

UNITED STATES PATENT AND TRADEMARK OFFICE

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BEFORE THE PATENT TRIAL AND APPEAL BOARD

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MIM SOFTWARE INC.,  
*Petitioner,*

v.

EXINI DIAGNOSTICS AB,  
*Patent Owner.*

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IPR2025-00827  
U.S. Patent No. 11,941,817

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**DECLARATION OF MILAN SONKA, PH.D.**

## TABLE OF CONTENTS

I.	INTRODUCTION .....	1
II.	QUALIFICATIONS .....	1
III.	MATERIALS CONSIDERED .....	1
IV.	LEGAL PRINCIPLES .....	3
	A. Priority Date .....	4
	B. A Person of Ordinary Skill in the Art .....	4
	C. Claim Construction.....	5
	D. Novelty and Non-Obviousness.....	6
V.	TECHNOLOGY BACKGROUND.....	7
	A. Fundamental Differences Between Machine (Supervised Deep) Learning and Template-Based Approaches .....	8
	B. Challenges of Dimensionality and Data in Medical Image Analysis .....	10
VI.	THE PRIOR ART .....	12
VII.	THE '817 PATENT AND ITS PROSECUTION HISTORY .....	12
	A. The '817 Patent .....	12
	B. Prosecution History of the '817 Patent .....	16
VIII.	CLAIM CONSTRUCTION .....	17
	A. “using one or more machine learning modules, for each of a plurality of target tissue regions” .....	17
	B. “a 3D segmentation map” .....	25
IX.	ANALYSES OF THE PETITION GROUNDS .....	29
	A. Ground A: Renisch does not anticipate claims 1-5, 7, 10-14, 16, 19, and 26. ....	29

1.	Claim 1 .....	29
a.	Renisch does not disclose supervised deep learning artificial neural networks, such as CNNs, as recited in claim 1. ....	29
i.	The supervised deep learning techniques described and claimed in the '817 Patent are fundamentally distinct from template-based approaches like those described in Renisch. ....	31
ii.	Renisch's mere mention of "clustering" and "neural network" is insufficient to disclose, or even suggest, a supervised deep learning approach as described in the '817 Patent. ....	32
iii.	Renisch does not disclose using one or more supervised deep learning modules, where each is trained to identify one or more specific target three-dimensional VOIs within the 3D anatomical image.....	34
b.	Renisch does not disclose "determining . . . a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI" as recited in claim 1. ....	35
i.	Renisch does not disclose a 3D segmentation map that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume. ....	37
ii.	Renisch does not create a 3D segmentation map that combines the results of a supervised deep learning multi-organ segmentation process. ....	40
iii.	Renisch does not inherently disclose a 3D segmentation map.....	42

c.	Conclusion .....	44
2.	Claim 10.....	45
3.	Claims 2-5, 7, 11-14, 16, 19, and 26.....	45
B.	Ground B: Renisch in view of Zhao does not render obvious claims 1-5, 7, 10-14, 16, 19, and 26.....	45
1.	Claim 1 .....	46
a.	Zhao does not disclose “determining . . . a 3D segmentation map representing a plurality of 3D segmentation masks” as recited in claim 1.....	46
b.	Renisch in view of Zhao does not render obvious limitation (c), as recited in claim 1.....	48
i.	Both Renisch and Zhao would require nonobvious modification to combine and arrive at Patent Owner’s claimed subject matter, as recited in claim 1. ....	49
ii.	Neither Renisch nor Zhao contemplate the particular challenges that motivated the approach claimed in the ’817 Patent. ....	51
iii.	A POSA would not have a reasonable expectation of success in combining Renisch and Zhao. ....	53
c.	Conclusion .....	54
2.	Claim 10.....	55
3.	Claims 2-5, 7, 11-14, 16, 19, and 26.....	55
C.	Ground C: Renisch, or Renisch-Zhao, each in view of Baker, do not render obvious claims 8-9, 17-18, 22-25, and 29-32. ....	55
D.	Ground D: Renisch, or Renisch-Zhao, each in view of Eiber, do not render obvious claims 8-9, 17-18, 22, 24-25, 29, and 31-32. ....	56

E.	Ground E: Baker in view of Zhao does not render obvious claims 1-2, 7-11, 16-18, 22-25, and 29-32. ....	56
1.	Claim 1 .....	56
2.	Claim 10.....	57
3.	Claims 2, 7-9, 11, 16-18, 22-25, and 29-32.....	57
F.	Ground F: Baker-Zhao in view of Eiber does not render obvious claims 3-5 and 12-14.....	58
G.	Ground G: Baker-Zhao in view of Suehling does not render obvious claims 19, 26, and 28.....	58
X.	CONCLUSION.....	59

**PATENT OWNER’S EXHIBIT LIST**

<b>EXHIBIT</b>	<b>DESCRIPTION</b>
EX2001	Defendant’s Memorandum of Law in Support of its Motion to Stay Pending <i>Inter Partes</i> Review, <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, Dkt. 89, Apr. 8, 2025.
EX2002	MIM’s Invalidity and Noninfringement Contentions, Civil Action No. 1:24-cv-10437-PBS.
EX2003	PACER Docket, <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS (as of June 30, 2025).
EX2004	Defendant’s Motion to Dismiss the Second Amended Complaint, <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, Dkt. 43, June 17, 2024.
EX2005	Motion to Dismiss Hearing Transcript (excerpted pp. 1, 4-6), <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, Oct. 8, 2024.
EX2006	Order Granting in Part and Denying in Part Defendant’s Motion to Dismiss the Second Amended Complaint, <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, Dkt. 72, Jan. 14, 2025.
EX2007	Motion to Stay Hearing Transcript (excerpted pp. 1, 5-6), <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, May 12, 2025.
EX2008	Order Granting in Part and Denying in Part Defendant’s Motion to Stay Pending <i>Inter Partes</i> Review, <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, Dkt. 102, May 13, 2025.
EX2009	Scheduling Order, <i>Progenics Pharmaceuticals v. MIM Software Inc.</i> , Civil Action No. 1:24-cv-10437-PBS, Dkt. 85, Mar. 5, 2025.
EX2010	U.S. District Courts, Judicial Caseload Profile 2024 (D. Mass. excerpted).
EX2011	<i>Cancer Control Month, 2025 – The White House</i> (Apr. 3, 2025).
EX2012	<i>NIH Strategic Plan for Data Science FY 2025-2030</i> , Nat’l Institutes of Health.

EXHIBIT	DESCRIPTION
EX2013	Rowe, S.P. et al., <i>PET Imaging of Prostate-Specific Membrane Antigen in Prostate Cancer: Current State of the Art and Future Challenges</i> , Prostate Cancer & Prostatic Diseases (2016).
EX2014	Declaration of Dr. Milan Sonka, August 6, 2025.
EX2015	Curriculum Vitae of Dr. Milan Sonka, August 6, 2025.
EX2016	RESERVED
EX2017	Crisan, et al., <i>Radiopharmaceuticals for PET and SPECT Imaging: A Literature Review over the Last Decade</i> , International Journal of Molecular Sciences 23(9):5023 (2022).
EX2018	<i>PET Scans</i> , CancerQuest, Emory Winship Cancer Institute (2025).
EX2019	Rowe, S.P., et al., <i>PSMA-Based [<sup>18</sup>F]DCFPyL PET/CT Is Superior to Conventional Imaging for Lesion Detection in Patients with Metastatic Prostate Cancer</i> , Molecular Imaging and Biology 18(3):411-419 (2016).
EX2020	<i>FDA Approves First PSMA-Targeted PET Imaging Drug for Prostate Cancer</i> , Oncology Practice Management (2020).
EX2021	<i>FDA Approves Second PSMA-Targeted PET Imaging Drug for Men with Prostate Cancer</i> , Food and Drug Administration (2021).
EX2022	<i>Atlas-Based vs. AI Auto-Contouring in Clinical Practice</i> , MIM Software Inc. (2023).
EX2023	Brown, <i>Machine Learning, Explained</i> , MIT Sloan (Apr. 21, 2021).
EX2024	RESERVED
EX2025	Krizhevsky, et al., <i>ImageNet Classification with Deep Convolutional Neural Networks</i> , Advances in Neural Information Processing Systems 25 (2012).
EX2026	Deng, et al., <i>ImageNet: A large-scale hierarchical image database</i> , IEEE Conference on Computer Vision and Pattern Recognition (2009).
EX2027	Bushberg, J.T., et al., <i>The Essential Physics of Medical Imaging</i> (2012), Ch. 1, Sec. 1.1, pp. 3-15.
EX2028	Bushberg, J.T., et al., <i>The Essential Physics of Medical Imaging</i> (2012), Ch. 3, Sec. 3.1, pp. 33-38.

EXHIBIT	DESCRIPTION
EX2029	Kelleher, <i>Deep Learning</i> (2019), Ch. 1, “What Is Machine Learning?,” pp. 9-17.
EX2030	Kelleher, <i>Deep Learning</i> (2019), Ch. 1, “The Key Ingredients of Machine Learning,” pp. 22-30.
EX2031	Kelleher, <i>Deep Learning</i> (2019), Ch. 3, “Neural Networks: The Building Blocks of Deep Learning,” pp. 65-67.
EX2032	Kelleher, <i>Deep Learning</i> (2019), Ch. 4, “The Era of Deep Learning,” pp. 143-145.
EX2033	Kelleher, <i>Deep Learning</i> (2019), Ch. 4, “Layer-Wise Pretraining Using Autoencoders,” pp. 145-148.
EX2034	Kelleher, <i>Deep Learning</i> (2019), Ch. 4, “Weight Initialization and ReLU Activation Functions,” pp. 148-153.
EX2035	Kelleher, <i>Deep Learning</i> (2019), Ch. 4, “The Virtuous Cycle: Better Algorithms, Faster Hardware, Bigger Data,” pp. 153-156.
EX2036	Declaration of Anita M.C. Spieth in Support of Patent Owner’s Notice of Intent to Designate Anita M.C. Spieth, a Provisionally Recognized PTAB Attorney, as Back-Up Counsel Under 37 C.F.R. § 42.10(c)(2).
EX2037	Declaration of Michael H. Bunis in Support of Patent Owner’s Motion for <i>Pro Hac Vice</i> Admission of Michael H. Bunis Under 37 C.F.R. § 42.10(c).
EX2038	Declaration of John C. Calhoun in Support of Patent Owner’s Notice of Intent to Designate John C. Calhoun, a Provisionally Recognized PTAB Attorney, as Back-Up Counsel Under 37 C.F.R. § 42.10(c)(2).
EX2039	Chang, K., et al., <i>Automatic assessment of glioma burden: a deep learning algorithm for fully automated volumetric and bidimensional measurement</i> , <i>Neuro-Oncology</i> , 21(11):1412-1422 (2019).
EX2040	Chang, K., et al., <i>Residual Convolutional Neural Network for the Determination of IDH Status in Low- and High-Grade Gliomas from MR Imaging</i> , <i>Clinical Cancer Research</i> , 24(5):1073-1081 (2018).

