

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

Caption Health, Inc.
Petitioner

v.

University of British Columbia
Patent Owner

IPR2025-01422

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

SUPPLEMENTAL DECLARATION OF DR. RAHUL DEO, M.D., PH.D.

TABLE OF CONTENTS

	Page
I. OVERVIEW	3
II. CLAIM CONSTRUCTION	4
A. “Extracted Feature Representations”	4
III. GROUND A: KRISHNAN	7
A. Krishnan’s Module 102 Can Implement Neural Network Classifiers..	7
B. Krishnan’s Quality Assessment Classifier 105 Produces a Quality Assessment Value	9
IV. GROUND B: KRISHNAN-CHEN	10
A. The Combination Proposed in the Petition	10
B. The “Scaffold” Framing Is Consistent with the Petition	11
C. Technical Compatibility of Feature Representations	12
D. The Patent’s Architecture Is Essentially Identical to Chen’s	14
V. GROUND C: KRISHNAN-AASE	15
VI. GROUND D: KRISHNAN-CHEN-WU	16
A. Standard Training Techniques	16
VII. SECONDARY CONSIDERATIONS.....	17

I. OVERVIEW

1. I, Rahul C. Deo, M.D., Ph.D., previously submitted a declaration (Ex1002) in support of the Petition for *Inter Partes* Review of U.S. Patent No. 10,751,029 (“the ’029 Patent”) in IPR2025-01422. I have been retained by Thompson Hine LLP on behalf of Caption Health, Inc. (“Petitioner”) as an independent expert to provide my opinions concerning the ’029 Patent.

2. I set forth the information below as a supplement to my original declaration, as Patent Owner raised new issues in its Patent Owner’s Response (“POR”) on which I had not previously been given an opportunity to offer testimony. Having considered Patent Owner’s arguments, and the testimony of Patent Owner’s declarant, Dr. Milan Sonka (Ex2049), my opinions on the invalidity of the ’029 Patent remain the same.

3. I have reviewed additional material in conjunction with my analysis set forth herein. This includes the Patent Owner’s Response (Paper 21), the Declaration of Dr. Milan Sonka (Ex2049), the transcript of Dr. Sonka’s deposition (Ex1060) and my deposition transcripts (Ex2051, Ex2052). A list of the materials I considered includes everything cited in this declaration, and the materials disclosed in my original declaration (Ex1002). The publications I cite herein, and in my original declaration, including the peer-reviewed journal articles and conference papers addressing neural network (“NN”) applications for image

processing and feature extraction, are reliable authorities in the fields of computer science, machine learning, and medical imaging. These publications are recognized within the scientific community as authoritative sources on the subjects they address.

II. CLAIM CONSTRUCTION

A. “Extracted Feature Representations”

4. Patent Owner proposes to construe “extracted feature representations” as requiring that the feature representations be “learned using a neural network.” POR at 29-37. It is apparent from Dr. Sonka’s deposition testimony that this is intended to mean not only that the feature representations are extracted by a NN, but also that the NN learns, through training, which features to extract, rather than relying on expert-designed, hand-crafted features. *See, e.g.*, Ex1060 at 35:23-36:13, 42:25-43:5. I disagree with this proposed construction. Patent Owner’s construction improperly reads limitations into the claims based solely on certain disclosed embodiments, which I understand is in contravention of well-established claim construction principles. In my opinion, the ordinary and customary meaning of “extracted feature representations” is not limited to just feature representations that are learned by a NN. Nor, in my opinion, would a person of ordinary skill in the art (“POSITA”), after reading the ’029 Patent and its prosecution history, believe that the ’029 Patent has narrowed the ordinary and customary meaning of

“extracted feature representations” in the manner that Patent Owner and Dr. Sonka propose.

5. The specification of the '029 Patent explicitly contemplates alternatives to neural networks for feature extraction. Additionally, the '029 Patent contemplates neural networks other than the neural networks depicted in, for example, FIG. 4 of the '029 Patent, which Dr. Sonka characterizes as “deep-learning” neural networks. Specifically, the specification states: “In various embodiments, alternative or additional feature extracting functions and/or neural networks may be used to extract features.” Ex1001, 11:39-42. This language demonstrates that the patentee did not intend to limit “extracted feature representations” to those derived exclusively from deep-learning neural networks, or even neural networks generally.

