

Case No. IPR2023-01046

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

MICROSOFT, CORP.,
Petitioner,

v.

REALD SPARK, LLC,
Patent Owner

Case No. IPR2023-01046
Patent No. 10,740,985

**PATENT OWNER'S PRELIMINARY RESPONSE TO THE
PETITION FOR *INTER PARTES* REVIEW OF
U.S. PATENT NO. 10,740,985**

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TABLE OF CONTENTS

I.	INTRODUCTION	1
II.	BACKGROUND	2
A.	The '985 Patent	2
B.	Procedural History	5
C.	The Alleged Prior Art.....	6
1.	Ganin.	6
2.	Chalom.	8
3.	Aslan.....	8
III.	PERSON OF ORDINARY SKILL IN THE ART (POSITA).....	9
IV.	CLAIM CONSTRUCTION OF THE '985 PATENT CLAIM TERMS.....	9
V.	PETITIONER HAS FAILED TO SHOW THAT THE CHALLENGED CLAIMS ARE UNPATENTABLE.....	9
A.	Ground I: Petitioner's Unsupported Testimony Cannot Demonstrate that the Second Machine Learning Elements of Claims 1-3, 5, 10, 12-14, and 18 are Anticipated by Ganin.	10
1.	Ganin does not disclose the “second machine learning algorithm” elements 1[E] and 18[E] of the independent claims.....	10
a)	The '985 Patent requires two machine learning algorithms that both receive the same training data...10	
b)	Ganin discloses one alleged algorithm, not two.....	13
2.	The Petition's reliance on unsupported expert testimony about what a POSITA “can” infer about Ganin having two	

	machine learning algorithms cannot qualify as substantial evidence.....	17
3.	Petitioner’s unsupported inferences about Ganin’s training data fail to account for the fact that the coarse and fine module training data would be different.	18
B.	Ground II: Petitioner Fails to Demonstrate that Claims 16 and 19 are Rendered Obvious by the Combination of Ganin and Liu for the Same Reasons as Ground I.	21
C.	Ground III: Petitioner’s Improper Combination of Chalom and Aslan Fails to Disclose a Second Machine Learning Algorithm that Uses First Reference Data as Recited in Claims 1-3, 5-6, 8-14, 16-19.....	22
1.	A POSITA would Not have been Motivated to Combine Chalom and Aslan.	22
2.	The Combination of Chalom and Aslan Does Not Disclose the Claimed “Second Machine Learning Algorithm . . . [that] Us[es] . . . the First Reference Data”.....	26
a)	The Petition fails to allege that the second machine learning algorithm receives both first editing and first selection instructions as required by claim 1.	26
b)	On the merits, the combination of Chalom and Aslan does not disclose a second machine learning algorithm that uses the first reference data.....	28
D.	Ground IV: Petitioner Fails to Demonstrate That Claim 4 is Rendered Obvious by the Combination of Chalom, Aslan, and Grau.	32
E.	Ground V: Petitioner Fails to Demonstrate That Claim 7 is Rendered Obvious by the Combination of Chalom, Aslan, and Pace.....	32
VI.	CONCLUSION.....	33

TABLE OF AUTHORITIES

Page(s)

Federal Cases

<i>Avaya Inc., et al. v. Network-1 Security Sol'ns, Inc.</i> , IPR2013-00071, Paper 103 (May 22, 2014)	18, 19, 20, 21
<i>Bettcher Indus. V. Bunzl USA, Inc.</i> , 661 F.3d 629 (Fed. Cir. 2011)	18
<i>Finnigan Corp. v. United States ITC</i> , 180 F.3d 1354 (Fed. Cir. 1999)	18
<i>Insite Vision, Inc. v. Sandoz, Inc.</i> , 783 F.3d 853 (Fed. Cir. 2015)	30
<i>In re Magnum Oil Tools Int'l, Ltd.</i> , 829 F.3d 1364 (Fed. Cir. 2016)	27
<i>Orexo AB v. Actavis Elizabeth LLC</i> , 903 F.3d 1265 (Fed. Cir. 2018)	31
<i>TQ Delta, LLC v. Cisco Sys.</i> , 942 F.3d 1352 (Fed. Cir. 2019)	17
<i>Wellman, Inc. v. Eastman Chem. Co.</i> , 642 F.3d 1355 (Fed. Cir. 2011)	9

Federal Statutes

35 U.S.C.	
§ 314(a)	10
§ 316(e)	27

Other Authorities

Code of Federal Regulations, 37 C.F.R. § 42.107(b)	1
Manual of Patent Examining Procedure, MPEP § 2142.....	30

TABLE OF EXHIBITS

Exhibit #	Reference Name
EX-2001	Declaration of Dr. Eli Saber, PhD
EX-2002	<i>Curriculum Vitae</i> of Dr. Eli Saber, PhD
EX-2003	Microsoft’s Answering Claim Construction Brief as filed in <i>RealD Spark, LLC v Microsoft Corporation</i> , U.S. District Court, Western District of Washington, Case No. 2:22-cv-00942-TL
EX-2004	Exhibit 1 to Microsoft’s Answering Claim Construction Brief as filed in <i>RealD Spark, LLC v Microsoft Corporation</i> , U.S. District Court, Western District of Washington, Case No. 2:22-cv-00942-TL): Kononenko <i>et al.</i> “Learning to look up: Realtime monocular gaze correction using machine learning.” <i>CVPR 2015: IEEE/CVF Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7-12 June 2015 (pp. 4667-4675).</i>
EX-2005	Exhibit 2 to Microsoft’s Answering Claim Construction Brief as filed in <i>RealD Spark, LLC v Microsoft Corporation</i> , U.S. District Court, Western District of Washington, Case No. 2:22-cv-00942-TL: File History, Restriction Notice, Aug. 15, 2019; Response to Restriction Notice, Oct. 15, 2019
EX-2006	Exhibit 3 to Microsoft’s Answering Claim Construction Brief as filed in <i>RealD Spark, LLC v Microsoft Corporation</i> , U.S. District Court, Western District of Washington, Case No. 2:22-cv-00942-TL: U.S. Provisional Application 62/542,661
EX-2007	Exhibit 4 to Microsoft’s Answering Claim Construction Brief as filed in <i>RealD Spark, LLC v Microsoft Corporation</i> , U.S. District Court, Western District of Washington, Case No. 2:22-cv-00942-TL: Adriana Romero <i>et al.</i> , <i>Fitnets: Hints for Thin Deep Nets</i> (2014)

I. INTRODUCTION

REALD SPARK, LLC, (“RealD” or “Patent Owner”) respectfully submits this Preliminary Response, timely filed under 37 C.F.R. § 42.107(b), to the petition seeking *inter partes* review (“Petition” or “IPR”) of claims 1-14 and 16-19 of U.S. Patent No. 10,740,985 (“the ’985 Patent”) (EX-1001).

None of Petitioner’s Grounds disclose or render obvious the ’985 Patent’s second machine learning algorithm claim elements as recited in 1[E] and [G], 16[E] and [G], 17[E], 18[E], and 19[E].

Regarding Grounds I and II, Ganin does not disclose the “second machine learning algorithm” elements recited at 1[E], 16[E], 18[E], and 19[E]. Ganin’s fine module cannot be a second machine learning algorithm because it does not use the same training data as the first machine learning algorithm. Nor can Ganin’s fine module work this way as it does not have the proper training data to train itself to operate as a second machine learning algorithm. Ganin therefore does not disclose the second machine algorithm element as claimed in independent claims 1 and 18, and Grounds I and II fail to support institution.