<b>EXHIBIT</b>	<b>DESCRIPTION</b>
EX2041	Beers, A., et al., <i>DeepNeuro: an open-source deep learning toolbox for neuroimaging</i> , Neuroinformatics, 19(1):127-140 (2021).
EX2042	Deposition of Bruce Rosen, M.D., Ph.D., Transcript, January 6, 2026.
EX2043	Declaration of Dr. Milan Sonka, January 26, 2026.

I, Milan Sonka, hereby declare as follows:

## **I. INTRODUCTION**

1. I have been retained by Progenics Pharmaceuticals, Inc. and their subsidiary, EXINI Diagnostics AB (collectively “Progenics”) to provide expert opinions in this *Inter Partes* Review (IPR). I am being compensated for my time at my customary rate of \$715 per hour for my work on this matter. I am being paid for my time regardless of the outcome of this IPR. Beyond the compensation I received for my time in this matter, I will not be affected in any way, positively or negatively, by the outcome of this case.

2. I previously provided expert opinions in an Expert Declaration submitted as Exhibit 2014 (EX2014) with a Patent Owner’s Preliminary Response filed by Progenics in this IPR on August 6, 2025 (my “August 2025 Declaration”).

## **II. QUALIFICATIONS**

3. My qualifications have been described in detail previously, in my August 2025 Declaration. EX2014, ¶¶2-7.

4. My curriculum vitae was provided previously, with my August 2025 Declaration, as EX2015.

## **III. MATERIALS CONSIDERED**

5. In forming my opinions, I have read U.S. Patent No. 11,941,817 (the “817 Patent”) (EX1001) and reviewed relevant parts of its prosecution history. I have also reviewed the Petitioner’s Petition for *Inter Partes* Review (IPR) dated April

4, 2025 (the “Petition”) along with the accompanying Declaration of Dr. Rosen (EX1002). I have also reviewed the Patent Trial and Appeal Board’s Decision Granting *Inter Partes* Review of the ’817 Patent dated November 2, 2025 (the “Institution Decision”). I have also reviewed the following references, which the Petitioner cited in their Petition against the ’817 Patent:

- U.S. Patent Application Publication No. 2012/0123253 (“Renisch”) (EX1005);
- U.S. Patent Application Publication No. 2011/0007954 (“Suehling”) (EX1006);
- U.S. Patent No. 10,140,544 (“Zhao”) (EX1007);
- U.S. Patent Application Publication No. 2018/0144828 (“Baker”) (EX1008);
- Eiber, “Prostate Cancer Molecular Imaging Standardized Evaluation (PROMISE): Proposed miTNM Classification for the Interpretation of PSMA-Ligand PET/CT,” *The Journal of Nuclear Medicine* 59(3):469-478 (March 2018) (“Eiber”) (EX1009).

6. I have also reviewed the following references, which were relied upon by Petitioner and its expert, Dr. Bruce Rosen, to support certain statements pertaining to the technological background and its conclusions regarding what is and is not disclosed in the above-listed references:

- D. Kaur and Y. Kaur, “Various Imaging Segmentation Techniques: A Review,” *International Journal of Computer Science and Mobile Computing*, 3(5): 809-814 (2014) (“Kaur”) (EX1015);
- N. Sharma and L. Aggarwal, “Automated Medical Image Segmentation Techniques,” *Journal of Medical Physics*, 35(1):3-14 (2009) (“Sharma”) (EX1016);

- H. Greenspan, B. van Ginneken, and R. M. Summers, “Deep Learning in Medical Imaging: Overview and Future Promise of an Exciting New Technique,” *IEEE Transactions on Medical Imaging*, 35(5):1153-1159 (2016) (“Greenspan”) (EX1017);
- G. Litjens et al., “A Survey on Deep Learning in Medical Image Analysis,” *Medical Image Analysis* 42:60-88 (2017) (“Litjens”) (EX1018); and
- D. Shen, G. Wu, and H. Suk, “Deep Learning in Medical Image Analysis,” *Annual Review of Biomedical Imaging*, 19:221-248 (2017) (“Shen”) (EX1019).

7. I have also reviewed other references that illuminate the state of the art as of January 7, 2019, which I have been instructed to use as the “priority date” of the ’817 Patent. I have also called upon my extensive knowledge and experience in the field of medical imaging, medical image analysis, and artificial intelligence and machine learning.

8. I reserve the ability to review documents, deposition transcripts, or other information provided to me after the date of this Declaration and to supplement my opinions based upon such review.

#### **IV. LEGAL PRINCIPLES**

9. As previously explained in my August 2025 Declaration, I have been informed of certain legal standards by Patent Owner’s attorneys. In particular, I have been informed of the following legal standards by Patent Owner’s attorneys. I am not an attorney, but I have applied these understandings in my analysis herein.

**A. Priority Date**

10. I have been instructed to assume for purposes of my analysis that January 7, 2019, is the “priority date” for assessing the state of the art and for determining what is “prior art” when considering whether the claims of the ’817 Patent would have been obvious.

**B. A Person of Ordinary Skill in the Art**

11. I have been asked to develop and offer opinions related to how a person of ordinary skill in the art (“POSA”) would have understood the ’817 Patent and the relevant references cited herein as of the priority date (January 7, 2019).

12. I have been informed and understand that certain factors may be considered in determining the level of ordinary skill in the art, for example, (1) the types of problems encountered in the art, (2) the prior art solutions to these problems, (3) the rapidity with which innovations are made, (4) the sophistication of the technology, and (5) the educational level of active workers in the field.

13. It is my opinion that a POSA for purposes of the ’817 Patent would include a person with a medical (MD) degree and/or an advanced degree in Computer Engineering, Computer Science, Physics, or other field related to computer imaging, and at least 3 years of field experience with medical imaging devices, such as PET/CT or SPECT/CT systems.

14. I consider myself to be at least a POSA and to have been at least a POSA as of the priority date, January 7, 2019.

**C. Claim Construction**

15. I have been informed and understand that, in an IPR proceeding, the claims of a patent are to “be construed using the same claim construction standard that would be used to construe the claim in a civil action under 35 U.S.C. § 282(b), including construing the claim in accordance with the ordinary and customary meaning of such claim as understood by one of ordinary skill in the art and the prosecution history pertaining to the patent.” 37 C.F.R. § 42.100(b).

16. Specifically, I have been informed and understand that under the standard set forth in *Phillips v. AWH Corp.*, 415 F.3d 1303 (Fed. Cir. 2005) (*en banc*), the claims of a patent are given their ordinary and customary meaning as would be understood by a POSA at the time of the invention. I have been informed that a *Phillips* construction of a claim is based on the entire record, including both intrinsic evidence (*i.e.*, the claims, specification, and prosecution history) as well as extrinsic evidence (*e.g.*, dictionary definitions and expert testimony). I have applied this standard in formulating my opinions in this matter.

17. I reserve the right to supplement my opinions in view of any additional information regarding the interpretation of the claims of the '817 Patent that becomes

available to me and any matters raised by the parties, the Board, and/or other experts in this matter.

**D. Novelty and Non-Obviousness**

18. I have been informed that to be valid patent claims must be novel and nonobvious. 35 U.S.C. §§ 102-103.

19. I have been informed that a patent claim is not novel if it is anticipated by a prior art reference. I have been informed that in order for a prior art reference to anticipate a claim, that prior art reference must disclose each and every limitation as set forth in the claim.

20. I have been informed and understand that a patent claim is obvious if the differences between what is set forth in the claims and what is disclosed in the prior art are such that what is claimed would have been obvious to a POSA as of the patent's priority date (January 7, 2019, in the case of the '817 Patent). I have been informed and understand that a POSA is presumed to have knowledge of all of the relevant art as of the priority date. I have further been informed and understand that as part of the analysis of whether a patent claim is obvious, I should consider: (a) the scope and content of the prior art; (b) the level of ordinary skill in the art; (c) the differences between what is claimed and the prior art; and (d) any secondary considerations that may indicate that the claim is not obvious.

21. I have been informed and understand that obviousness can be established by combining or modifying the teachings of the prior art to produce the claimed invention where there is some teaching, suggestion, or motivation to do so; and that a reasonable expectation of success in achieving the subject matter of the claim at issue must also be shown. Further, I have been informed and understand that the teaching, suggestion, or motivation test is flexible and that an explicit suggestion to combine the prior art is not necessary – the motivation to combine may be implicit and may be found in the knowledge of one of ordinary skill in the art, from the nature of the problem to be solved, market demand, or common sense. In undertaking an obviousness analysis, I have been informed and understand that I may take into account the inferences and creative steps that a person of ordinary skill would have employed in reviewing the prior art at the time of the invention. If the claimed invention combines elements known in the prior art and the combination yields results that would have been predictable to a person of ordinary skill at the time of the invention, then this evidence would make it more likely that the claim was obvious.

## **V. TECHNOLOGY BACKGROUND**

22. As explained in my August 2025 Declaration, the '817 Patent is generally directed to computer-implemented methods and systems for analyzing

medical images that facilitate decision making in the context of cancer diagnosis, monitoring, and treatment. EX2014, ¶25.

23. As such, in order to frame my analysis and provide the proper context for my opinions, I previously provided, in my August 2025 Declaration, an overview of certain relevant technologies at issue and relevant to my analysis and opinions in my August 2025 Declaration. In particular, my August 2025 Declaration included an overview of Medical Imaging Techniques, Image Analysis methods, and Deep Learning and Convolutional Neural Networks. EX2014, ¶¶26-49.

24. My previously provided overview of the aforementioned relevant technologies and technical concepts continues to frame and provide context for my analysis and opinions below. I also provide, here, the following discussion of two facets of deep learning and medical image analysis, relevant to my further analysis and opinions in this declaration.

**A. Fundamental Differences Between Machine (Supervised Deep) Learning and Template-Based Approaches**

25. In my August 2025 Declaration, I provided an overview of conventional image segmentation techniques, like thresholding and atlas-based segmentation. EX2014, ¶¶35-38.

26. Atlas image segmentation, for example, is an atlas-based technique that relies on one or more templates, referred to as atlas images, in which various structures of interest, like organs or bones, have been manually delineated. When a

new image of a patient is received, one of the atlas images is registered with the new patient image, and the manually delineated contours from the atlas image are transferred to the new patient image. EX2014, ¶38.

27. A related technique is model-based segmentation, whereby a stored geometric model of a structure of interest is used as a template to identify and define boundaries of a structure of interest in an image of a patient to be segmented. EX1005, [0027]; EX1016, 10.

28. Accordingly, atlas-based and model-based segmentation techniques are “template-based” approaches. They rely on stored geometric models or an atlas of one or more structure(s) of interest to perform segmentation.