6. Moreover, the specification repeatedly uses permissive language—“may” and “in some embodiments”—when describing neural network implementations. *See* Ex1001, 6:35-41 (“In some embodiments, the analyzer 14 may implement a neural network including a feature extracting neural network”), 5:34-35 (“In various embodiments, this may be done through the use of a deep learning neural network”). This language indicates that neural networks are but one of several approaches for extracting feature representations from ultrasound images and the patentee intended the invention to extend beyond just

neural network implementations. When the patentee intended to claim neural network implementations specifically, in my opinion, it plainly knew how to do so in the various dependent claims.

7. In the field of automated image analysis, including image classification, feature extraction is a common step before classification. Many varied techniques for extracting feature representations from images were known well before the priority date of the '029 Patent. These include, for example: (1) principal component analysis and other statistical methods (Ex1044, “Feature Extraction Methods for Character Recognition—A Survey” (1995)); (2) various handcrafted feature descriptors such as SIFT, HOG, and wavelet-based methods (Ex1043, “A Detailed Review of Feature Extraction in Imaging Processing Systems” (2014)); and (3) additional feature extractors that are “not necessarily a neural network” (Ex1045). The latter include color-based attributes (moments, skew, histograms), texture-focused approaches based on grey-level co-occurrence matrices, and geometric characterization of segmented structures derived from images.

8. In my opinion, a POSITA at the time of the alleged invention would have understood “extracted feature representations” to encompass any numerical representations derived from image data through any feature extraction technique—not solely those learned by neural networks.

III. GROUND A: KRISHNAN

A. Krishnan's Module 102 Can Implement Neural Network Classifiers

9. Krishnan expressly states that its feature extraction module 102 can implement neural network classifiers. Krishnan discloses that “[t]he classifiers are implemented by the various decision support modules (102~105) for performing their respective functions.” Ex1005, [0023]. Krishnan further discloses that these classifiers can be “built using neural networks.” Ex1005, [0044].

10. Neural network-based feature extraction from images was well-known before Krishnan's 2005 filing date. *See, e.g.* Ex1047 (2002) (surveying over 20 neural network applications for feature extraction) (“Among the ANNs that have been trained to perform feature extraction, feed-forward ANNs have been used in most of the reviewed applications.”) (“Most of the ANNs trained for feature extraction obtain pixel data as input.”); Ex1051 (1996) (reviewing “unsupervised neural network learning procedures which can be applied to the task of preprocessing raw data to extract useful features for subsequent classification”); Ex1052 (1995) (providing in Fig. 1 a “taxonomy of neural networks for feature extraction”). The methods described vary across several dimensions, including architectures (e.g., number of hidden layers, kernel sizes, use of non-linear transformations, feed-forward vs Hopfield), supervised vs unsupervised training approaches, and downstream applications of the extracted features (e.g., image

classification, segmentation, processing). Additionally, Krishnan expressly states that its “[f]eature extraction can implement known segmentation ... methods for segmenting features or anatomies of interest” (Ex1005, [0034]), where known segmentation methods prior to Krishnan’s 2005 filing date likewise included neural network methods. *See, e.g.*, Ex1048 (1991) (“Segmentation of Ultrasonic Images with Neural Networks”); Ex1057 (1998) (employing deep-learning convolutional neural networks for lung segmentation). This is entirely consistent with Krishnan’s disclosure that the function of feature extraction can be performed by a trained NN “classifier” since segmentation is itself a classification task—specifically, a pixel-by-pixel classification of image regions. Ex1050 (“the image segmentation problem may be regarded as a classification problem”).

11. Patent Owner and Dr. Sonka argue that Krishnan’s disclosure of neural network classifiers for modules 102-105 is a “typographical error.” POR at 40-46; Ex2049 ¶ 164. I disagree.