Regarding Ground III, the combination of Chalom and Aslan also cannot support institution. First, there is no motivation to combine Chalom with Aslan. Chalom touts that it overcomes the very deficiencies Petitioner suggests it has. And adding a second algorithm from Aslan does nothing to remedy these deficiencies.

In fact, Petitioner’s combination causes further issues in terms of accuracy and efficiency. Second, Petitioner does not address, much less prove, that Chalom and Aslan provide the first selection instructions to the second machine learning algorithm as required by independent claim 1. Finally, Petitioner fails to prove that its combination of Chalom and Aslan provide reference data from the first machine algorithm to the second machine algorithm, as required by all of the independent claims. The Board should deny institution as Ground III does not support institution.

Grounds IV and V relate to further obviousness combinations directed at dependent claims 4 and 7, and therefore also cannot serve as a basis to institute.

II. BACKGROUND

A. The ’985 Patent

The ’985 Patent describes methods and devices for adjusting a digital representation of a head region—such as correcting a video conference user’s gaze—using two machine learning algorithms. A machine learning algorithm is a computer model that trains itself to perform a specific task by using training data. EX-2001 at ¶ 41. The training data is a specific set of data that includes input images (sometimes called “before” images) and output images (sometimes called “after” images). *Id.* at ¶¶ 42-45. A machine learning algorithm will take the training data and learn how to turn input images into output images. *Id.* The training data of the ’985 Patent includes (1) input patches that represent an unadjusted target feature of

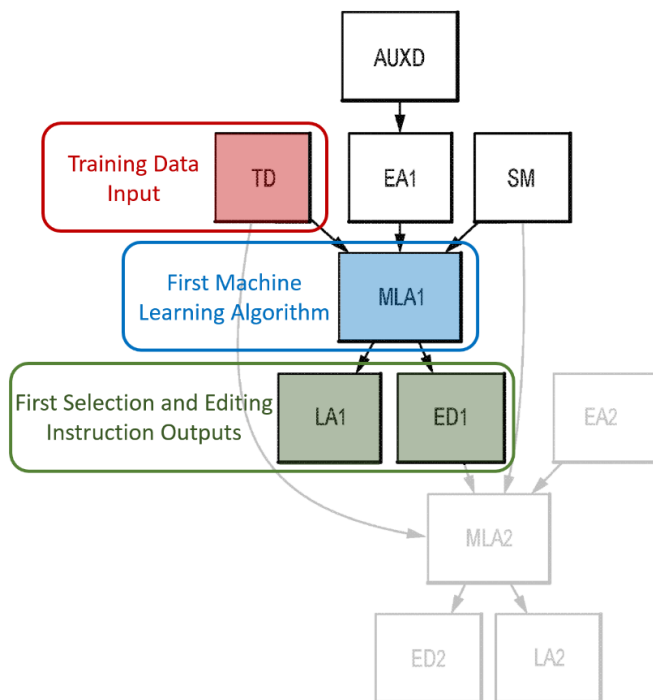
the head, such as unadjusted eyes that gaze off-camera,¹ and (2) output patches that represent an adjusted target feature of the head, such as adjusted eyes that gaze into the camera. EX-1001 at 26:35-44; EX-2001 at ¶ 52. The better the training data, the better the algorithm will be at taking new non-training data and creating output images that accomplish the algorithm's task. EX-2001 at ¶ 42.

In the '985 Patent, the task is to adjust the head region of a user, such as adjusting a user's eyes to gaze at the camera rather than off-camera. *Id.* at ¶¶ 48-50. That task is accomplished by the '985 Patent's instructions, which adjust the digital representation of the head region. *Id.* Both the first machine learning algorithm and the second machine learning algorithm of the '985 Patent provide instructions for adjusting the head region. *See, e.g.,* EX-1001 at 26:45-49 (reciting that the first machine learning algorithm provides instructions “for adjusting the digital representation of the head region”) and 26:50-57 (reciting that the second machine learning algorithm provides instructions “for adjusting the digital representation of the head region.”). In short, both of the '985 Patent's machine learning algorithms are trained using training data and then provide instructions to adjust the head region

¹ As used in this brief, the term ‘off-camera gaze’ or ‘gaze off-camera’ refers to a person's eyes not looking toward the camera, but instead looking elsewhere, for example, a screen that is offset from the camera.

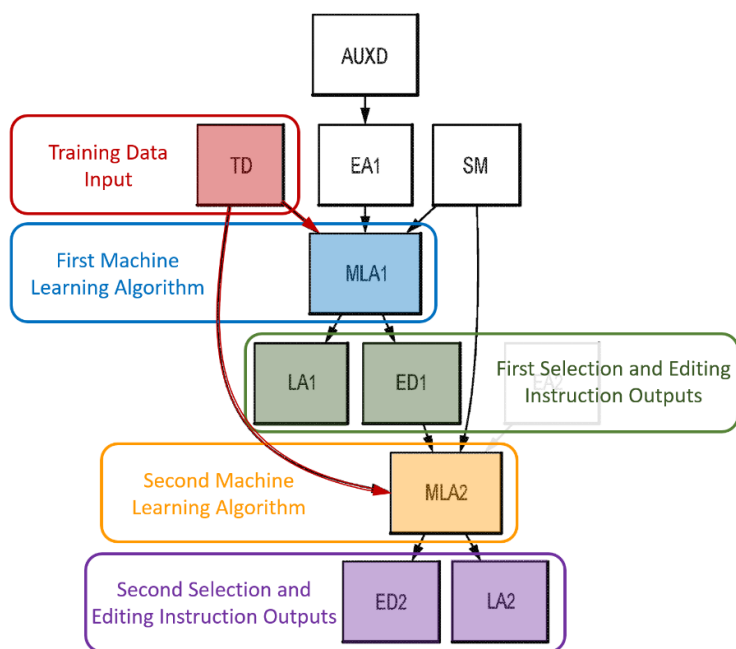
based on the training data. EX-2001 at ¶ 49.

This process is shown in Figure 9 to the right. *Id.* at ¶ 53. The '985 claimed methods include a **first machine learning algorithm** that receives **training data** and then generates first reference data. *Id.* The reference data includes one or both of the **first selection instructions** and **first editing instructions** for determining how the head region is to be adjusted.



Id.; see also, e.g., EX-1001 at 26:45-49 and 26:58-63.

The same process happens for the **second machine learning algorithm**



shown to the left. It receives **training data** as input, and outputs **second selection instructions** and/or **second editing instructions** for determining how the head region is to be adjusted. See, e.g., *id.* at 26:50-57 and 26:64-

27:3; EX-2001 at ¶ 54. The second machine learning algorithm also receives the **selection and/or editing instructions** output from the first machine learning algorithm. *See, e.g.*, EX-1001 at 26:50-54; EX-2001 at ¶ 54. In short, both machine learning algorithms receive the training data as input, and output instructions for adjusting the head region of a user. EX-2001 at ¶ 54.

The reason for having two machine learning algorithms that both receive training data and output instructions is that the first machine learning algorithm may create its instructions using a computationally intensive process to create highly accurate results, which can be fed to the second machine learning algorithm to create instructions using less complexity while still arriving at highly accurate results. EX-1001 at 16:12-44; EX-2001 at ¶ 56.