29. These template-based approaches, however, rely on a central assumption that anatomical structures have shapes and positions that are consistent from patient to patient. EX1005, [0027]; EX1016, 10. As a result, when this assumption does not match reality, template-based approaches provide insufficient accuracy or may fail altogether. *See, e.g.*, EX2022, 1-5. This may occur in clinically relevant situations, where, for example, image quality is low and/or a patient’s anatomy is abnormal due to disease. *Id.* Of particular relevance to cancer-related applications is that cancer patients will harbor tumors, which are unique from patient to patient and will not be present in an atlas or model that represents the human anatomy. Accordingly, as demonstrated in Petitioner’s own studies (published in

2023), when image contrast is low, artifacts are present, or patient anatomy is unusual, conventional template-based approaches like atlas-based segmentation are inadequate. *Id.*

30. In contrast, machine (supervised deep) learning techniques do not rely on matching a template to an image. When properly trained, machine learning techniques, like Convolutional Neural Networks (CNNs), can learn patterns directly from images and can then, when presented with new images, identify individual pixels or voxels that make up either the contour or the interior of object(s) of interest within those new images.

31. Accordingly, machine learning techniques, like CNNs, operate based on a fundamentally different principle than template-based approaches. Machine learning techniques do not store and rely on pre-defined geometric models or atlases (*e.g.*, atlas images).

### **B. Challenges of Dimensionality and Data in Medical Image Analysis**

32. Medical images are particularly challenging images to analyze for computer vision applications. Among other things, fully three-dimensional (3D) images, like full 3D CT images, contain a large number of voxels. Analyzing this large quantity of 3D data can be computationally difficult. Computational challenges are especially significant for machine learning approaches, whereby memory

limitations of graphics processing units (GPUs) and the need to store and update a large number of learned parameters pose non-trivial obstacles.

33. Accordingly, in applying computer algorithms to analyze medical images, researchers may opt to limit themselves to 2D representations to reduce computational complexity and memory requirements. EX1016, 5; *see also* EX1017, 1155. For example, rather than analyze a full 3D medical image, a researcher might extract an individual slice from a full 3D image and analyze it as they would a 2D image. *Id.*

34. For example, around 2016, most work was performed in 2D, and it was questioned whether the transition to 3D would be a key to major steps forward in performance. EX1017, 1155 (“In most works to date we see analysis performed in 2D. It is often questioned if the transition to 3D will be a key to major step forward in performance.”).

35. Accordingly, analysis techniques applied to medical image analysis do not necessarily involve handling 3D images, but, rather, can be performed in 2D, for example on 2D CT images or individual 2D image slices, to circumvent computational and/or complexity challenges. These 2D analysis approaches, however, do not provide computational methods with 3D context.

## **VI. THE PRIOR ART**

36. A short summary of the prior art cited in the Petition against the '817 Patent has been provided in my previous August 2025 Declaration. EX2014, ¶¶50-54.

## **VII. THE '817 PATENT AND ITS PROSECUTION HISTORY**

### **A. The '817 Patent**

37. Based on my review of the '817 Patent, I understand it concerns machine (supervised deep) learning-based techniques for analyzing three-dimensional (3D) medical images in order to support identifying, assessing, and monitoring cancer. EX1001, 3:1-48. The '817 Patent describes convolutional neural network (CNN)-based 3D image segmentation methods that one can use to identify specific target tissue volumes of interest (VOIs) within 3D anatomical images. EX1001, 31:60-32:21, 34:41-37:10, 42:5-48:41.

38. From a technical perspective, two features of the disclosed techniques are particularly notable: (i) their applicability to multiple organs and (ii) their ability to handle 3D images. The '817 Patent highlights both these achievements, stating the following:

Notably, the image analysis approaches described herein are not limited to a single particular organ or portion of the body. Instead, they are robust and widely applicable, providing for consistent, efficient, and accurate detection of anatomical regions, including tissue and/or organs, in the entire body.

...

The capability of the approaches described herein to handle 3D images is an important advantage over certain other image analysis that only identify 2D regions in 2D images.

EX1001, 3:7-24.

39. As I understand the disclosure, the '817 Patent achieves its unique capabilities through an approach that uses multiple machine learning algorithms (such as CNNs) to analyze and segment multiple different target tissue regions in various anatomical subregions of a patient's body.

40. For example, FIGs. 6A and 6B illustrate an approach in which the problem of multi-organ anatomical segmentation is simplified by subdividing the anatomy into multiple anatomical subregions (like an abdomen, a pelvic region, and so forth). Rather than trying to train and use a single machine learning module to segment every single desired organ and/or bone, the '817 Patent describes how a different machine learning module can be used for each anatomical subregion. Each individual machine learning module then is able to focus on a simpler problem, and is trained to segment a portion of organs and/or bones within the particular anatomical subregion that the module is associated with. EX1001, 6:40-42, 42:66-46:51, 34:27-29.

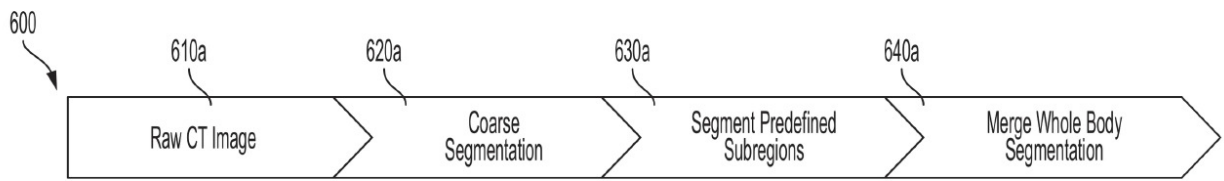


FIG. 6A

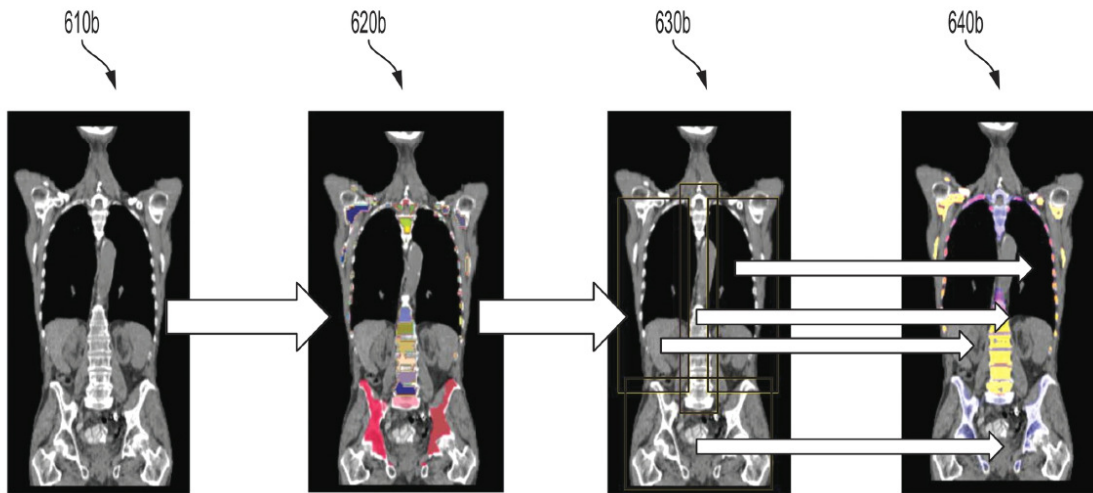


FIG. 6B

**FIGs. 6A and 6B of the '817 Patent**

41. After subdividing the body and segmenting different anatomical subregions with different machine learning modules, the '817 Patent describes recombining the different segmentation results from different machine learning modules to create a 3D segmentation map that represents the identified VOIs within a common volumetric framework. EX1001, 31:64-32:21. It is thus my opinion that this 3D segmentation map is a specific element that is created via the approach

described in the '817 Patent. EX1001, 34:27-39. An example of such a map is shown in FIG. 8 of the '817 Patent:

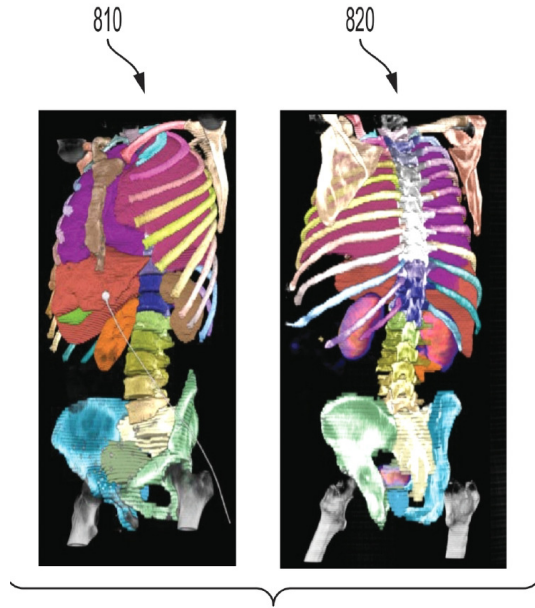


FIG. 8

**FIG. 8 of the '817 Patent**

42. The '817 Patent further explains that the resultant 3D segmentation map may then be used as an input for subsequent image analysis operations, including the analysis of 3D functional images, like full PET or SPECT images, which can be acquired with different radiopharmaceuticals. *See, e.g.*, EX1001, 31:65-33:40.

43. By way of example, the '817 Patent describes using the 3D segmentation map to isolate specific regions for lesion detection, classify lesions, correct for physiological uptake in regions such as the bladder and kidneys, and quantify lesion severity in an improved fashion by virtue of the 3D nature of the segmented volumes. EX1001, 3:49-5:11. FIGs. 10A-D illustrate how the anatomical

context provided by such a 3D segmentation map can be leveraged for analysis of a PET image.

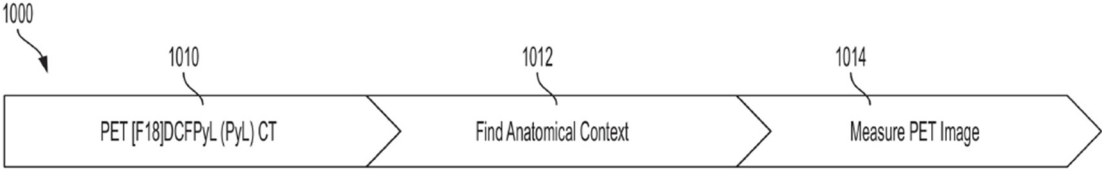
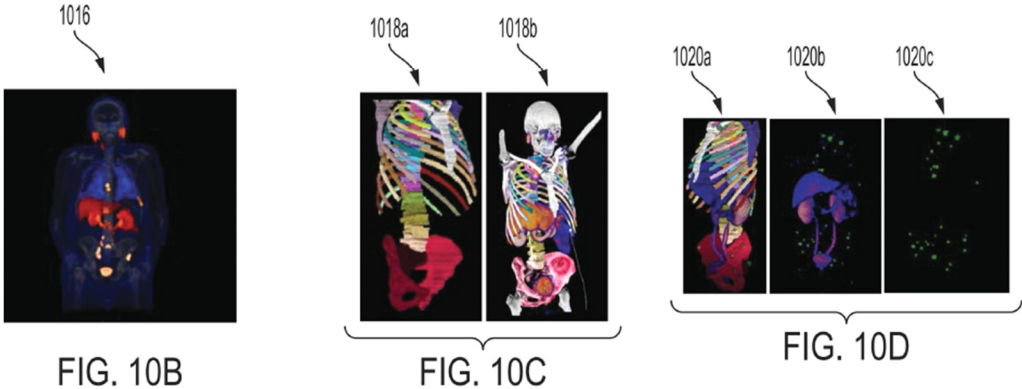


FIG. 10A



**FIGs. 10A-D of the '817 Patent**

44. It is thus my opinion that the claimed methods provide numerous advantages over prior art methods.

**B. Prosecution History of the '817 Patent**

45. As discussed in my August 2025 Declaration that was filed with Patent Owner's Preliminary Response in this IPR, I have reviewed relevant parts of the publicly available prosecution history of the '817 Patent. EX2014, ¶¶64-68.

