaluating module 550" does not receive images as these limitations require—instead, it receives outputs from the image factor extracting module 540 (e.g., sharpness, blur, etc.) to extract a total quality score.

> The image factor extracting module 540 may extract image quality factor scores with respect to the image based on at least some of an image or image information that is transferred from the image managing module 510. For example, the image factor extracting module 540 may extract an image quality factor such as sharpness, noise, contrast, color accuracy, distortion, blur, or the like of the image, measure the extracted image quality factor, and determine a score of each image quality factor.

Id., [00154].

> The image quality evaluating module 550 (e.g., a total image quality evaluator) may extract a total image quality score with respect to the image <u>using the image quality factor scores transferred from the image factor extracting</u>

module 540 and the image quality classifier transferred from the classifier selecting module 530.

Id., [0160]. Further, it would not have been obvious to modify Lee to input images into a neural network for image quality assessment. *See* §V.C.

B. All Grounds: Petitioner Has Failed to Demonstrate That a POSITA Would Have Been Motivated to Combine Krishnan and Lee With a Reasonable Expectation of Success/Predictable Results

It is Petitioner's "burden to demonstrate both that a skilled artisan would have been motivated to combine the teachings of the prior art references to achieve the claimed invention, and that the skilled artisan would have had a reasonable expectation of success in doing so." *Apple Inc. v. Uniloc USA, Inc.*, IPR2017-00220, Paper 9, 12 (May 25, 2017) (quoting *In re Magnum Oil Tools Int'l, Ltd.*, 829 F.3d 1364, 1381 (Fed. Cir. 2016)). Here, Petitioner's evidence and arguments regarding the alleged motivation to combine Krishnan and Lee fall far short of meeting its burden.

The Petition states "[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." Pet. 35. As support, Petitioner relies on (1) general knowledge of neural networks used for image quality assessments, (2) Krishnan's template and classifier embodiments discussed above, and (3) Lee's alleged teaching of assessing image quality of different categories using different assessment parameters. *Id*., 34-36. From this, Petitioner concludes: "When this teaching [in Lee] 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." *Id*., 36 (citing Ex1002, ¶125). Petitioner's cited expert testimony merely repeats this conclusion, and any additional explanation is based on alleged "common sense" without objective support. *See* Ex1002, ¶125.

Of course, Lee does not discuss any of this, instead mentioning medical imaging devices in a laundry list of possible applications, which also include a navigation device for a ship and a light bulb. Ex1006, [0038]. Lee never discusses how its teachings apply to "[i]mages in different categories" with "only a partially overlapping set of anatomic structures," as Dr. Deo admits would be necessary for the proposed Krishnan-Lee combination (Ex1002, ¶125). Instead, Lee's disclosure focuses on determining the scene category for an image taken with a mobile phone, such as mountain, ocean, sky, night, etc. E.g., Ex1006, [0152], [0153] (explaining that a night view image may have good quality even though the image has low brightness and low exposure and that a cloud image may have good quality even though the image has a low blur factor score), Figs. 12A-12B. Dr. Deo does not explain how such teachings in Lee would be applied to Krishnan such that "image quality would depend on which structures in the image are required for successful analysis." *See* Ex1002, ¶125.

Because neither Petitioner nor Dr. Deo explain why a POSITA would have been motivated to combine the references "to use respective view-specific neural networks to assess the quality of echocardiographic images in the respective view categories" (Pet. 36), the Petition fails to provide sufficient evidence regarding a POSITA's alleged motivation to combine. *See ActiveVideo Networks, Inc. v. Verizon Commc'ns, Inc.*, 694 F.3d 1312, 1328 (Fed. Cir. 2012) (citing *KSR*, 550 U.S. at 418) (finding generic statements regarding motivation to combine to be deficient because they "fail[ed] to explain why a person of ordinary skill in the art would have combined elements from specific references *in the way the claimed invention does*.") (emphasis in original).

Petitioner's and Dr. Deo's arguments regarding reasonable expectation of success are also conclusory and fail to meet Petitioner's burden. Petitioner states that "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." Pet. 36 (citing Ex1005, [0045]). However, paragraph 45 of Krishnan contains only boilerplate language as to how Krishnan's systems and methods may be implemented using "various forms of hardware, software, firmware, special purpose processors, or a combination thereof" without explanation. *See* EX1005, [0045]. In other words, Petitioner fails to point to anything in Krishnan that would have given a POSITA a reasonable expectation of success in modifying Krishnan in view of Lee to allegedly obtain "respective view-specific neural networks to assess the quality of echocardiographic images in the respective view categories." Pet., 36. And Dr. Deo improperly repeats the Petition's arguments with no further explanation. *See* Ex1002, ¶121; *see Xerox Corp. v. Bytemark, Inc.*, IPR2022-00624, Paper 12, 2, 5 (Feb. 10, 2023) ("Board was correct in giving little weight to Petitioner's expert because the expert declaration merely offered conclusory assertions…and repeated, *verbatim*, Petitioner's conclusory arguments.").