B. Procedural History

RealD filed a first provisional application describing their innovative ideas on August 8, 2017, as application no. 62/542,661 (EX-1011), and a second provisional application on August 10, 2017, as application no. 62/543,587 (EX-1012). On August 7, 2018, RealD filed the corresponding non-provisional application no. 12/454,560, which ultimately issued as the '985 Patent on August 11, 2020.

On July 7, 2022, RealD filed a lawsuit against Petitioner that, among other things, asserted infringement of the '985 Patent. That case is styled *RealD Spark, LLC v. Microsoft Corporation*, WDWA-2-22-cv-00942. Then, on June 16, 2023,

Microsoft Corporation filed this Petition. Microsoft Corporation seeks to institute an IPR on claims 1-14 and 16-19 on five grounds that allege three primary references: (1) Ganin et al., “Deepwarp: Photorealistic image resynthesis for gaze manipulation,” (“Ganin”) (EX-1006), (2) U.S. Patent No. 10,664,949 (“Chalom”) (EX-1005), and (3) U.S. Patent Pub. No. 2017/0132528 (“Aslan”) (EX-1007).

C. The Alleged Prior Art

Petitioner asserts the following grounds:

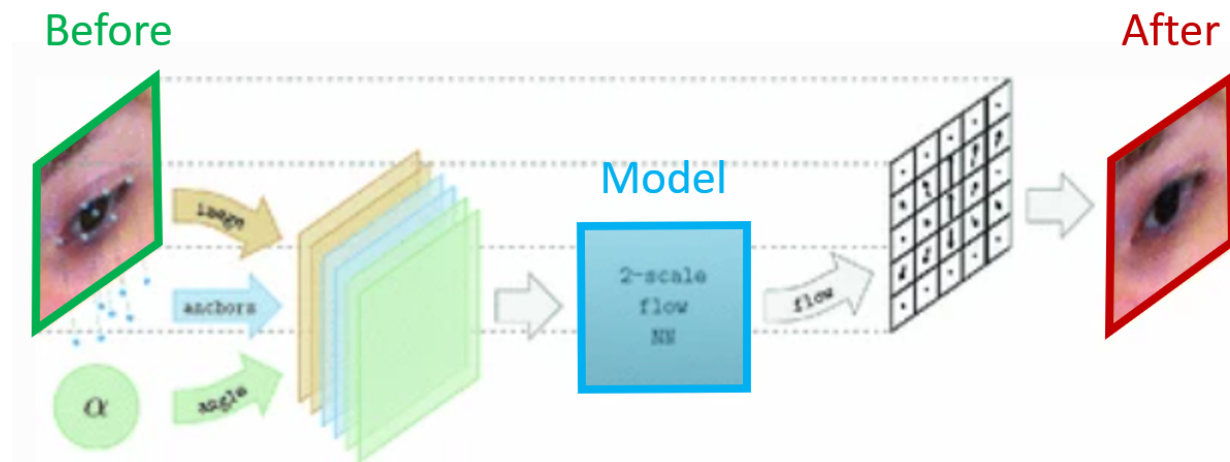
- Ground I:** Claims 1-3, 5, 10, 12-14, and 18 are anticipated by Ganin;
- Ground II:** Claims 16 and 19 are obvious over Ganin in view of Liu;
- Ground III:** Claims 1-3, 5-6, 8-14, and 16-19 are obvious over Chalom in view of Aslan;
- Ground IV:** Claim 4 is obvious over Chalom in view of Aslan and Grau; and
- Ground V:** Claim 7 is obvious over Chalom in view of Aslan and Pace.

In this Preliminary Response, RealD will address the independent claim arguments, and thus focuses on the deficiencies of Ganin, Chalom, and Aslan.

1. Ganin.

Ganin teaches, at best, a single machine learning algorithm. EX-2001 at ¶¶ 68, 77-96. For instance, Ganin explains that “[a]ll operations outlined above are implemented in a *single* feed-forward *architecture*.” EX-1006, page 4, Section 3 – “The Model.” Ganin’s single model uses a two-step process composed of a coarse

module and a fine module. *Id.* at 4 (stating that “**the** network . . . predict[s] [the gaze redirection] **in two stages** in a coarse-to-fine manner.”); EX-2001 at ¶ 78. In this two-step model there is one set of training data that includes before images that are images prior to entering the coarse module and after images that are images after exiting the fine module as shown below:



EX-1006 at Fig. 2 (annotated); EX-2001 at ¶ 78.

Ganin’s “coarse” step adjusts the image in large blobs or quadrants to provide a coarse adjustment to the image. EX-2001 at ¶ 79. Then that semi-adjusted image would be passed to the “fine” step to adjust the image on, for example, a pixel-by-pixel basis so that the eyelashes, pupil, and iris are rendered correctly. EX-1006 at 4 (explaining that “the coarse module gives a rough estimate [while] . . . problematic regions [] can only be fixed by a neural network operating at a finer scale.”); EX-2001 at ¶ 79. Only at the end of the second step does the system provide a usable, adjusted “after” image. EX-2001 at ¶ 79.

2. Chalom.

Chalom also teaches only a single machine learning algorithm for gaze correction based on a camera's location. EX-2001 at ¶ 70. Chalom trains its algorithm "offline[]" and a real time component . . . provides eye contact correction" in real time. *Id.*; EX-1005 at 3:21-24. The offline training takes a "database of faces with a known gaze angle . . . [and] train[s] a machine learning system." EX-1005 at 3:24-27; EX-2001 at ¶ 70. That system is a "random forest classifier" that determines which random forest to implement based on the camera's angle. EX-1005 at 10:35-39; EX-2001 at ¶ 70. For example, if the camera is above the display, one random forest model may be implemented by the classifier, while if the camera is to the left of the display, a different random forest model may be implemented by the classifier. EX-1005 at 10:35-39; *see also id.* at 10:40-64; EX-2001 at ¶ 70.

3. Aslan.

Aslan discloses a student-teacher model that can jointly train two machine learning models. EX-1007 at ¶ 20; EX-2001 at ¶ 71. For the "teacher" to learn from the "student," Aslan explains that the models "pass[] information" to one another through "an objective function." *Id.* at ¶ 28; EX-2001 at ¶¶ 71-72. The objective function has terms, such as a penalty term, that "measure[s] the agreement/disagreement . . . of the two models." EX-1007 at ¶ 31; EX-2001 at ¶ 72. To force the two models to agree, the objective function and its penalty term may be

optimized. EX-1007 at ¶ 31; EX-2001 at ¶ 72.

III. PERSON OF ORDINARY SKILL IN THE ART (POSITA)

A Person of Ordinary Skill in the Art (“POSITA”) at the time of the invention in August 2017, would have had at least a bachelor’s or master’s degree in electrical engineering, computer engineering, electrical and computer engineering, computer science, or similar educational background; or equivalent on-the-job training, including approximately two to three years of experience in machine learning and/or pattern recognition. EX-2001 at ¶ 21. This level of skill is approximate and more experience would compensate for less formal education and vice versa. *Id.* For example, an individual having no degree in engineering, but several years of experience developing machine learning and/or pattern recognition systems would qualify as a POSITA. *Id.*

IV. CLAIM CONSTRUCTION OF THE ’985 PATENT CLAIM TERMS

RealD agrees with Petitioner that there are no claim terms that require construction for purposes of the Board’s decision on institution. *See Wellman, Inc. v. Eastman Chem. Co.*, 642 F.3d 1355, 1361 (Fed. Cir. 2011) (“[C]laim terms need only be construed to the extent necessary to resolve the controversy.”).