## VIII. CLAIM CONSTRUCTION

46. As noted above, I understand that claim terms are construed under the standard set forth in *Phillips v. AWH Corp.*, 415 F.3d 1303 (Fed. Cir. 2005) (*en banc*).

47. Under the *Phillips* standard, I understand that the claims of a patent are given their ordinary and customary meaning as would be understood by a POSA at the time of the invention, not only in the context of the particular claim in which the term appears, but in the context of the entire patent, including the specification.

A. **“using one or more machine learning modules, for each of a plurality of target tissue regions”**

48. Independent claim 1 of the '817 Patent recites the following:

(b) automatically identifying, by the processor, **using one or more machine learning modules, for each of a plurality of target tissue regions, a corresponding target volume of interest (VOI)** within the 3D anatomical image;

EX1001, 79:14-18 (emphasis added).

49. Substantially the same language also appears in claim 10, which is a system version of claim 1.

50. After reviewing this language in the context of the claim itself and the entire '817 Patent, including the specification, it is my opinion that a POSA would understand it to mean the following: “using one or more supervised deep learning artificial neural networks, such as convolutional neural networks (CNNs), each trained to identify one or more specific target three-dimensional volume(s) of interest

(VOIs) within the 3D anatomical image.” The table below shows the proposed construction alongside the language of claim 1.

<b>Claim Term</b>	<b>Proposed Construction</b>
“using one or more machine learning modules, for each of a plurality of target tissue regions”	“using one or more supervised deep learning artificial neural networks, such as convolutional neural networks (CNNs), each trained to identify one or more specific target three-dimensional volume(s) of interest (VOIs) within the 3D anatomical image.”

51. My opinion is based on several aspects of the intrinsic record:

52. First, beginning with the first portion of the term “using one or more machine learning modules,” it is my opinion that a POSA reading the claim language in the context of the entire ’817 Patent would understand “using one or more machine learning modules” to mean “using one or more supervised deep learning artificial neural network, such as CNNs.”

53. Throughout the specification of the ’817 Patent, when referring to machine learning, the specification repeatedly and consistently refers to deep learning and/or CNNs. The ’817 Patent does not refer to other categories of machine learning.

54. For example, Examples 2, 3, 6, and 9 each expressly use the term “deep learning” in describing the disclosed technologies. Example 2 states that “this example demonstrates automating the process of accurate bone segmentation in

whole body CT images *using deep learning approaches in accordance with the whole body segmentation technology described herein.*” EX1001, 47:60-64 (emphasis added). Example 3 says that “[t]his example demonstrates automated segmentation of 49 bones and 27 soft-tissue regions in whole body CT images using *deep learning approaches in accordance with the whole body segmentation technology described herein.*” EX1001, 48:47-50 (emphasis added). Example 6 also explains that it uses “deep learning.” EX1001, 56:40-43 (“For each scan, a semantic segmentation of the CT image was performed using *the deep learning approaches described herein* in order to identify a set of specific bone and soft-tissue regions (e.g., organs).”) (emphasis added). Example 9 describes “a cascaded deep learning pipeline.” EX1001, 60:47.

55. The specification also repeatedly links CNNs with the term “machine learning,” *e.g.*, as a single example of machine learning, when referring to machine learning. For example, the specification of the ’817 Patent notes:

In certain embodiments, the 3D anatomical image is a full body image and step (b) comprises: automatically determining, using one or more localization modules implementing machine learning technique(s) (e.g., wherein each localization module *is a CNN module that implements a CNN*), a plurality of initial VOIs within the 3D anatomical image, each initial VOI corresponding to a particular anatomical region (e.g., a group of related tissue, such as a pelvic region, a chest region, a head and/or neck region, a spine region, an upper body region, a lower body region, etc.) and in which an associated subset of the target VOIs are located; and for each initial VOI, automatically identifying, using one or more segmentation modules implementing machine learning technique(s) (e.g., wherein

each segmentation module *is a CNN module that implements a CNN*) the associated subset of target VOIs.

EX1001, 6:33-38 (emphasis added).

56. Similar language appears throughout the specification. *See, e.g.*, EX1001, 6:28-48, 12:17-32, 13:51-14:3, 15:21-56, 15:57-16:14, 23:1-17, 24:34-58, 26:5-42, 31:64-32:21, and 34:4-26.

57. In addition, the specification of the '817 Patent devotes an entire section to “Image Segmentation Using Convolutional Neural Networks (CNNs).” EX1001, 34:44-37:10. All Examples fall under the heading “C. Example CNN-Based Whole Body Segmentation and Lesion Detection Approaches,” and the '817 Patent's first example extensively describes three different versions of CNN networks. EX1001, 42:17-47:50.

58. Taken together, these disclosures would lead a POSA to understand that the “machine learning modules” recited in the claims mean “deep learning artificial neural networks, such as CNNs.”

59. A POSA would also understand that the “deep learning artificial neural networks, such as CNNs” are *supervised* deep learning artificial neural networks, such as CNNs.

60. As I explained in my August 2025 Declaration, supervised machine learning algorithms are trained using labeled datasets. EX2014, ¶40; *see also* EX2023, 4; EX2030, 26. In labeled datasets, each example is labeled with the desired

output (e.g., “ground truth”) that the machine learning algorithm is intended to reproduce. EX2014, ¶40; *see also* EX2030, 26.

61. The ’817 Patent expressly describes training the supervised deep learning artificial neural networks in this supervised fashion. For example, Example 2 states that “[a] training set (N=90) and validation set (N=22) of pairs of low-dose CT images and *manually crafted* segmentation maps were used to develop the deep learning algorithm.” EX1001, 48:7-10 (emphasis added). Example 3 states that “. . . in order to train the machine learning modules used to perform the segmentations, numerous *pre-labeled sample images*, such as the three images (710, 720, 730) shown in FIG. 7, were used as a training data set.” EX1001, 50:22-25 (emphasis added). Example 6 states “[t]raining and validation was performed and evaluated for each particular region (bone or soft tissue region) using a manual identification of that region in a CT image. For example, 140 manually identified livers were used to train the algorithm for liver segmentation, and 37 manually identified livers were used for validation. Similarly, 61 and 14 manually identified aortas were used for training and validation of the aorta region segmentation, respectively.” EX1001, 57:10-18. All of these Examples describe training CNNs using labeled datasets, in other words, in a supervised fashion.

62. In my opinion, these disclosures confirm that the term “using one or more machine learning modules” as recited in claim 1 means “using one or more

supervised deep learning artificial neural networks, such as convolutional neural networks (CNNs).”

63. As for the remaining portion of the claim term, “for each of a plurality of target tissue regions,” it is my opinion that a POSA would also understand from the ’817 Patent that each of the one or more supervised deep learning artificial neural networks, such as CNNs, is “trained to identify one or more specific target three-dimensional volume(s) of interest (VOIs) within the 3D anatomical image.”

64. The ’817 Patent describes its technology as used for multi-organ segmentation, including examples showing how multiple CNNs are trained to identify multiple target VOIs. For instance, Example 1 of the specification states the following:

In a first example version of a CNN network used for whole body segmentation, the first machine learning module (localization module) in this example is referred to as “coarse-seg”, and was trained to identify 49 bones in sub-sampled CT images (a sub-sampling factor of 4 along each dimension). The localization module was used to differentiate regions of the body in to a pelvic region, a spine, a left upper body, and a right upper body. ***The four fine segmentation networks were as follows:***

***“fine-seg-pelvic”***: ***Trained to identify*** the left and right ilium and the sacrum and coccyx;

***“fine-seg-spine”***: ***Trained to identify*** 12 thoracic vertebrae, 5 lumbar vertebrae, and the sternum;

***“fine-seg-left-upper-body”***: ***Trained to identify*** 12 ribs on the left side of the body, the left scapula, and left clavicle; and

***“fine-seg-right-upper-body”***: ***Trained to identify*** 12 ribs on the right side of the body, the right scapula, and right clavicle.

EX1001, 42:61-43:12 (emphasis added).

65. The example provides tables reporting the number of trainable parameters for each network, like Table 3 below:

TABLE 3

Number of parameters in five neural networks			
Network Name	Total params.	No. trainable params.	No. non-trainable params.
coarse-seg	5,881,978	5,878,678	3,300
fine-seg-pelvic	5,880,276	5,877,068	3,208
fine-seg-spine	1,472,815	1,471,177	1,638
fine-seg-left-upper-body	1,472,731	1,471,101	1,630
fine-seg-right-upper-body	1,472,731	1,471,101	1,630

**Table 3 of the '817 Patent**

66. Another example CNN system described in the '817 Patent uses seven fine segmentation networks trained to identify 49 bones and multiple soft tissue regions:

The seven fine segmentation networks for this 3rd example version of the CNN whole-body segmentation system are as follows:

“fine-seg-abdomen”: Trained to identify the liver, left and right kidney, and gallbladder;

“fine-seg-left-lung”: Trained to identify the left lung;

“fine-seg-right-lung”: Trained to identify the right lung

“fine-seg-pelvic-region-mixed”: Trained to identify the left and right ilium, the prostate, the urinary bladder, and the sacrum and coccyx;

“fine-seg-spine-bone”: Trained to identify 12 thoracic vertebrae, 5 lumbar vertebrae, and the sternum;

“fine-seg-left-upper-body-bone”: Trained to identify 12 ribs on the left side of the body, the left scapula, and left clavicle; and

“fine-seg-right-upper-body-bone”: Trained to identify 12 ribs on the right side of the body, the right scapula, and right clavicle.

EX1001, 46:32-51.

67. Table 10 in the same example highlights the number of trainable parameters of each network:

**TABLE 10**

---

Number of parameters in seven neural networks and two localization networks.