The Petition also argues, alternatively, that it would have been obvious to a POSITA to combine Krishnan and Lee because the 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." *See* Pet. 37. Petitioner, however, provides no explanation of how it would have been within the ordinary skill and knowledge of a POSITA to successfully implement a plurality of view-category-specific neural networks based on the references' teachings. *See id*. For example, the Petition provides no evidence of the alleged predictable nature of the resulting view-category-specific neural networks—as described above, the Petition acknowledges that neither Krishnan nor Lee discloses view-category-specific neural networks and fails to cite any other material showing such disclosure. Petitioner has not shown applying Lee's teachings to an echocardiographic image use case, as taught in Krishnan, would lead to predictable results (or that such results would teach 1[i], 11[m], or 15[i]).

C. All Grounds: Petitioner's Assertions Regarding Obviousness, Reasonable Expectation of Success, and Predictable Results Are Belied by Krishnan and Other Extrinsic Evidence

Petitioner's assertions regarding obviousness, reasonable expectation of success, and predictable results when modifying Krishnan in view of Lee (*see* Pet., 36-37) are not only unsupported—they also are belied by Krishnan's disclosures and other extrinsic evidence.

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

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

Modifying Krishnan's described methods to be implemented using view-category-specific neural networks that receive images rather than extracted features would not have been obvious, would not have been expected to succeed, and would not have yielded predictable results. Although methods relying on template-based feature extraction like in Krishnan had shortcomings, it was known that applying deep learning to images rather than extracted features to implement an end-to-end neural network architecture handling feature extraction and quality assessment like in the '591 Patent was not a simple matter. This is evidenced not only by Petitioner's failure to rely on any reference disclosing use of view-category-specific neural networks that receive images for quality assessment as described above, but also by the recognition of others in the field that the inventors' work related to the '591 Patent was pioneering with respect to implementing neural networks for view-category-specific quality assessment of images.

For example, a 2021 paper—which was several years after the priority date of the ’591 patent—identifies problems with conventional “model-based methods” such as those disclosed in Krishnan that rely on extracted features from images:

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

See Ex2047 at 8.

The same paper goes on to describe the use of alternative deep learning-based methods by citing the inventors’ academic paper describing the subject matter of the ’591 Patent. *See id*. (explaining that “[Abdi] et al....extends their previous work...to include other cardiac views” and citing the inventors’ academic paper describing the subject matter of the ’591 Patent); *see also* Ex2025 (cited paper).

Other publications in the field similarly cite and describe the methods and systems described in the ’591 Patent with respect to implementations using deep learning neural networks that receive images as inputs. *See e.g.*, Ex2048 at 192. (explaining that "[o]ne of the earliest works on objective assessment of cardiac image quality is Abdi et al. He demonstrated the feasibility of objective assessment using convolutional neural network models in five apical views using six criteria scoring methods" and citing Ex2026); Ex2049 at 2 (explaining that "[i]n the realm of echocardiography, representation learning becomes challenging due to the dynamic nature of cardiac motion and various imaging artifacts" and that "[p]ioneering work introduced a Convolutional Neural Network (CNN) framework for real-time quality assessment of echocardiograms, demonstrating potential generalizability across different cardiac views," citing Ex2026); Ex2050 at 6, 9 (explaining that the "[v]ariability in the clarity and visibility of TTE images can arise due to differences in probe handling by various clinicians. To address this, Abdi et al. [citing Ex2026] developed a CNN model," showing metrics indicating improvements in image quality using the CNN model); *see also* Ex2026.

Thus, despite Petitioner's bald assertions to the contrary, there is ample evidence that a POSITA would not have found it obvious to implement view-category-specific neural networks that receive images (not extracted features) as inputs and perform quality assessment. Moreover, a POSITA would not have reasonably expected success or predictable results.

VI. CONCLUSION

For the reasons set forth above, the Petition fails to demonstrate a reasonable likelihood that any of the challenged claims of the ’591 Patent are unpatentable.

Respectfully submitted,

Dated: September 24, 2025

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

Under 37 C.F.R. § 42.24(d), the undersigned certifies that the word count for this Patent Owner's Preliminary Response to the Petition for *inter partes* review totals 6,095, excluding the parts exempted by 37 C.F.R. § 42.24(a). The word count was made using the built-in word count function in the Microsoft® Word software used to prepare this document.

Respectfully submitted,

Dated: September 24, 2025

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CERTIFICATE OF SERVICE

Pursuant to 37 C.F.R. § 42.6(e), I certify that I caused to be served a true and correct copy of the foregoing: PATENT OWNER'S PRELIMINARY RESPONSE and EXHIBITS 2047-2050 and accompanying exhibits by email to the electronic service addresses for Petitioner on the date indicated below:

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