V. PETITIONER HAS FAILED TO SHOW THAT THE CHALLENGED CLAIMS ARE UNPATENTABLE.

As explained in detail below, RealD respectfully requests that the Board deny institution because Petitioner has failed to show a reasonable likelihood that it will

prevail on any of its Grounds. 35 U.S.C. § 314(a).

A. Ground I: Petitioner’s Unsupported Testimony Cannot Demonstrate that the Second Machine Learning Elements of Claims 1-3, 5, 10, 12-14, and 18 are Anticipated by Ganin.

Ground I fails for several reasons. First, as explained in more detail below, Ganin does not disclose the “second machine learning algorithm” element of claims 1[E] and 18[E]. Second, Petitioner’s unsupported expert testimony about what a POSITA “can” infer from Ganin fail as a matter of law. Finally, even if the Board considered this testimony that a POSITA can infer Ganin teaches two machine learning algorithms, these “algorithms” do not use the same training data as required by elements 1[E] and 18[E].

1. Ganin does not disclose the “second machine learning algorithm” elements 1[E] and 18[E] of the independent claims.

Ganin does not disclose the “second machine learning algorithm” element recited in 1[E] and 18[E]. EX-2001 at ¶ 77-96.

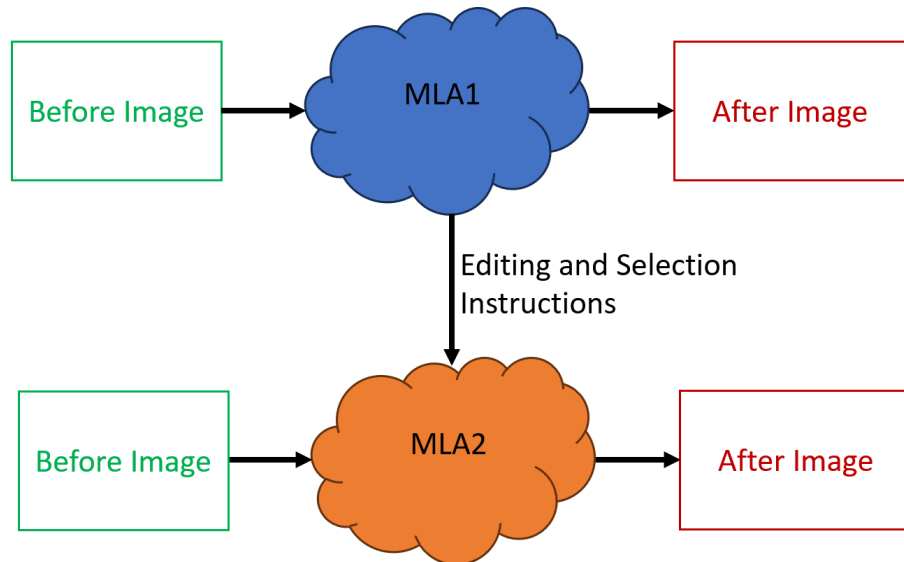
a) The ’985 Patent requires two machine learning algorithms that both receive the same training data.

It is helpful to start with an understanding of machine learning algorithms to better appreciate the distinction between the ’985 Patent claims and Ganin. A machine learning algorithm receives training data to train it to perform a desired task. *See* EX-2001 at ¶¶ 41-44. As Petitioner describes it, a machine learning algorithm for adjusting images would be provided with training data that includes

“before” images and “after” images. *See* EX-2003 at 6-7. In the context of gaze correction, a “before” image may be one where the user is gazing off-camera and the “after” image is one where the user is gazing directly into the camera. EX-2001 at ¶ 45. The machine learning algorithm would then train itself with this information to take an input similar to the “before” image from the training data and make adjustments so that the output is similar to the “after” image from the training data. *See* EX-2003 at 7. After training is complete, the machine learning algorithm will generate instructions to take a received video stream with a user gazing off-camera, turn it into a corrected video stream where the user is gazing directly into the camera, and output that corrected video stream to the end user. EX-2001 at ¶ 45.

The '985 Patent claims two machine learning algorithms. EX-1001 at 26:45-57; 29:53-30:5; EX-2001 at ¶ 49. Both algorithms receive the same training data, which includes (1) “input patches” that relate to the unadjusted target features of the head region (such as the user’s eyes gazing off-camera) and (2) “output patches” that relate to the adjusted target features of the head region (such as the user’s eyes gazing directly into the camera). *See, e.g.*, EX-1001 at 26:34-54; 29:43-52; EX-2001 at ¶ 52. Both of the claimed machine learning algorithms also adjust the head region by generating selection instructions, and in some instances editing instructions, that are informed by the training data as shown below. *See, e.g.*, EX-1001 at 26:45-49 (reciting that the first machine learning algorithm provides instructions “for

adjusting the digital representation of the head region”) and 26:50-57 (reciting that the second machine learning algorithm provides instructions “for adjusting the digital representation of the head region.”); *see also* EX-2001 at ¶ 52.



EX-2001 at ¶ 57.

The '985 Patent's first machine learning algorithm (in blue) provides its instructions to the second machine learning algorithm (in orange), essentially operating as a shortcut so that the second machine learning algorithm may still provide highly accurate “after” images (in red) even though it may use less complex instructions or fewer parameters than the first machine learning algorithm to do so. *Id.* at ¶ 58; EX-1001 at 16:8-44; *see also id.* at 17:15-17 (explaining that the “second machine learning algorithm (MLA2) thus gets the editing instructions to match or to approximate, and does not have to infer these from the matched input images as MLA1.”); 21:40-45 (explaining that the second machine learning algorithm “will be

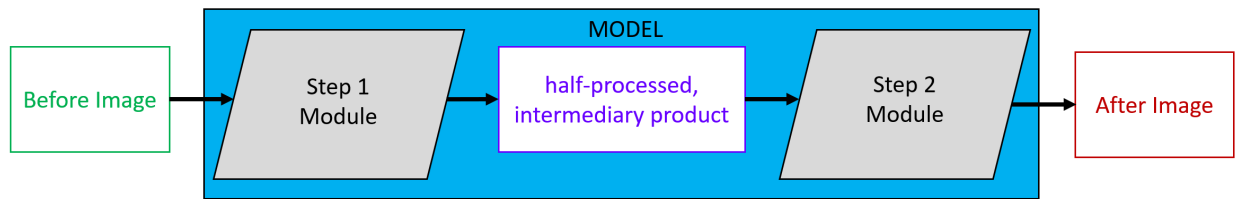
able to provide accurate conversion . . . using a simpler trained machine learning model (which can be stored and operated using fewer computing resources than the first machine learning algorithm MLA1).”).

b) Ganin discloses one alleged algorithm, not two.

This is very different than Ganin, which discloses, at best, a single alleged “machine learning algorithm.” EX-2001 at ¶¶ 68, 77-96. As Petitioner’s expert explains, the words “algorithm,” “model,” and “architecture” are interchangeable. *See* EX-1003 at ¶ 23 (stating that a “machine learning [] algorithm (or architecture), also referred to as [a] machine learning model, is an algorithm (or architecture) that learns from data to perform a task . . .”); EX-2001 at ¶¶ 85-86. Thus, Ganin’s description confirms that it is one, single alleged “machine learning algorithm” rather than two. For example, Ganin explains that “[a]ll operations outlined above are implemented in a **single** feed-forward **architecture**.” EX-1006 at 4. Ganin repeatedly describes its proposed system as being a singular model, using the terms “**the** model,” “**the** network,” and “**the** architecture” throughout. *See, e.g., id.* at 2, 4, 5, and 8 (emphasis added); *see also* EX-2001 at ¶ 85.