12. I have been advised and understand that a prior art reference is prior art for all it states unless it contains an error that is “apparent or obvious.” In my opinion, neither Patent Owner nor Dr. Sonka has demonstrated that Krishnan’s express disclosure that feature extraction module 102 can be implemented by a neural network classifier is an “apparent or obvious” error. To the contrary, given that neural network-based feature extraction from images—including ultrasound

images—was well-established by 2005, it is my opinion that a POSITA would not dismiss Krishnan’s express disclosure as an obvious error.

13. In my opinion, a POSITA at the time of Krishnan’s filing in 2005 would have understood the disclosure of neural network classifiers for modules 102-105 as entirely consistent with the state of the art. Neural networks were a well-known tool for image analysis tasks, including feature extraction, segmentation, and classification of medical images.

B. Krishnan’s Quality Assessment Classifier 105 Produces a Quality Assessment Value

14. Patent Owner mischaracterizes my testimony as admitting that Krishnan’s quality assessment module 105, when implemented as a classifier, does not necessarily produce a quality assessment score. Response, 49 (citing Ex1002, ¶ 267). To the contrary, as I clearly explained in at least Paragraphs 189-192 of my original Declaration (Ex1002), it is my opinion that Krishnan discloses a NN classifier that produces a quality assessment score. Furthermore, in the paragraph of my Declaration that Patent Owner cites—which is addressing training—my explanation reinforces rather than undermines my prior testimony. I state that the output of a trained model could be either a “continuous score” or “if a hard threshold is applied to the continuous score, a binary output.” Ex1002, ¶ 267 (emphasis added). In both cases, the NN classifier produces a continuous quality assessment score, but in the second scenario an additional process is applied to the

continuous score to convert it to a binary output. And even that output is described as a score of 0 or 1.

IV. GROUND B: KRISHNAN-CHEN

A. The Combination Proposed in the Petition

15. As I explained in my original declaration (Ex1002), the proposed combination for Ground B uses Krishnan (Ex1005) as the primary reference—the functional scaffold—and Chen (Ex1009) as a secondary reference that provides a modern neural-network implementation of the feature-extraction functionality already disclosed in Krishnan. Patent Owner mischaracterizes my presentation of this combination.

16. At my deposition, I explained that “Krishnan already discloses the critical features—critical functions that are present in [the Patent]” and that Chen and other secondary references “are really there to provide some of these more modern implementations of how that could be done, but still working off of the same scaffold of functions that have already been disclosed by Krishnan.” Ex2052, 23:10-24:9.

17. This framing is consistent with my original declaration. Krishnan discloses a complete ultrasound guidance system with modules for feature extraction (102), anatomy identification (103), view identification (104), and quality assessment (105). Ex1005, [0016]. The combination with Chen represents

an obvious implementation of the feature-extraction step for a series of images using convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—a technique that was well-known long before the priority date of the '029 Patent.

B. The “Scaffold” Framing Is Consistent with the Petition

18. Patent Owner argues that my deposition testimony regarding the “scaffold” framing contradicts the Petition. POR at 50-53. This is incorrect. When I used the term “scaffold,” I was explaining that Krishnan provides the functional architecture—the overall system framework of ultrasound image acquisition, feature extraction, view classification, and quality assessment while Chen provides more modern implementation details for the feature-extraction step using specific neural network architectures relevant to the dependent claims of the Patent.

19. This is precisely what the Petition (and my declaration) proposes. The Petition identifies Krishnan as disclosing the overall system architecture and identifies Chen as teaching the use of CNNs for feature extraction from ultrasound images. There is no contradiction.

20. Patent Owner seizes on isolated deposition testimony to argue that I proposed a wholesale “swap” or “replacement” of Krishnan’s components with Chen’s. This mischaracterizes my testimony. At my deposition, I explicitly stated: “the word swap was never my intention.” Ex2052, 23:17. I clarified that “one

specific way one could have a feature extracting module could be using either a single convolutional neural net in isolation... or in sequence with a second feature extraction RNN and could supply extracted features to either a quality assessment or view identification network.” Ex2052, 23:19-24:5. My opinion has always been that the Krishnan-Chen combination involves using Chen’s neural network approach to implement the feature-extraction functionality that Krishnan already discloses.