---

Network Name	Total Params	No. trainable params	No. non-trainable params
coarse-seg-02	5,882,432	5,879,132	3,300
coarse-seg-03	5,882,469	5,879,167	3,302
fine-seg-abdomen	1,473,003	1,471,369	1,634
fine-seg-left-lung	1,472,752	1,471,120	1,632
fine-seg-right-lung	1,472,752	1,471,120	1,632
fine-seg-left-upper-body	1,472,731	1,471,101	1,630
fine-seg-right-upper-body	1,472,731	1,471,101	1,630
fine-seg-pelvic-region-mixed	3,883,812	3,881,200	2,612
fine-seg-spine-bone	1,472,815	1,471,177	1,638

---

**Table 10 of the '817 Patent**

68. Based on these disclosures, a POSA reading the claim would understand that each machine learning module (*i.e.*, each supervised deep learning artificial neural network) is trained to identify one or more specific target three-dimensional VOIs within the 3D anatomical image.

69. Accordingly, it is my opinion that a POSA, reading the term “using one or more machine learning modules, for each of a plurality of target tissue regions” in claim 1 of the ’817 Patent in the context of the Patent, would understand it to mean: “using one or more supervised deep learning artificial neural networks, such as convolutional neural networks (CNNs), each trained to identify one or more specific target three-dimensional volume(s) of interest (VOIs) within the 3D anatomical image.”

**B. “a 3D segmentation map”**

70. The term “3D segmentation map” appears in independent claims 1 and 10, as well as in dependent claims 3, 12, 19, and 26. Step (c) of claim 1 recites the following:

(c) determining, by the processor, *a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI;*

EX1001, 79:19-21 (emphasis added).

71. Reading this claim term in the context of the claim itself and the entire ’817 Patent, it is my opinion that a POSA, reading the term in the context of the claim itself and the entire ’817 Patent, including its specification, would understand it to mean the following: “a consolidated representation of 3D objects in space that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume.” The table below shows the proposed construction alongside the language of claim 1.

<b>Claim Term</b>	<b>Proposed Construction</b>
“a 3D segmentation map”	“a consolidated representation of 3D objects in space that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume.”

72. It is my opinion that this construction is correct for at least the following reasons.

73. First, the construction is consistent with the claim language, which dedicates a specific step, separate from step (b), to the creation of the 3D segmentation map. Second, the construction is consistent with the specification of the '817 Patent, which also states that the 3D segmentation map is a single element, created by combining multiple 3D segmentation masks in a single volume. The annotated version of FIGs. 6A and 6B, shown below, summarizes these points.

Step (b) (“automatically identifying...using one or more machine learning modules...”)



Step (c) (“determining, by the processor, a 3D segmentation map...”)

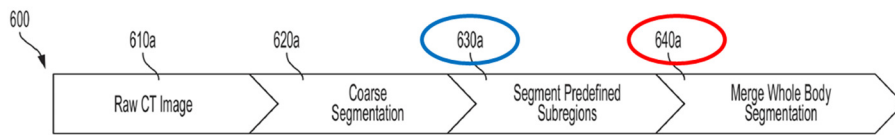


FIG. 6A

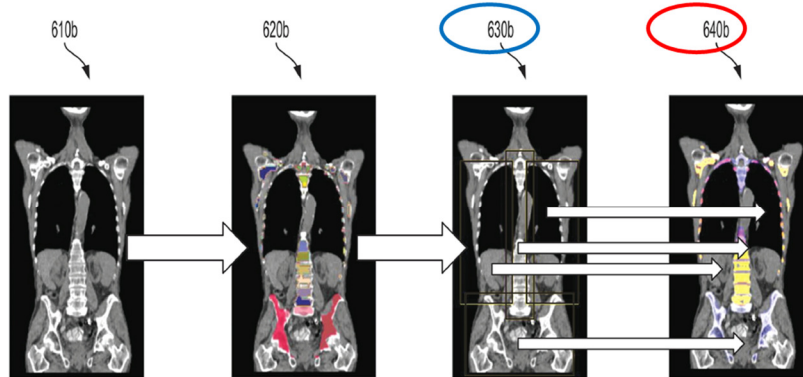


FIG. 6B

**Annotated version of FIGs. 6A and 6B of the '817 Patent, with color boxes and circles illustrating corresponding claim steps for the circled reference numerals**

74. For example, as illustrated above, FIGs. 6A and 6B of the '817 Patent show how segmentation masks representing different identified target volumes are merged to provide a whole body segmentation map. The '817 Patent states, in reference to the creation of a 3D segmentation map (reference numeral 640a), that “[s]egmentation masks representing the identified target volumes can be created, and merged 640a, for example to create a 3D whole body segmentation map.” EX1001, 49:7-10. The '817 Patent also describes how multiple 3D segmentation masks are *stitched together* to create a 3D segmentation map. EX1001, 31:66-32:13 (“The multiple segmentation masks, identifying multiple target tissue regions across a

patient's body, can be stitched together to form a segmentation map.”), 34:27-39 (“The target volumes are stitched together 506 to form a segmentation map 510 that comprises a plurality of segmentation masks 512, with each segmentation mask representing an identified target volume.”), 16:17-19 (“In certain embodiments, at step (c) the instructions cause the processor to digitally stitch together the plurality of 3D segmentation masks to form the 3D segmentation map.”).

75. That the 3D segmentation map combines the multiple 3D segmentation masks in a common volume is illustrated in FIGs. 6A and 6B. The '817 Patent states the following:

“In certain embodiments, at step (c) the instructions cause the processor to *digitally stitch together the plurality of 3D segmentation masks to form the 3D segmentation map* {e.g., by *creating an initially empty image volume* (e.g., initializing all voxel values to zero) and *then inserting labels from each segmentation mask into the image volume* [e.g., by mapping labeled (e.g., as representing a particular target tissue region as determined by a machine learning module) voxels of input images to one or machine learning modules to voxels of the image volume (e.g., *so as to match voxels of the image volume to voxels of the input images that represent a same physical location, thereby labeling voxels of the image volume correctly*)]}.”

EX1001, 16:17-29 (emphasis added); *see also id.*, 5:36-48.

76. In my opinion, a POSA would therefore understand the term “3D segmentation map” recited in the '817 Patent to be “a consolidated representation of 3D objects in space that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume.”

## **IX. ANALYSES OF THE PETITION GROUNDS**

### **A. Ground A: Renisch does not anticipate claims 1-5, 7, 10-14, 16, 19, and 26.**

77. It is my opinion that the Petition does not establish that Renisch anticipates claims 1-5, 7, 10-14, 16, 19, and 26.

#### **1. Claim 1**

##### **a. Renisch does not disclose supervised deep learning artificial neural networks, such as CNNs, as recited in claim 1.**

78. Limitation (b) of claim 1 states “automatically identifying, . . ., using one or more machine learning modules, for each of a plurality of target tissue regions, a corresponding target volume of interest (VOI) within the 3D anatomical image.” Pet., 22; EX1001, 79:14-18. The Petition alleges that Renisch discloses this element. Respectfully, I disagree.

79. As explained above, as properly construed, limitation 1(b) of claim 1 requires “using one or more supervised deep learning artificial neural networks, such as CNNs, each trained to identify one or more specific target three-dimensional VOIs within the 3D anatomical image.”

80. As discussed above, this interpretation is consistent with how the '817 Patent describes supervised deep learning technologies for performing platform agnostic whole-body anatomical segmentation, and for using accurate machine (supervised deep) learning-based segmentation to support assessment of cancer

progression and treatment. The '817 Patent includes detailed descriptions showing how multiple convolutional neural networks can be trained and used together to segment various organs and/or bones of interest within a 3D anatomical image. The disclosed Examples demonstrate how different CNNs can be assigned to segment different collections of organs in different anatomical subregions, and how their outputs can be combined and unified in a consolidated 3D segmentation map that provides a single unified representation for subsequent processing.

81. Renisch, on the other hand, references previously developed segmentation techniques in substantially more general terms:

The segmentation unit 76 is capable of employing different types of segmentation methods. *For example, the segmentation unit 76 can employ a model-based segmentation in which the central assumption is that the anatomical structures of interest have, to some extent, relatively consistent forms of geometry and position across patients.* A library of three-dimensional anatomical structure models explaining the shape, geometrical location, size, and variations thereof are defined in an anatomical database 84 prior to the segmentation. During segmentation, the models act as templates to identify 86 and define the boundary of the structure of interest. It is to be appreciated, however, that other segmentation methods such as clustering, edge detection, region growing, principle components analysis, neural network, and the like are also contemplated.

*The segmentation unit 76 can also employ an atlas of normal anatomical structures which is mapped to the actual anatomical image.* In such an embodiment, the atlas includes the anatomical database 84.

EX1005, [0027]-[0028] (emphasis added).

82. In my review of these two paragraphs, only two segmentation techniques are described with any explanatory detail. Those two techniques are, as explained above, template-based approaches (*e.g.*, Renisch’s “model-based segmentation” referenced in paragraph [0027] and atlas-based approach referenced in paragraph [0028]) that rely on pre-defined models of structure geometry or atlases). For the other segmentation techniques, Renisch only lists the name of the techniques, without describing how any given technique actually would or could be used.

- i. The supervised deep learning techniques described and claimed in the ’817 Patent are fundamentally distinct from template-based approaches like those described in Renisch.

83. The template-based approaches discussed in Renisch are fundamentally distinct from the detailed supervised deep learning techniques described in the ’817 Patent.

84. As Renisch explicitly notes, its template-based segmentation relies on the central assumption that geometries and positions of anatomical structures of interest are relatively consistent across patients. EX1005, [0027]. As I explained above, that central assumption is often violated, and template-based approaches can thus fail quite severely when dealing with images of patients where the stored templates (geometric models or atlas image) do not closely match the observed structures. For example, Petitioner’s own 2023 study comparing an atlas-based

approach and a CNN-based approach in clinical settings shows several case studies whereby atlas-image-based segmentation approaches failed for lower quality, non-contrast CT images and/or where a patient with liver disease had a small body but an enlarged liver. EX2022, 1-5.

85. In contrast, deep learning techniques, like those described in the '817 Patent, follow an entirely different paradigm. In my opinion, then, neither of template-based techniques described in Renisch suggest the machine (supervised deep) learning approaches described in the '817 Patent. Renisch thus not only fails to disclose any type of supervised deep learning based segmentation – Renisch is, instead, focused on a fundamentally distinct template-based approach.

- ii. Renisch's mere mention of "clustering" and "neural network" is insufficient to disclose, or even suggest, a supervised deep learning approach as described in the '817 Patent.

86. The Petition relies on a single sentence in Renisch that lists "clustering" and "neural network" among several possible segmentation methods: "It is to be appreciated, however, that other segmentation methods such as clustering, edge detection, region growing, principle components [sic] analysis, neural network, and the like are also contemplated." EX1005, [0027]; Pet., 22-23. In my view, this passage of Renisch does not disclose or explain the use of machine (supervised deep) learning as described in the '817 Patent.