Ganin’s *single* model uses a two-step process, but this is not the same as having *two* machine learning algorithms. EX-2001 at ¶ 77. For instance, as an illustration, consider a single model that adjusts a headshot image. EX-2001 at ¶ 82. In step one, the model takes the background of the image and adjusts it to correct,

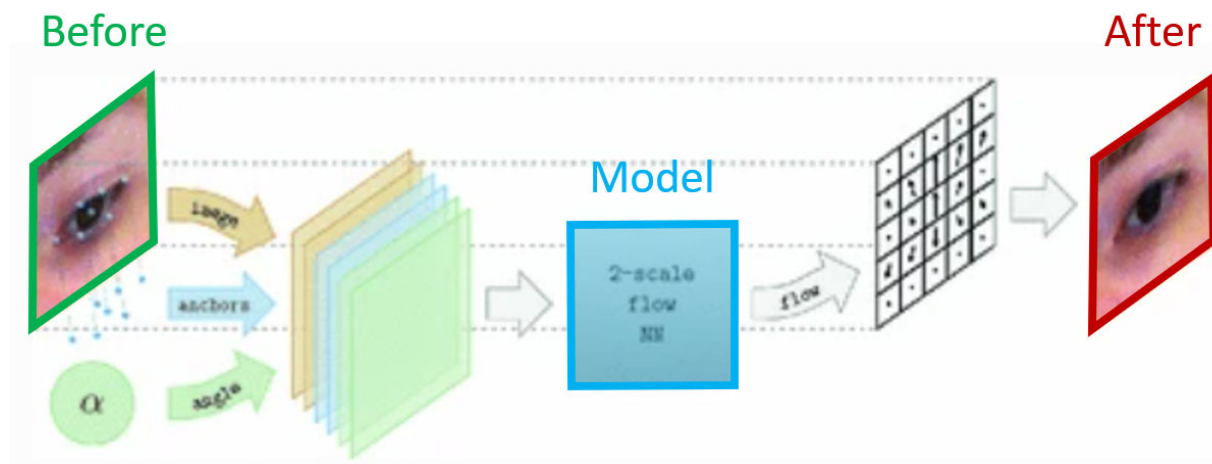
for example, the lighting or focus. *Id.* The model then passes the semi-completed image to a second step that adjusts the foreground to correct the lighting or focus. *Id.* Between steps one and two, there is no completed output, no highly-accurate corrected image. *Id.* There is simply a half-processed, unusable intermediary product as shown below in purple:



Id. at ¶¶ 81-82.

The two-step model (shown in blue) operates this way during both training and run-time. *Id.* at ¶ 83. During training, the model receives the before images (in green) and the after images (in red). *Id.* This training data allows the model to train itself to produce an “after” image for a given input through two steps. *Id.* When training is complete, the model may be used in run-time to operate on live data rather than training data. *Id.* In the run-time scenario, the model receives an input stream with a before image (in green) and uses its training to create an after image (in red) that will ultimately be displayed to a user. *Id.* In this two-step model there is one set of training data. *Id.* It provides the before images and the after images, but not any of the half-processed, intermediary products between the two steps (shown in purple). *Id.* at ¶¶ 81-83.

Ganin operates the same way, but instead of having background and foreground steps, Ganin uses a coarse step and then a fine step. *Id.* at ¶ 78. Ganin makes this explicit, stating that “the network . . . predict[s] [the gaze redirection] in two stages in a coarse-to-fine manner.” EX-1006 at 4 (emphasis added); EX-2003 at ¶ 78. Taking the headshot example again, Ganin’s “coarse” step adjusts the image in large blobs or quadrants to provide a coarse adjustment to the image. EX-2003 at ¶ 79. Then that semi-adjusted image would be passed to the “fine” step to adjust the image on, for example, a pixel-by-pixel basis so that the eyelashes, pupil, and iris are rendered correctly. *Id.*; see also EX-1006 at 4 (explaining that “the coarse module gives a rough estimate [while] . . . problematic regions [] can only be fixed by a neural network operating at a finer scale.”). Only at the end of the second step does the system provide a usable, adjusted “after” image as shown in Ganin’s Figure 2 below:



EX-1006 at Fig. 2 (annotated); EX-2003 at ¶ 79.

As with the prior example, Ganin’s training data provides a single set of before and after images. EX-2003 at ¶ 79. The before images (in green) are the inputs with an off-camera gaze. *Id.* They are input to the single model (shown in blue as the “2-scale flow”) and the after images (in red) are the final, adjusted images with the corrected gaze. *Id.* Ganin does not teach or disclose any intermediary, half-processed “after” images that would operate as “after” image training data for the coarse module. *Id.* at ¶¶ 84, 87-96. Nor does Ganin teach or disclose any intermediary, half-processed “before” images that would operate as “before” image training data for the fine module. *Id.* Petitioner’s expert concedes this point, stating that “[e]nd-to-end training refers to training the whole system together . . . as opposed to, for example, training the coarse warping module . . . and then separately training the fine warping module.” EX-1003 at ¶ 116. In fact, Petitioner’s expert also concedes that Ganin does not disclose how its training data filters in to each of the coarse and fine modules (if at all). *Id.* (explaining that Ganin teaches training the whole system together “end-to-end” using one “cost function” rather than using two cost functions, one for each of the coarse and fine modules). This is a critical distinction because it means that Ganin’s fine module cannot be a second machine learning algorithm. EX-2001 at ¶ 92.

In summary, Ganin teaches **one** set of training data, **one** training to complete **one** task, **one** error measurement, and thus **one** machine learning algorithm. *Id.* at ¶

83. This is confirmed by Petitioner’s expert. EX-1003 at ¶ 116. Ganin therefore does not disclose the second machine algorithm element as claimed in independent claims 1 and 18. EX-2001 at ¶¶ 67-68, 77-96.

2. **The Petition’s reliance on unsupported expert testimony about what a POSITA “can” infer about Ganin having two machine learning algorithms cannot qualify as substantial evidence.**

Petitioner’s only argument on this point is to backfill the material missing from Ganin with Petitioner’s unsupported expert testimony. As one example, Petitioner’s expert agrees that Ganin’s “end-to-end” training means that the whole system is trained together with one “before” image and one “after” image, rather than providing intermediate, half-processed images to train each of the coarse and fine modules separately. EX-1003 at ¶ 116. Petitioner’s expert then ignores this distinction and concludes—without any support whatsoever—that a person of skill in the art “can” provide the “after” image to both the coarse and fine modules. *Id.* This is insufficient under the law. *See TQ Delta, LLC v. Cisco Sys.*, 942 F.3d 1352, 1358 (Fed. Cir. 2019) (rejecting the adoption of “[c]onclusory expert testimony [because it] does not qualify as substantial evidence.”). Otherwise, these conclusory statements are “fraught with hindsight bias.” *Id.* at 1360.