C. Technical Compatibility of Feature Representations

21. Patent Owner and Dr. Sonka argue that Chen’s neural network outputs are incompatible with Krishnan’s downstream modules (103-105). POR at 54-56; Ex2049 ¶ 203. This argument is technically incorrect.

22. Feature representations, regardless of whether they are derived through handcrafted methods or neural network extraction, are numerical vectors. Even Dr. Sonka characterizes conventional, non-NN feature extraction functions as producing “numerical features/descriptors (called feature vectors)” (Ex2049, ¶ 74) that “serve as inputs to a classifier” (*id.*, ¶ 75). These are functionally the same as the “vector of real valued numbers” that the ’029 Patent describes as being produced by its feature extracting neural networks. Ex1001, 11:30-39. Krishnan’s modules 104 and 105 process feature representations as inputs. Chen’s CNN outputs feature representations. There is no fundamental incompatibility between

the output of a CNN-based feature extractor and the input expected by a downstream classifier or assessment module. Indeed, Chen's own architecture demonstrates this compatibility: Chen first trains its CNN for feature extraction and then takes the output of that CNN and feeds it into its view classifier. Ex1009, Fig. 2.

23. As I testified at my deposition, Chen's view-classifying module "takes extracted features as inputs." Ex2052, 14:14-16. This is the same type of input that Krishnan's modules 103-105 accept. A POSITA would have understood that numerical feature vectors can be processed by downstream classification modules regardless of how those features were originally extracted.

24. Indeed, the highly cited 2014 work (6000+ citations) by Donahue, et al. (Ex1053) opens as follows: "We evaluate whether features extracted from the activation of a deep convolutional network trained in a fully supervised fashion on a large, fixed set of object recognition tasks can be re-purposed to novel generic tasks." The authors convincingly show that learned features extracted from internal layers of an image classification convolutional neural network can serve as numerical inputs to a variety of classifiers, optimized for disparate downstream tasks. This work thus addresses Patent Owner's argument regarding the subject reference combination and whether one can modularize a neural network so that its feature extraction step can be fed into another functional module. A POSITA

would be familiar with this work and readily view its applicability to the Krishnan-Chen combination.

25. Because Krishnan already contemplates the use of neural networks for all of its functional modules, including feature extraction module 102, in my opinion, there is no basis for Patent Owner's (and Dr. Sonka's) argument that incorporating Chen's CNN-based feature extraction would be incompatible with Krishnan's other NN classifier modules. To the contrary, Krishnan's architecture is designed to accept the types of outputs that neural network-based feature extractors produce. Both references operate on the same fundamental principle: extracting meaningful features from ultrasound images and using those features for downstream classification tasks.

D. The Patent's Architecture Is Essentially Identical to Chen's

26. FIG. 4 of the '029 Patent depicts parallel feature-extracting CNNs feeding into LSTM models for subsequent view classification and quality assessment. Chen's Figure 2 depicts a substantially identical architecture without the additional quality assessment classifier. The '029 Patent does not claim a novel architecture; rather, it claims the application of well-known neural network techniques to ultrasound image analysis—the very approach taught by the combination of Krishnan and Chen.

27. Patent Owner's attempt to distinguish the Krishnan-Chen combination from the '029 Patent on technical grounds fails because the underlying architectures are functionally the same. The Patent describes a view identification and quality assessment neural network 300 made up of functional elements that are referred to interchangeably as networks (Ex1001, 2:51-53), subnetworks (Ex1001, 15:28-30), and modules (Ex1001, 17:65-18:1). Krishnan describes the same. Krishnan discloses a view identification and quality assessment data processing module 101 made up of functional modules 102-105, where Krishnan states that each of the modules can implement neural network classifiers for performing their functions (Ex1005, [0023]). In my opinion, a POSITA reviewing Krishnan would have been motivated to use the feature extraction neural networks described in Chen to arrive at the same system architecture claimed in the '029 Patent.

28. For the foregoing reasons, my opinion that the combination of Krishnan and Chen renders obvious the claims challenged under Ground B remains unchanged.