87. Methods such as edge detection, region growing, and principal component analysis are not supervised deep learning approaches as described in the '817 Patent.

88. Instead, the Petition points to the isolated references to “clustering” and “neural network.” In my opinion, the presence of those terms, without further description, does not disclose machine learning as recited in the '817 Patent.

89. In my opinion, listing isolated method names does not transform Renisch's system and disclosure, which is directed towards template-based (atlas- and model-based) segmentation, rather than the '817 Patent's fundamentally distinct deep learning (CNN)-based segmentation techniques.

90. With regard to “clustering,” “clustering” is not a supervised deep learning approach as described in the '817 Patent. Instead, clustering refers to a general class of methods for grouping similar objects into different groups, or more precisely, for partitioning a data set into subsets (*e.g.*, according to some defined distance measure in the (multi-dimensional) space of features (descriptors)). Clustering is an expressly unsupervised technique. It expressly avoids use of labeled data – directly contrasting with the extensive use of labeled data described in the '817 Patent. *See, e.g.*, EX1001, 48:7-10, 50:22-25, 57:10-18. Accordingly, a reference to “clustering” does not disclose or even suggest (if anything, in fact, it teaches away from) use of supervised deep learning as described in the '817 Patent.

91. With respect to the single mention of “neural network,” as explained above and in my previous August 2025 Declaration, a neural network is a specific computational model that uses variable weights and interconnected neurons to capture behavior. EX2014, ¶43. A neural network is not the same thing as, and does not necessitate the use of, supervised deep learning approaches as described in the ’817 Patent. In my opinion, a POSA would not infer a supervised deep learning approach from Renisch’s isolated reference to the term “neural network.”

- iii. Renisch does not disclose using one or more supervised deep learning modules, where each is trained to identify one or more specific target three-dimensional VOIs within the 3D anatomical image.

92. As discussed above, when read in view of the claims and the specification, limitation 1(b) requires “using one or more supervised deep learning artificial neural networks, such as CNNs, *each trained to identify one or more target three-dimensional VOIs within the 3D anatomical image*” (emphasis added).

93. In my review, Renisch refers only to the isolated terms “clustering” and “neural network” within a list of possible segmentation methods. In my opinion, those references do not sufficiently disclose or suggest the use of supervised deep learning segmentation of the type disclosed in the ’817 Patent..

94. I also do not identify any portion of Renisch that describes how particular machine learning modules could be trained to identify one or more specific

VOIs as described in the '817 Patent. Renisch does not include any discussion of training that the Petition could point to.

95. For these reasons, in my opinion, Renisch fails to disclose, or even suggest, the use of one or more supervised deep learning artificial neural networks, each trained to identify one or more specific target 3D VOIs, as described in the '817 Patent.

96. Based on the foregoing, it is my opinion that Renisch does not teach limitation 1(b).

- b. Renisch does not disclose “determining . . . a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI” as recited in claim 1.**

97. Representative limitation (c) of claim 1 recites: “determining, by the processor, a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI[.]” As explained above, as properly construed, a “3D segmentation map” as recited in limitation 1(c) of claim 1 is “a consolidated representation of 3D objects in space that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume.”

98. The claim language reflects that step (c) follows and depends on particular preceding steps and results – namely, it combines multiple 3D

segmentation masks representing VOIs identified via the machine (supervised deep)

learning modules received at step (b) of claim 1. Claim 1 recites:

(b) automatically identifying, by the processor, using one or more machine learning modules, for each of a plurality of target tissue regions, *a corresponding target volume of interest (VOI)* within the 3D anatomical image;

(c) determining, by the processor, *a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI*;

EX1001, 79:14-22 (emphasis added).

99. Thus, this order of steps indicates that the 3D segmentation map that is created at limitation 1(c) of claim 1 is an additional step, separate from the machine (supervised deep) learning-based segmentation performed at step (b) and is used to combine results into a specific unified element (a 3D segmentation map), as illustrated in the annotated version of FIGs. 6A and 6B, below.

Step (b) (“automatically identifying...using one or more machine learning modules...”)



Step (c) (“determining, by the processor, a 3D segmentation map...”)

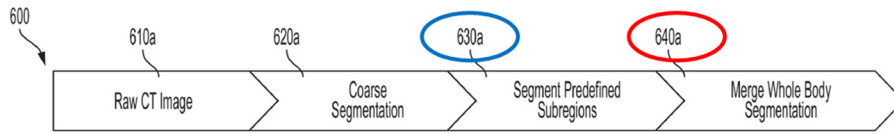


FIG. 6A

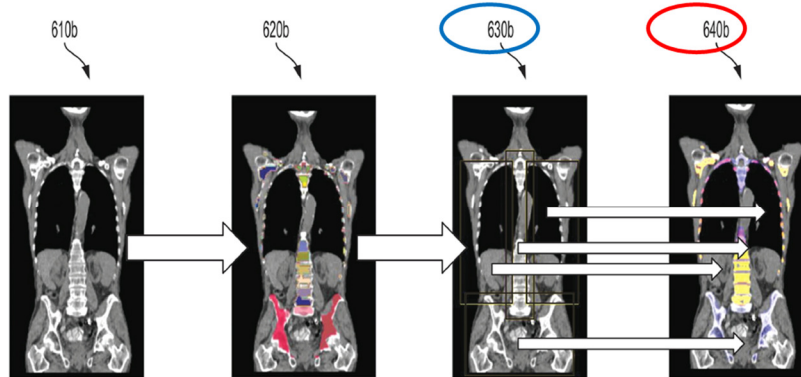


FIG. 6B

**Annotated version of FIGs. 6A and 6B of the '817 Patent, with color boxes and circles illustrating corresponding claim steps for the circled reference numerals**

100. As explained in further detail below, it is my opinion that Renisch does not disclose limitation 1(c).

- i. Renisch does not disclose a 3D segmentation map that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume.

101. The Petition alleges that “Renisch discloses [1(c)] to a POSITA even though Renisch does not use the same terminology.” Pet., 24. However, in my opinion, the distinctions between Renisch and claim 1 go beyond terminology.

102. Limitation 1(c) of claim 1 is a dedicated step, separate from the machine (supervised deep) learning-based segmentation performed at step (b). As described in the '817 Patent and reflected in the claim language, the action performed in limitation 1(c) combines multiple 3D segmentation masks that represent VOIs identified via one or more machine learning modules to create a new structure - a 3D segmentation map.

103. The Petition, however, proposes and appears to base its contention that Renisch discloses limitation 1(c) of claim 1 on a construction that renders the term “3D segmentation map” and step (c) of claim 1 meaningless or irrelevant. In particular, the Petition’s proposed construction for a 3D segmentation map is “a plurality of 3D segmentation masks distinguishing a plurality of regions within a 3D image.” Pet., 9-10.

104. Petitioner’s proposed construction, however, is at odds with the language of the claim, which recites more than “a plurality of 3D segmentation masks.” Rather, the claim uses a particular term (“3D segmentation map”) to refer to the particular element that is created at step (c), and differentiates that particular element from a plurality of 3D segmentation masks that it combines within a common volume. Petitioner’s proposed construction is also at odds with the specification of the '817 Patent, which repeatedly and consistently describes the 3D segmentation map as being created by merging or stitching together multiple distinct 3D

segmentation masks in a common volume. EX1001, 49:7-10, 31:66-32:13, 34:27-39.

105. It is my opinion that under the correct construction Renisch does not disclose a 3D segmentation map. The Petition does not, in my opinion, point to a specific step in Renisch whereby multiple 3D segmentation masks are merged or digitally stitched together and combined in a common volume. Instead, the Petition states the following:

A ‘segmentation map,’ as properly construed, is simply “a plurality of 3D segmentation masks distinguishing a plurality of regions within a 3D image.” See Section VII.A. Therefore, the image segmentation results produced by Renisch are collectively a segmentation map representing a plurality of 3D segmentation masks, each mask representing a 3D segmented organ volume. Ex1002, ¶166. Accordingly, Renisch discloses [1(c)].

Pet., 24-25.

106. The Petition’s argument, accordingly, appears to require their specific proposed construction (which, as explained above, is incorrect) and, in turn, that any segmentation results are equivalent to producing a 3D segmentation map (which, as explained above, is also incorrect).

107. Thus, in my opinion, the Petition does not show that Renisch discloses a 3D segmentation map as recited in claim 1 of the ’817 Patent.

- ii. Renisch does not create a 3D segmentation map that combines the results of a supervised deep learning multi-organ segmentation process.

108. Limitation 1(c) operates on and combines the output of the supervised deep learning-based segmentation performed at limitation 1(b).

109. Because, as explained above, Renisch does not disclose using supervised deep learning-based segmentation, Renisch does not disclose a 3D segmentation map that combines multiple 3D segmentation masks, where each 3D segmentation mask represents a particular target VOI identified using supervised deep learning-based segmentation.

110. As a result, in my opinion, Renisch does not disclose “determining . . . a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI,” as recited in claim 1.

111. Having reviewed the Institution Decision, I also note that the Institution Decision stated the following regarding Renisch:

Moreover, on this record, it appears that Renisch discloses the elements of limitation [1(c)] at paragraphs 26–31, where it discloses ***obtaining a scanned 3D image of a fuller anatomy, i.e., a segmentation map, and then using a segmentation unit*** (76) to define the boundaries of anatomical structures of interest within that fuller anatomy, i.e., creating a plurality of segmentation masks, using a library, models, clustering, edge detection, region growing, neural networks, and/or an atlas of normal anatomical structures, and then identifying hot spots of interest within those anatomical structures of interest, and identifying organs with lesions and those without.

IPR2025-00827, Paper 13, 21 (PTAB Nov. 3, 2025) (“Institution Decision”) (emphasis added).

112. To begin with, I understand that the proposed construction for “a 3D segmentation map” explained above was not yet under consideration, and that the Institution Decision did not perceive a need to construe any claim limitations at the time. Institution Decision, 15. As explained above, at least when the term “3D segmentation map” is construed in line with the entire ’817 Patent, including the specification, it is my opinion that Renisch does not disclose limitation 1(c) of claim 1.

113. Additionally, in reviewing the above-referenced passage in the Institution Decision, it appears that the Institution Decision identified a 3D segmentation map with “a scanned 3D image of a fuller anatomy,” which is obtained *before* Renisch’s segmentation unit is used (the passage states “*obtaining* a scanned 3D image of a fuller anatomy, i.e., a segmentation map, and *then* using a segmentation unit (76)...”). However, as explained above, it is my opinion that limitation 1(c) of claim 1 operates on and combines the output of the supervised deep learning-based segmentation performed at step (b) of claim 1. Therefore, it is my opinion that “a scanned 3D image of a fuller anatomy” that is obtained *before* using a segmentation unit cannot be an output of a segmentation process and therefore cannot be a 3D segmentation map as recited in claim 1.