Further, it is not enough for an expert to fill a gap in a reference with unsupported conjecture that a POSITA “could” infer Ganin’s missing disclosures. *See id.* at ¶¶ 115-116 (explaining that “outout O_{output} **could** refer to both coarse

estimate O_{coarse} . . . and final output O ,” that “the ground-truth O_{gt} **can** be provided to both coarse warping module and fine warping module,” and that “the cost function **may** be established . . .”). “The mere fact that a certain thing may result from a given set of circumstances is not sufficient” to establish anticipation. *Finnigan Corp. v. United States ITC*, 180 F.3d 1354, 1365 (Fed. Cir. 1999); *see also Bettcher Indus. V. Bunzl USA, Inc.*, 661 F.3d 629, 640 (Fed. Cir. 2011) (holding that “[t]he speculative notion that by happenstance the [prior art] might, under hypothetical circumstances, be capable of operating” as claimed is insufficient to prove anticipation.); *Avaya Inc., et al. v. Network-1 Security Sol’ns, Inc.*, IPR2013-00071, Paper 103 at 21 (May 22, 2014) (holding that the expert’s assumptions, although possible, are not enough to prove that the prior art expressly or inherently discloses the claim limitation). As Petitioner’s expert does nothing more than posit the mere possibility that Ganin “can,” “could,” or “may” include the missing training data, the Petition fails as a matter of law without reaching the merits.

3. **Petitioner’s unsupported inferences about Ganin’s training data fail to account for the fact that the coarse and fine module training data would be different.**

Even if the Board credits Petitioner’s unsupported testimony, it still fails on the merits. To start, Petitioner’s expert is incorrect that “end-to-end” training would include separate training data for the coarse and fine modules in Ganin. EX-2001 at ¶¶ 78-96. But even if this conclusion were correct, the separate trainings for Ganin’s

coarse and fine modules would necessarily require *different* training data, meaning that Ganin does not teach using the *same* training data for both the first and second machine learning algorithms as required by the claims. *Id.*

As explained above at Section V.A.1.a, to train a machine learning algorithm, it needs a set of training data that includes “before” and “after” images. EX-2001 at ¶¶ 41-45. The algorithm then trains itself how to take a “before” image and create the “after” image so that at run-time an unknown “before” image can be altered into an accurate “after” image. *Id.* If Ganin’s coarse module were a machine learning algorithm, it would need training data specific to the task of creating a coarse output image, i.e., a training set of “before” images and coarse “after” images. *Id.* at ¶¶ 78-96. Similarly, if Ganin’s fine module were a machine learning algorithm, it would need training data to teach it to take the coarse module’s coarse image and create a final “after” image. *Id.* But this is not what Ganin discloses. *Id.*

The training procedure proposed by Ganin makes this clear. Ganin’s before images are the uncorrected, off-camera gaze images, and Ganin’s after images are the final, gaze-corrected images. EX-1006 at 13, Fig. 8. There are no coarse module after images; there are no fine module before images. *Id.* Thus, there is no training data specific to the coarse module or specific to the fine module, and Ganin’s coarse and fine modules cannot be two machine learning algorithms. EX-2001 at ¶¶ 88-92.

Ganin’s optimization procedure also supports this conclusion. Ganin provides

only one “ l_2 -distance,” which is measure of how good an algorithm is at taking the “before” image and creating the “after” image. EX-1006 at 8. There is no coarse l_2 -distance and no fine l_2 -distance, such that there is no ability to assess the performance of Ganin’s coarse module or Ganin’s fine module. EX-2001 at ¶ 93. This also means Ganin’s coarse and fine modules cannot be two machine learning algorithms. *Id.*

Even if Ganin’s teachings supported two training sets, one for the coarse module and one for the fine module, they would not be the same set of training data as required by the independent claims. EX-2001 at ¶¶ 78-96. Claim elements 1[E] and 18[E] require that the “second machine learning algorithm . . . us[e] **the same training data as the first machine learning algorithm.**” EX-1001 at 26:50-52; 29:58-60 (emphasis added). However, if Ganin uses a set of training data for the coarse module and a set of training data for the fine module as Petitioner suggests, these training datasets would necessarily be different. EX-2001 at ¶ 88. The coarse module’s training data would include the “before” image and the intermediate, half-processed coarse output identified by Petitioner’s expert as O_{coarse} . *See* EX-1003 at ¶ 116 (noting that the distance calculation would be calculated using O_{coarse}); *see also* EX-2001 at ¶¶ 94-96. In contrast, the fine module’s training data would include the intermediate, half-processed coarse output and the “after” image output identified by Petitioner’s expert as O . *See* EX-1003 at ¶ 116 (noting that the distance calculation for the fine module would be calculated using O); *see also* EX-2001 at

¶¶ 94-96. As a result, the coarse module’s training data and the fine module’s training data are not “the same training data.” EX-2001 at ¶¶ 88-96. This means that Ganin’s fine module cannot be the claimed “second machine learning algorithm” because it does not use “the same training data as the first machine learning algorithm” as required by the claims. *Id.*

For all the reasons noted above, Ganin does not anticipate the “second machine learning algorithm” element as claimed in independent claims 1 and 18 of the ’985 Patent. EX-2001 at ¶¶ 76-96. Because Ganin does not anticipate independent claims 1 and 18, Ground I is insufficient to institute the Petition.

B. Ground II: Petitioner Fails to Demonstrate that Claims 16 and 19 are Rendered Obvious by the Combination of Ganin and Liu for the Same Reasons as Ground I.

Ganin does not anticipate the “second machine learning algorithm” recited in elements 1[E] and 18[E]. *See* Section V.A.1 above. These elements are also present in independent claim 16 and 19—specifically elements 16[E] and 19[E]—and are not disclosed in Ganin for the same reasons. *Id.* Liu does not remedy these deficiencies as Liu has not been raised as disclosing any portion of elements 16[E] and 19[E]. *See* Petition at 38 (noting “16[A-G] collectively are substantively identical to 1[A-E] collectively and are therefore disclosed in Ganin for the same reasons.”). As a result, the combination of Ganin and Liu cannot render claims 16 and 19 obvious.

C. **Ground III: Petitioner’s Improper Combination of Chalom and Aslan Fails to Disclose a Second Machine Learning Algorithm that Uses First Reference Data as Recited in Claims 1-3, 5-6, 8-14, 16-19.**

The combination of Chalom and Aslan (“Chalom-Aslan”) fails for several reasons. First, there is no motivation to combine Chalom and Aslan as Petitioner suggests. Second, even if a POSITA combined them, Chalom-Aslan does not disclose a “second machine learning algorithm” that uses “the first reference data” as recited in elements 1[E], 16[E], 17[E], 18[E], and 19[E].

1. **A POSITA would Not have been Motivated to Combine Chalom and Aslan.**

All of the ’985 Patent’s independent claims require both a “first machine algorithm” and a “second machine algorithm.” EX-1001 at 26:45-50; 28:55-57; 29:20-25; 29:53-58; 30:40-45. As Petitioner admits, Chalom does not disclose a second machine learning algorithm. Petition at 56; *see also* EX-1003 at ¶ 209 (admitting that Chalom does not disclose “the training of two MLAs”). Petitioner suggests that a POSITA would look to Aslan and combine it with Chalom to arrive at a system with a first and second machine learning algorithm. A POSITA would allegedly be motivated to do so because of “accuracy and/or efficiency gains.” Petition at 42. This is incorrect for several reasons.

First, nothing in Chalom indicates it is inaccurate or inefficient and thus there is no reason to look to Aslan to correct this nonexistent issue. EX-2001 at ¶ 99. In

fact, Chalom claims quite the opposite for its performance. *Id.* It laments that “current techniques may not be fast enough . . . , or may not be robust enough in terms of quality.” EX-1005 at 1:16-21; *see also* EX-2001 at ¶ 99. To overcome this problem, Chalom offers an “offline component” and “online component” to “provide improved corrected eye images, robustness . . . , real time capability (e.g., faster operation), and flexibility.” EX-1005 at 3:21-43; *see also* EX-2001 at ¶ 99. Chalom explains that its techniques “provide for high quality eye contact correction in real time” (EX-1005 at 9:50-55) and “provide a robust appearance model for an eye region” (*id.* at 13:37-40). *See also* EX-2001 at ¶ 99. Petitioner has therefore failed to provide any reason that would cause a POSITA to look outside of Chalom. *Id.* at ¶¶ 97-99.