V. GROUND C: KRISHNAN-AASE

29. Patent Owner and Dr. Sonka argue that Aase's neural network modules cannot be combined with Krishnan because of alleged incompatibilities. POR at 57-62; Ex2049 ¶¶ 212-217. I disagree because in the Krishnan-Aase combination—as it is presented in the Petition—the NNs of Aase are not used or

otherwise combined with the NN classifiers of Krishnan. Instead, Aase is only used to provide the teaching to implement Krishnan quality assessment and view identification modules as separate, dedicated NNs.

30. For the foregoing reasons, my opinion that the combination of Krishnan and Aase renders obvious the claims challenged under Ground C remains unchanged.

VI. GROUND D: KRISHNAN-CHEN-WU

A. Standard Training Techniques

31. Patent Owner argues that the combination of Krishnan, Chen, and Wu (Ex1010) fails to render obvious the training-related claims (Claims 12-20) of the Patent. POR at 63-71. I disagree. The training techniques implemented in the '029 Patent—including backpropagation, gradient descent, and the use of labeled training data—were standard, well-known techniques at the time of the alleged invention.

32. These training techniques were not novel in 2018 or at any time relevant to the '029 Patent. Backpropagation was introduced in the 1980s and was the dominant training algorithm for neural networks by the 1990s. The use of labeled training data (i.e., supervised learning) is the most basic form of neural network training and was well-established decades before the '029 Patent's priority date.

33. Pagoulatos (Ex1018) corroborates that these training techniques were part of the general knowledge of a POSITA working in the field of ultrasound image analysis using neural networks. In my opinion, a POSITA would not have needed an express teaching in a prior art reference to understand that a neural network trained for ultrasound image classification would be trained using backpropagation with labeled training data.

34. The neural network training techniques claimed in Claims 12-20—i.e., using training images as the input to the neural network and using the training labels as the desired output of the neural network—are precisely the type of well-known implementation details that would be within the general knowledge of a POSITA. A POSITA reading Krishnan, Chen, and Wu would already have been familiar with the technique of training a neural network using backpropagation without needing express step-by-step instructions in the references.

35. For the foregoing reasons, my opinion that the combination of Krishnan, Chen, and Wu, supplemented by general knowledge of standard neural network training techniques, renders obvious the claims challenged under Ground D remains unchanged.

VII. SECONDARY CONSIDERATIONS

36. I have reviewed Patent Owner's arguments regarding secondary considerations of non-obviousness. POR at 74-76. Patent Owner's evidence of

secondary considerations does not alter my opinion that the challenged claims are obvious.

37. Patent Owner points to citations of the '029 Patent in other patent applications as evidence of its alleged pioneering status. I disagree that citations to the patent indicate pioneering status. In my experience, citation of a patent in subsequent patent applications is routine and does not establish that the cited patent represents a pioneering invention. Patents are cited in later applications for many reasons, including to distinguish the prior art or to satisfy the duty to disclose information that might be relevant to the patentability of such applications. Such citations do not demonstrate or even imply non-obviousness of the cited patent.

38. Moreover, even assuming *arguendo* that Patent Owner's secondary considerations evidence has some probative value, I understand that evidence must be weighed against the strong showing of obviousness established by the prior art combinations discussed above. The Patent claims the application of well-known neural network techniques (CNNs, LSTMs, backpropagation) to ultrasound image analysis—a field in which neural networks were already being applied before the Patent's priority date. *See* Ex1048 (neural networks for ultrasound image segmentation, 1991); Ex1047 (survey identifying 50+ neural network applications for feature extraction, 2002).

39. For these reasons, Patent Owner's alleged secondary considerations evidence does not alter my opinions with respect to the validity of the challenged claims.

In signing this declaration, I understand that the declaration will be filed as evidence in the contested case before the Patent Trial and Appeal Board of the United States Patent and Trademark Office. I acknowledge that I may be subject to cross-examination in this case and that that cross-examination will take place within the United States. If cross-examination is required of me, I will appear for cross-examination within the United States during the time allotted for cross-examination.

I declare that all statements made herein of my knowledge are true, and that all statements made on information and belief are believed to be true, and that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code.

Dated: 2026-08-17 By: /Rahul C. Deo /

Rahul C. Deo, M.D., Ph.D.