- iii. Renisch does not inherently disclose a 3D segmentation map.

114. In my opinion, Renisch does not determine a 3D segmentation map as required by claim 1. As explained above, I do not identify in Renisch any disclosure describing the combining of multiple 3D segmentation masks to create a 3D segmentation map, as recited in limitation 1(c) of claim 1 and described in the '817 Patent.

115. I also do not identify support in Renisch for the proposition that the missing element of a “3D segmentation map,” created to represent multiple machine (supervised deep) learning module-identified VOIs in a unifying way as recited in claim 1, is necessarily present in Renisch.

116. As discussed above, and as described in the '817 Patent, the “3D segmentation map” element represents multiple 3D volumes corresponding to target tissue regions such as organs and skeletal regions (*e.g.*, bones) that are identified via machine learning-based image segmentation methods, *i.e.*, supervised deep learning techniques like CNNs. The specification describes identifying multiple target volumes using CNN-based image segmentation techniques and stitching those target volumes together to form a segmentation map. EX1001, 34:27-39.

117. Limitation 1(c)'s recited “3D segmentation map” is, specifically, created from and used to represent multiple target VOIs that are identified by segmenting a 3D anatomical image with one or more machine learning modules. This

specific step reflects the particular way that the '817 Patent performs detailed multi-organ 3D image segmentation using deep learning techniques like CNNs. EX1001, 49:7-10, 50:20-21; *see also id.*, 5:37-48, 32:1-21, 34:27-39.

118. Renisch, by contrast, does not describe multi-organ segmentation using supervised deep learning approaches, like CNNs, that would motivate, let alone necessitate, combining multiple 3D segmentation masks in a single volume via creation of a 3D segmentation map.

119. I have also reviewed the portions of Renisch that Petitioner cites as allegedly inferring elements like 3D anatomical segmentation masks, and I find that those passages do not describe what the Petition says they do. For example, Renisch explains that “[e]ach segmented VOI is represented by its own segmentation mask because, as explained below, each can be used separately to selectively suppress (or mask) uptake within corresponding volumes of a 3D functional image. Ex1005, [0030]-[0031].” Pet., 24. However, the word “mask” does not appear in those passages. Nor is there any specific element in those passages that is allegedly equivalent to a 3D segmentation mask, let alone a 3D segmentation map as recited in claim 1. Finally, the regions that Renisch describes as being suppressed are *not* volumes that correspond to VOIs that are segmented, via machine learning, in a 3D anatomical image. Instead, they are “regions of high intensity...in the functional second image representation.” EX1005, [0031] (“[a] suppression unit, processor, or

algorithm 102 uses the results of the classification unit to **suppress the regions of high intensity 92 in the functional second image representation 74.**”) (emphasis added); *see also* EX1005, [0006], [0029]. As Renisch explains, these regions of high intensity 92 are not segmented anatomical structures, but rather, are “regions in the functional second image representation that indicate high metabolic activity” (*e.g.*, which might be tumors or might be organs with high metabolic activity such as the heart, bladder, liver, kidney, and brain). EX1005, [0029]. Renisch states that these high intensity regions are detected by a classical watershed algorithm. *Id.*

120. Thus, it is my opinion that the suppressed regions in Renisch are not volumes representing anatomical structures and segmented within a 3D anatomical image via a supervised deep learning approach. Instead, they are hotspots, identified in a “functional second image representation,” via a classical watershed algorithm.

121. Thus, in my opinion, the Petition’s arguments regarding Renisch’s suppression unit deviate from the actual disclosure of Renisch. Thus, in my opinion, Renisch fails to disclose “determining . . . a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI,” as recited in claim 1.

### **c. Conclusion**

122. Based on the foregoing, it is my opinion that Renisch does not anticipate independent claim 1.

## **2. Claim 10**

123. Claim 10 is the second independent claim in the '817 Patent and is similar to claim 1.

124. Since the same limitations above (in Section IX.A.1) appear in independent claim 10, in my opinion, Renisch does not anticipate independent claim 10.

## **3. Claims 2-5, 7, 11-14, 16, 19, and 26.**

125. Claims 2-5, 7, and 19 are dependent claims, each depending from claim 1. Similarly, claims 11-14, 16, and 26 are dependent claims, each depending from claim 10. As I understand it, each of these claims necessarily includes the limitations of claim 1 or claim 10, from which each depends. Therefore, at least because, as explained above, Renisch does not anticipate claims 1 and 10, Renisch does not anticipate any of these dependent claims.

### **B. Ground B: Renisch in view of Zhao does not render obvious claims 1-5, 7, 10-14, 16, 19, and 26.**

126. It is my opinion that the Petition does not establish that Renisch in view of Zhao renders claims 1-5, 7, 10-14, 16, 19, and 26 obvious.

**1. Claim 1**

- a. Zhao does not disclose “determining . . . a 3D segmentation map representing a plurality of 3D segmentation masks” as recited in claim 1.**

127. Limitation (c) of claim 1 recites “determining, by the processor, a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI.” Pet., 23; EX1001, 79:19-22.

128. The Petition contends that Zhao discloses a 3D segmentation map because Zhao mentions “[a] multi-value mask . . . may be decomposed into a combination [sic] the more fundamental binary masks each for one type of ROI.” Pet., 26 (quoting EX1007, 5:30-42). Respectfully, I disagree.

129. In my opinion, Zhao does not disclose three-dimensional segmentation masks, let alone a 3D segmentation map representing a plurality of 3D segmentation masks. It is my opinion that Zhao does not describe three-dimensional image processing, nor does Zhao mention three-dimensional segmentation. Instead, Zhao repeatedly limits his description explicitly to two-dimensional images throughout. For instance, throughout the specification, Zhao repeatedly uses the term “pixel,” as opposed to “voxel.” See EX1007, 7:56-64. Zhao describes a “100-pixel by 100-pixel input” – i.e., a two-dimensional image. *Id.* When describing image processing techniques, such as pooling and down-sampling, Zhao refers to “two spatial

dimensions.” EX1007, 7:65-8:7. In fact, Zhao always and only discusses two-dimensional image processing. *See, e.g.*, EX1007, 8:60-9:7, 10:29-34 (designating spatial locations as “(i,j)” – i.e., in two dimensions).

130. In my opinion, Zhao’s description, repeatedly referencing and describing *two-dimensional* image processing, is in sharp contrast with the ’817 Patent. The claims of the ’817 Patent expressly refer to three-dimensional images. *See, e.g.*, EX1001, 79:5-32. The description of the ’817 Patent emphasizes the importance and advantages of applying accurate machine-learning-based segmentation to handle *three-dimensional* images as input and to identify *volumes* therein. EX1001, 3:21-29; *see also id.*, 55:63-56:9. For example, the specification of the ’817 Patent states, “[t]he capability of the approaches described herein to handle 3D images is an important advantage over certain other image analysis that only identify 2D regions in 2D images.” EX1001, 3:21-29; *see also id.*, 55:63-56:9 (“Notably, a significant advantage of the approach described in this example . . . In contrast to such small 2D regions, the 3D volume that are identified via the approaches used herein capture intensities throughout entire organs, and thereby offer increased accuracy and repeatability.”). The specification further states:

For example, for a 6x3x3 array, a given 3x3x3 subpatch refers to a given 3x3x3 set of adjacent values (e.g., a neighborhood) of the array, such that there are five distinct 3x3x3 subpatches in the 6x3x3 array (each patch shifted one position over along the first dimension).

EX1001, 29:66-30:4; *see also id.*, 30:55-56 (“For example, an  $N \times M \times L \times K_0$  size input array, has three spatial dimensions and  $K_0$  output channels.”), Tables 1, 5, and 8 (listing explicitly three-dimensional inputs for the described CNN networks).

131. The Petition appears to equate Zhao’s mention of a CT image with a “3D medical image.” Pet., 25. However, it is my opinion that the Petition ignores the fact that Zhao repeatedly characterizes his analysis and his masks as two-dimensional, as I explained above. As I explained above, methods for analyzing medical images, like CT images, can be 2D methods. Accordingly, to the extent Zhao refers to CT images, he is, therefore, especially in view of his repeated and consistent references to two-dimensional elements, referring to analysis of entirely two-dimensional CT images or individual 2D slice(s) of a CT image.

132. Thus, it is my opinion that Zhao does not disclose determining a 3D segmentation mask, let alone a 3D segmentation map, as recited in claim 1.

**b. Renisch in view of Zhao does not render obvious limitation (c), as recited in claim 1.**

133. Limitation (c) of claim 1 states “determining, by the processor, **a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D segmentation mask representing a particular identified target VOI.**” Pet., 23; EX1001, 79:19-22 (emphasis added). Thus, as explained above, the method of claim 1 determines a 3D segmentation map that represents multiple target VOIs which, as recited at step (b), are identified via machine (supervised deep) learning-based

segmentation of a 3D anatomical image. EX1001, 79:14-18 (“(b) automatically identifying, by the processor, using one or more machine learning modules, for each of a plurality of target tissue regions, a corresponding target volume of interest (VOI) within the 3D anatomical image.”).

134. As discussed above, as described in the ’817 Patent, the “3D segmentation map” element represents multiple 3D volumes corresponding to target tissue regions such as organs and skeletal regions (*e.g.*, bones) that are identified via supervised deep learning techniques like CNNs.

135. It is my opinion that a POSA would not have been motivated to combine Renisch with Zhao, with a reasonable expectation that they would successfully achieve the particular processing described in limitations (b)-(e) of claim 1.

- i. Both Renisch and Zhao would require nonobvious modification to combine and arrive at Patent Owner’s claimed subject matter, as recited in claim 1.

136. In particular, achieving the claimed subject matter would require fundamental modifications to both Renisch and Zhao, then combining the fundamentally modified systems.

137. Renisch, as explained above, unlike the ’817 Patent, focuses on conventional template-based (*e.g.*, model-based or atlas-based) segmentation approaches. Renisch does not contemplate the kind of supervised deep learning

approaches like CNNs for performing image segmentation that are described in the '817 Patent.

138. Moreover, Renisch expressly notes that its template-based approaches are fundamentally distinct from the supervised deep learning techniques described in the '817 Patent. Renisch's techniques are based on "central assumption ... that the anatomical structures of interest have, to some extent, relatively consistent forms of geometry and position across patients." EX1005, [0027]. As explained above, supervised deep learning techniques like those described in the '817 Patent operate based on a fundamentally distinct paradigm. Therefore, it would not be obvious, in my opinion, to modify Renisch's systems to perform a fundamentally distinct segmentation approach – namely, supervised deep learning as described in the '817 Patent.

139. Zhao, for its part, and unlike the '817 Patent, is directed solely to 2D images. Zhao does not perform 3D image segmentation, nor does Zhao contemplate the need for anatomical context in functional images. Zhao also does not mention 3D functional images, let alone the particular shortcomings and advantages that benefit from the accurate 3D segmentation performed by the '817 Patent.