Even if a POSITA were to credit either alleged issue (inefficiency and/or inaccuracy) in Chalom, adding another machine learning does not solve either problem. EX-2001 at ¶¶ 100-105. Regarding inaccuracy, adding another machine learning algorithm does not improve accuracy. EX-2001 at ¶ 101. This would be the equivalent of suggesting that the proper way to make your car faster is to strap it to a second car. This obviously does not solve the problem. The same is true in the context of Chalom. If Chalom’s machine learning algorithm is inaccurate, a POSITA would look to the training data and resolution of the classifier to fix the problem. EX-2001 at ¶ 101. If the training data is not of sufficient quantity or diversity, then

the algorithm will be poorly trained and give inaccurate results. *Id.* Adding a second machine learning algorithm does not cause better training or better training data, and thus, would not improve the algorithm's accuracy. *Id.* Rather, it will increase the system's overall complexity, increase complexity of the training process, and still provide similar, inaccurate results. *Id.* If a POSITA were truly concerned with improving Chalom's accuracy, it would: (1) increase the size of the training dataset; (2) increase the diversity of the training dataset; and/or (3) improve the random forest classifier performance by adding more branches (finer resolution) to its structure. *Id.* at ¶ 103. The alleged inaccuracies of Chalom therefore do not motivate a POSITA to look to Aslan for a solution. *Id.* at ¶¶ 101-104.

Regarding inefficiency, adding a second machine learning algorithm does not improve efficiency. EX-2001 at ¶ 105. It does the opposite. *Id.* Petitioner suggests that Chalom's disclosure of a "random forest classifier [that] may apply different random forest models" somehow leads a POSITA to Aslan and a second machine learning algorithm to improve Chalom's efficiency. Petition at 41-47. This is incorrect. EX-2001 at ¶ 105. Chalom teaches using a specific model based on where the camera is located. EX-1005 at 5:37-50; 10:31-39. The camera may be above, below, left, or right of the display, and thus it may appear that the user is looking below, above, right, or left of the camera. *Id.* at 5:37-50. The gaze correction will be different depending on which direction the user is looking, so Chalom explains that

the forest classifier can choose a model that is particular to that camera orientation. *Id.* at 10:31-39. For example, if the camera is located above the display, the user will be looking down and the gaze correction will be to lift the gaze upward. *Id.* In contrast, if the camera is to the left of the display, the user will be looking right and thus the gaze correction will be to shift the gaze left. *Id.* The most efficient way to deploy Chalom's forest models is to select the most appropriate one based on the camera's location, rather than adding more machine learning algorithms such that each model for each camera location is run by a separate machine learning algorithm in parallel. *Id.*; *see also* EX-2001 at ¶ 105. Selecting the most appropriate model for the camera's location, which is what Chalom teaches, would provide Chalom's system with a more efficient operation, prevent a significant increase in complexity from adding a second machine learning algorithm, maintain accuracy, and still operate in real time as taught by Chalom. EX-2001 at ¶ 105.

Moreover, it makes no sense to add further machine learning algorithms as Petitioner suggests. A POSITA would not run a machine learning algorithm for the upward gaze correcting forest model when Chalom's system knows the user's gaze is to the left or right. The results would be extremely poor because the upward gaze correcting forest model would seek to correct the gaze upward, not left or right. So the motivation Petitioner relies on requires more resources and complexity to arrive at less accurate results. This is the opposite of increasing efficiency and thus a

POSITA would not be motivated to combine Chalom and Aslan. EX-2001 at ¶¶ 97-105.

2. The Combination of Chalom and Aslan Does Not Disclose the Claimed “Second Machine Learning Algorithm . . . [that] Us[es] . . . the First Reference Data”.

All of the challenged independent claims require “a second machine learning algorithm . . . [that] us[es] . . . the first reference data.” *See* EX-1001 at 26:50-54; 28:57-61; 29:25-29; 29:58-30:2; 30:45-48. Independent claim 1 adds that the “first reference data” includes both “first editing instructions” and “first selection instructions.” *See* EX-1001 at 26:58-63. As set forth below, Chalom/Aslan fails to disclose these requirements for two reasons: (1) the Petition fails to allege that the second machine learning algorithm uses the first selection instructions as required by claim 1, and (2) the combination fails to disclose a system that provides first reference data to the second machine algorithm. EX-2001 at ¶¶ 106-111.

a) The Petition fails to allege that the second machine learning algorithm receives both first editing and first selection instructions as required by claim 1.

Claim 1 recites “a second machine learning algorithm . . . [that] us[es] . . . the first reference data[,] . . . wherein the first reference data comprise first editing instructions . . . and first selection instructions for selecting editing instructions for a particular input patch . . .” *See* EX-1001 at 26:50-27:3. In summary, both the first editing instructions and first selection instructions must be provided to the second

machine learning algorithm. EX-2001 at ¶ 106-111.

The Petition fails to acknowledge this claim feature. Instead, the Petition only argues that Chalom-Aslan allegedly teaches providing the first editing instructions to the second machine algorithm. Petition at 62. There is a complete absence of allegation, much less proof, that Chalom-Aslan’s alleged first machine learning algorithm provides first selection instructions to the alleged second machine learning algorithm. In particular, the Petition argues that Chalom-Aslan’s “trained teacher model” is the alleged “first selection instructions.” *Id.* Yet nowhere does the Petition argue that the second machine learning algorithm use Chalom-Aslan’s “trained teacher model” as is required by the claims. *Id.* at 58-59. The Petition’s only other mention of the “trained teacher model” is with respect to claim 2 and has nothing to do with whether the “trained teacher model” is provided to any of the alleged machine learning algorithms. *Id.* at 63-65.

This absence of proof requires that Petitioner’s Chalom-Aslan combination fail without reaching the merits. *See In re Magnum Oil Tools Int’l, Ltd.*, 829 F.3d 1364, 1375 (Fed. Cir. 2016) (“In an inter partes review, the burden of persuasion is on the petitioner to prove ‘unpatentability by a preponderance of the evidence,’ 35 U.S.C. § 316(e), and that burden never shifts to the patentee.”).

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b) On the merits, the combination of Chalom and Aslan does not disclose a second machine learning algorithm that uses the first reference data.

As explained above, all of the challenged independent claims require a second machine learning algorithm that uses the first reference data's editing instructions from the first machine learning algorithm. EX-1001 at 26:45-54; 28:57-61; 29:20-29; 29:53-30:2; 30:40-49. Chalom-Aslan does not disclose this claimed feature. EX-2001 at ¶¶ 106-111.

Again, Petitioner admits that Chalom discloses only one alleged machine learning algorithm. Petition at 56; *see also* EX-1003 at ¶ 209 (admitting that Chalom does not disclose “the training of two MLAs”); EX-2001 at ¶ 107. Since Chalom does not disclose two machine learning algorithms, it likewise cannot teach or suggest what information (if any) may be passed between multiple machine learning algorithms. EX-2001 at ¶ 107. Petitioner is therefore left to cobble together a system with two machine algorithms by adding Aslan to the mix.

However, combining Chalom with Aslan does not arrive at a system having a second machine learning algorithm that uses first editing instructions from the first machine learning algorithm. EX-2001 at ¶ 108. Instead, at best, Chalom-Aslan would result in a system that provides an “objective function” between the teacher and student models during training, and Petitioner has made no effort to suggest—much less prove—that the “objective function” bears any resemblance to the claimed

“first editing instructions.” *Id.*

Petitioner attempts to sidestep this issue by suggesting that Chalom-Aslan “passes information” from teacher to student, and that “information” must be the claimed first reference data. Petition at 62-63. This is wrong. EX-2001 at ¶ 109. As explained above, Chalom has no disclosures regarding what passes between two machine learning algorithms because it does not have multiple machine learning algorithms. *Id.* And Petitioner makes clear that a POSITA “would have needed only to follow the instructions provided in Aslan” to arrive at the inventions claimed in the ’985 Patent. *Id.* at 45, 47. But the information passed between models in Aslan is the objective function. EX-1007 at ¶ 28 (explaining that “‘passing information’ between machine learning models [] comprises formulating an objective function.”); *id.* at ¶ 39 (explaining that “passing information between the models 100 and 102 [occurs] via the objective function”); EX-2001 at ¶ 109.

Petitioner admits that the objective function is not editing instructions as required by the ’985 Patent. Instead, Petitioner’s expert describes an objective function as a way to “assess” how well the algorithm is learning its task, i.e., a “performance measure.” EX-1003 at ¶ 23. She describes objective functions as including a “cross-entropy loss function,” or an “ l_2 -distance” that determines the error between the training data’s desired output and the actual output generated by the machine learning model. EX-1003 at ¶ 28. Aslan is much the same. It equates an

“objective function” with error or “distance” repeatedly. *See, e.g.*, EX-1007 at ¶ 29 (stating that the model can be biased “via a penalty (or distance) term in the objective function.”); *id.* at ¶ 31 (stating that “[t]he objective function . . . can include a penalty term (sometimes called a ‘distance term’) that optimizes the objective function.”). And Aslan’s passing of the objective function occurs during **training**, not at **run-time**. EX-2001 at ¶ 111.

In contrast, Petitioner explains that “editing instructions [are] for adjusting the digital representation of the head region.” Petition at 16. This is not the same as a performance measure of how well the models are learning, nor has Petitioner made any effort to explain how Aslan’s objective function could be interpreted as editing instructions. EX-2001 at ¶ 111. For example, a function used to assess **training** performance is not the same as making corrections to an image or video during **run-time**. *Id.* As a result, Chalom-Aslan does not render obvious the claimed second machine learning algorithm that “us[es] . . . the first reference data . . . [that] comprise first editing instructions for a range of possible configurations of the target feature.” EX-1001 at 26:45-54; 28:57-61; 29:20-29; 29:53-30:2; 30:40-49; EX-2001 at ¶ 111.

To suggest otherwise, as Petitioner does, is to use impermissible hindsight. *See, e.g., Insite Vision, Inc. v. Sandoz, Inc.*, 783 F.3d 853 (Fed. Cir. 2015); *see also* MPEP § 2142 (“impermissible hindsight must be avoided”). More specifically,

Petitioner cannot use the '985 Patent and its teachings as a roadmap to suggest the missing element is obvious when the references themselves are silent on this aspect. *Orexo AB v. Actavis Elizabeth LLC*, 903 F.3d 1265, 1271 (Fed. Cir. 2018) (holding “[i]t is inappropriate to use the template provided by the inventor to render the inventor’s contribution obvious.”).

Yet that is exactly what Petitioner does. Even assuming that a POSITA would be led to combine Chalom and Aslan (which RealD disputes), Petitioner simply suggests that a POSITA “would have been motivated to incorporate Aslan’s teacher-student training architecture by using Chalom’s already trained RFC as a teacher.” Petition at 44. Petitioner’s expert agrees, stating that a POSITA “would have needed only to follow the instructions provided in Aslan” to allegedly arrive at the '985 Patent claims. EX-1003 at ¶ 227. This means that a POSITA would have wholesale adopted Aslan’s teacher-student architecture in the alleged combination. EX-2001 at ¶ 109. But in doing so, a POSITA would likewise adopt Aslan’s “objective function” that is sent between the teacher and student models during training as explained above. *Id.* It would not mass delete the “objective function” in favor of a completely different set of information (i.e., editing instructions and selection instructions) sent during run-time, and which is not disclosed in either Chalom or Aslan. *Id.* at ¶¶ 109-111. This is where the Petition looks to the '985 Patent to recreate them in Chalom-Aslan with impermissible hindsight. The Board should

reject Petitioner's efforts to use the '985 Patent claims as a template to combine Chalom and Aslan as Petitioner suggests. For all the reasons noted above, Ground III is insufficient to institute the Petition. *See also* EX-2001 at ¶¶ 97-111.

D. Ground IV: Petitioner Fails to Demonstrate That Claim 4 is Rendered Obvious by the Combination of Chalom, Aslan, and Grau.

Because the combination of Chalom and Aslan does not teach or disclose the elements of claim 1, the combination also does not render dependent claim 4 obvious for the same reasons. *See* EX-2001 at ¶¶ 97-111; *see also* Section V.C. Grau does not remedy the deficiencies of Chalom-Aslan as Petitioner only argues that Grau allegedly discloses the elements of dependent claim 4. *See* Petition at 80 (suggesting that Chalom-Aslan relates to the elements of claim 1 and Grau relates to the elements of claim 4). As a result, the combination of Chalom, Aslan, and Grau does not render claim 4 obvious. *See* EX-2001 at ¶¶ 97-111.

E. Ground V: Petitioner Fails to Demonstrate That Claim 7 is Rendered Obvious by the Combination of Chalom, Aslan, and Pace.

Because the combination of Chalom and Aslan does not teach or disclose the elements of claim 1, the combination also does not render dependent claim 7 obvious for the same reasons. *See* EX-2001 at ¶¶ 97-111; *see also* Section V.C. Pace does not remedy the deficiencies of Chalom-Aslan as Petitioner only argues that Pace allegedly discloses the elements of dependent claim 7. *See* Petition at 83 (suggesting

that Chalom-Aslan relates to the elements of claims 1 and 5, and Pace relates to the elements of claim 7). As a result, the combination of Chalom, Aslan, and Pace does not render claim 7 obvious. *See* EX-2001 at ¶¶ 97-111.

VI. CONCLUSION

RealD respectfully requests that the Board deny institution because Petitioner has failed to show a reasonable likelihood that it will prevail on any of its Grounds.

Respectfully submitted,

Dated October 13, 2023

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CERTIFICATE OF COMPLIANCE WITH WORD COUNT

Pursuant to 37 C.F.R. § 42.24, I hereby certify that the above Patent Owner's Preliminary Response to the Petition for *Inter Partes* Review of U.S. Patent No. 10,740,985 contains 7576 words, excluding the parts exempted by 37 C.F.R. § 42.24(a)(1), in compliance with the 14,000 word limit set forth in 37 C.F.R. § 42.24(b)(1). This word count was prepared using Microsoft Word Office 365.

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CERTIFICATE OF SERVICE

A copy of Patent Owner's Preliminary Response to the Petition for *Inter Partes* Review of U.S. Patent No. 10,740,985 has been served on Petitioner via electronic mail at the following counsel of record for Petitioner:

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