140. Therefore, in my opinion, to arrive at Patent Owner's claimed subject matter, one would need to make non-obvious modifications to both Renisch and Zhao before even combining them. In my opinion, accordingly, it would not be obvious to

combine both Renisch and Zhao in a way that would yield Patent Owner's claimed subject matter.

- ii. Neither Renisch nor Zhao contemplate the particular challenges that motivated the approach claimed in the '817 Patent.

141. It also is my opinion that the Petition's reasons to combine the two references are insufficient. For example, the Petition states, as a rationale to combine Zhao and Renisch, that these two references "are directed to segmentation of 3D medical images, such as CT images, using neural networks." Pet., 26. However, as explained above, Renisch mentions a "neural network," but does not discuss or contemplate any practical approach by which neural network-based segmentation could be implemented. Moreover, Renisch does not contemplate the kind of deep-learning-based 3D image segmentation that Patent Owner's approach – including step (c) of claim 1 – allows to be performed in an efficient fashion across multiple organs within a patient. Further, as I discussed above, Zhao is not directed to 3D segmentation. Zhao only describes 2D segmentation, and, like Renisch, fails to contemplate the particular challenges that the technologies described in the '817 Patent and reflected in the claim are designed to address.

142. Elsewhere, the Petition argues that "improving Renisch with the teachings of Zhao would merely have amounted to applying a known technique (segmentation masks) to a known device (Renisch) ready for improvement to yield

predictable results.” Pet., 27. But, as discussed above, Zhao’s segmentation masks involved exclusively 2D images.

143. Furthermore, as explained above, limitation 1(c) of claim 1 recites more than segmentation masks. It recites determining a “3D segmentation map,” which, as explained above, is “a consolidated representation . . . that combines multiple 3D segmentation masks and accounts for their relative spatial relationships to each other within a common volume.”

144. As discussed above, as described in the ’817 Patent, the “3D segmentation map” element represents multiple 3D volumes corresponding to target tissue regions such as organs and skeletal regions (*e.g.*, bones) that are identified via machine learning-based image segmentation methods – namely, supervised deep learning techniques like CNNs. For instance, the ’817 Patent describes identifying multiple target volumes via CNN-based image segmentation techniques and stitching the target volumes together to form a segmentation map. EX1001, 34:27-39.

145. Accordingly, claim 1 of the ’817 Patent recites more than an arbitrary 3D segmentation map in isolation. Reading the claim as a whole, the recited “3D segmentation map” is, specifically, created from and used to represent multiple target VOIs that are identified by segmenting a 3D anatomical image with one or more machine learning modules. This specific step reflects the particular way that the ’817

Patent performs detailed multi-organ 3D image segmentation using deep learning techniques like CNNs.

146. Neither Renisch nor Zhao contemplate the particular challenges associated with performing detailed 3D image segmentation with deep learning techniques, as described in the '817 Patent, let alone the particular techniques that the '817 Patent describes for addressing them, which include stitching together the results of multiple machine learning modules (*e.g.*, each performing segmentation in a dedicated anatomical subregion) to create a 3D segmentation map.

iii. A POSA would not have a reasonable expectation of success in combining Renisch and Zhao.

147. Based on my analysis of the references and the state of the art, I do not believe a POSA would reasonably have expected that combining Renisch and Zhao could achieve the method recited in claim 1.

148. As discussed above, applying deep learning techniques to 3D medical image data presented significant technical challenges, particularly in clinical contexts. *See, e.g.*, EX1017, 1115; *see also* EX2022, 1 (referring to an “auto-contouring driven by artificial intelligence (AI)” approach and stating, even in 2023, that “[w]hile some clinicians have embraced the technology, others remain skeptical about its ability to provide accurate results in clinical practice”).

149. The '817 Patent describes an approach that achieves accurate and robust 3D segmentation, capable of identifying multiple organs within a patient body

via a unique approach that uses multiple machine (supervised deep) learning algorithms (such as CNNs) to analyze and segment multiple different target tissue regions (like organs and bones).

150. In contrast, neither Renisch nor Zhao appear to provide any such insight into how to achieve accurate and robust 3D multi-organ segmentation across a patient's body. Instead, Renisch is primarily directed to template-based approaches that do not provide adequate accuracy in performing image segmentation and Zhao is limited to 2D image analysis, primarily of a single organ (the lungs).

151. Given these gaps, I do not see a basis on which a POSA would have reasonably expected success in first modifying, and then combining, Renisch and Zhao, particularly given that neither reference offers any appreciation of the challenges associated with 3D multi-organ segmentation using deep learning, and neither reference offers any insight into how those challenges could be addressed.

152. Thus, in my opinion, a POSA would not have reasonably expected to succeed in combining Renisch and Zhao to achieve the claimed limitation. It is my opinion that the Petition thus fails to show that Renisch and Zhao render this limitation obvious.

### **c. Conclusion**

153. Based at least on the foregoing reasons, it is my opinion that Renisch in view of Zhao fail to render claim 1 obvious.

## **2. Claim 10**

154. Claim 10 is the second independent claim in the '817 Patent and is similar to claim 1. Since the same limitations above (in Section IX.B.1) appear in independent claim 10, in my opinion, the Petition also fails to show that a POSA would have had a motivation to combine Renisch and Zhao to achieve these same limitations in independent claim 10. The Petition thus also fails to carry its burden for claim 10.

## **3. Claims 2-5, 7, 11-14, 16, 19, and 26.**

155. Claims 2-5, 7, and 19 are dependent claims, each depending from claim 1. Similarly, claims 11-14, 16, and 26 are dependent claims, each depending from claim 10. As I understand it, each of these claims necessarily includes the limitations of claim 1 or claim 10, from which each depends. Therefore, at least because, as explained above, Renisch in view of Zhao fails to render claims 1 and 10 obvious, Renisch in view of Zhao also fails to render any of these dependent claims obvious.

## **C. Ground C: Renisch, or Renisch-Zhao, each in view of Baker, do not render obvious claims 8-9, 17-18, 22-25, and 29-32.**

156. The Petition challenges claims 8-9, 17-18, 22-25, and 29-32 as allegedly obvious based on Renisch, or Renisch-Zhao, each in view of Baker. Each of these claims depends from claim 1 or claim 10. As I understand it, each of these claims necessarily includes the limitations of claim 1 or claim 10, from which each depends.

157. As I explained above in Grounds A and B, respectively, Renisch fails to anticipate claims 1 and 10, and Renisch in view of Zhao fails to render claims 1 and 10 obvious. Accordingly, for at least the reasons above, Renisch, or Renisch-Zhao, each in view of Baker, fail to render dependent claims 8-9, 17-18, 22-25, and 29-32 obvious.

**D. Ground D: Renisch, or Renisch-Zhao, each in view of Eiber, do not render obvious claims 8-9, 17-18, 22, 24-25, 29, and 31-32.**

158. The Petition challenges claims 8-9, 17-18, 22, 24-25, 29, and 31-32 as allegedly obvious based on Renisch, or Renisch-Zhao, each in view of Eiber. Each of these claims depends from claim 1 or claim 10. As I understand it, each of these claims necessarily includes the limitations of claim 1 or claim 10, from which each depends.

159. As I explained above in Grounds A and B, respectively, Renisch fails to anticipate claims 1 and 10, and Renisch in view of Zhao fails to render claims 1 and 10 obvious. Accordingly, for at least the reasons above, Renisch, or Renisch-Zhao, each in view of Eiber, fail to render dependent claims 8-9, 17-18, 22, 24-25, 29, and 31-32 obvious.

**E. Ground E: Baker in view of Zhao does not render obvious claims 1-2, 7-11, 16-18, 22-25, and 29-32.**

**1. Claim 1**

160. Limitation (c) of claim 1 states “determining, by the processor, a 3D segmentation map representing a plurality of 3D segmentation masks, each 3D

segmentation mask representing a particular identified target VOI.” Pet., 49; EX1001, 79:19-22. The Petition argues that Baker in view of Zhao renders this limitation obvious because “a POSITA would have been motivated to combine the references to arrive at the limitation.” Pet., 50. The Petition further states that “Baker does not use the term ‘segmentation masks,’ but Zhao teaches and suggests the use of segmentation masks to implement 3D medical image segmentation like that discussed in Baker.” *Id.*

161. However, as I explained above in Section IX.B.1.a, Zhao fails to disclose, or even suggest, “a 3D segmentation mask,” let alone “a 3D segmentation map representing a plurality of 3D segmentation masks,” as recited in claim 1. Accordingly, for at least the reasons above, Baker in view of Zhao fails to render claim 1 obvious.

## **2. Claim 10**

162. Since limitation 1(c) above also appears in independent claim 10, in my opinion, the Petition also fails to show that a POSA would have been motivated to combine Baker and Zhao to achieve this limitation in independent claim 10. The Petition thus also fails to carry its burden for claim 10.

## **3. Claims 2, 7-9, 11, 16-18, 22-25, and 29-32**

163. Claims 2, 7-9, 11, 16-18, 22-25, and 29-32 are dependent claims, each depending from claim 1 or claim 10. As I understand it, each of these claims

necessarily includes the limitations of claim 1 or claim 10, from which each depends. Therefore, at least because, as explained above, Baker in view of Zhao fails to render claims 1 and 10 obvious, Baker in view of Zhao also fails to render any of these dependent claims obvious.

**F. Ground F: Baker-Zhao in view of Eiber does not render obvious claims 3-5 and 12-14.**

164. The Petition challenges claims 3-5 and 12-14 as allegedly obvious based on Baker-Zhao in view of Eiber. Each of these claims depends from claim 1 or claim 10. As I understand it, each of these claims necessarily includes the limitations of claim 1 or claim 10, from which each depends. For at least the reasons above in Ground E, Baker-Zhao in view of Eiber fails to render claims 3-5 and 12-14 obvious.

**G. Ground G: Baker-Zhao in view of Suehling does not render obvious claims 19, 26, and 28.**


165. The Petition challenges claims 19, 26, and 28 as allegedly obvious based on Baker-Zhao in view of Suehling. Each of these claims depends from claim 1 or claim 10. As I understand it, each of these claims necessarily includes the limitations of claim 1 or claim 10, from which each depends. For at least the reasons above in Ground E, Baker-Zhao in view of Suehling fails to render claims 19, 26, and 28 obvious.

## **X. CONCLUSION**

166. For the reasons stated herein, it is my view that claims 1-5, 7-14, 16-19, 22-26, and 28-32 of the '817 Patent are novel and nonobvious over the cited art. I reserve the right to expand or modify my opinions as my analysis continues, and to supplement my opinions in response to any additional information that becomes available to me and any matters raised by the parties, the Board, and/or the opinions provided by other experts.

I declare under penalty of perjury under the laws of the United States of America that the foregoing is true and correct. I hereby declare that all the statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true; and further 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 and may jeopardize the validity of the patent.

Date: 1/22/2026

By:   
Milan Sonka