

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 RESPONSE PURSUANT TO 37 C.F.R. § 42.120

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TABLE OF EXHIBITS

Exhibit #	Reference Name
EX-2001	Declaration of Dr. Eli Saber
EX-2002	<i>Curriculum Vitae</i> of Dr. Eli Saber
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)
EX-2008	Supplemental Declaration of Dr. Eli Saber
EX-2009	Deposition Transcript of Dr. Lina J. Karam, Expert for Petitioner
EX-2010	A. Murat Tekalp, “Digital Video Processing”, Prentice Hall 1995

I. INTRODUCTION

REALD SPARK, LLC, (“RealD” or “Patent Owner”) respectfully submits this Response, timely filed under 37 C.F.R. § 42.120, to the decision granting institution of *inter partes* review (“IPR”) of claims 1-14 and 16-19 of U.S. Patent No. 10,740,985 (“the ’985 Patent”).

Grounds I and II (based on Ganin) do not render the ’985 Patent claims unpatentable. Ganin does not disclose two machine learning algorithms, nor does it disclose first and second machine learning algorithms that use “the same training data” as required by the independent claims. Ganin therefore cannot anticipate any of the ’985 Patent claims under Ground I or render any of the ’985 Patent claims obvious under Ground II.

Grounds III-V (based on a combination of Chalom and Aslan) also do not render the ’985 Patent claims unpatentable. There is no motivation to combine these references, as Petitioner’s motivation is contradicted by Chalom itself. Indeed, Chalom discloses a machine learning algorithm that performs perfectly well in a limited power, mobile device scenario such that there is no need to look elsewhere for alleged improvements. Further, even if a POSITA were to seek to improve Chalom, a POSITA would not add another machine learning algorithm. Doing so actually renders the Chalom-Aslan combination less efficient, requiring more resources and complexity to arrive at less accurate results. Petitioner’s “image”

context also does not provide a basis for combining these references as motion vector fields and classes/labels use vastly different structures and functions.

Even if a POSITA were to combine Chalom and Aslan, the combination would not operate as claimed in the '985 Patent. Chalom-Aslan does not disclose a second machine learning algorithm that receives both first editing and first selection instructions as required by Claim 1. In a similar vein, the Chalom-Aslan combination does not disclose a second machine learning algorithm that uses first reference data. Finally, Chalom-Aslan does not disclose first reference data and second data that are different from each other. As a result, none of the Chalom-Aslan Grounds pass muster. RealD requests that the Board find each of claims 1-14 and 16-19 not unpatentable over the prior art.

II. BACKGROUND

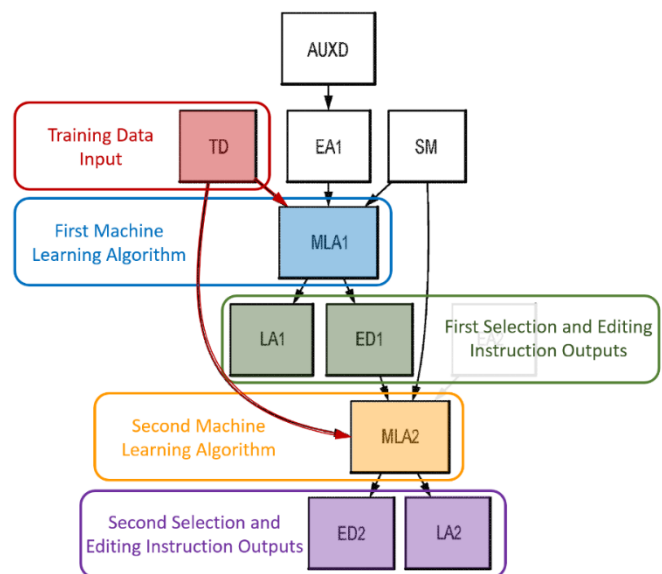
A. The '985 Patent

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. EX-2008 at ¶ 42. In the '985 Patent, two machine learning algorithms learn how to adjust a user's features (e.g., eye gaze). EX-2008 at ¶¶ 50-52. They do so with training data that includes (1) input patches representing an unadjusted target feature (e.g., unadjusted eyes that

gaze off-camera) and (2) output patches representing an adjusted target feature (e.g., adjusted eyes that gaze into the camera). EX-1001 at 26:35-44; EX-2008 at ¶ 53. The better the training data, the better the algorithm will accomplish the algorithm’s task during deployment in the real world. EX-2008 at ¶ 43.

The ’985 Patent uses two machine learning algorithms that, once trained, provide instructions on how to adjust the user’s eye gaze for example. *Id.* at ¶ 53. Both the first and second machine learning algorithms provide these instructions. *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-2008 at ¶ 50.

This process is shown in Figure 9 to the right. *Id.* at ¶ 54. Both the **first machine learning algorithm (“MLA1”)** and **second machine learning algorithm (“MLA2”)** receive the same **training data**. *Id.* at ¶¶ 54-55. **MLA1** then uses the



training data to generate **first reference data**. *Id.* at ¶ 54. The reference data includes

first editing instructions and, optionally, first selection instructions for determining how the head region is to be adjusted. *See, e.g.*, EX-1001 at 26:45-49 and 26:58-63.

The same process happens for **MLA2**. EX-2008 at ¶ 55, 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-2008 at ¶ 55. However, **MLA2** also receives the **selection and/or editing instructions** from **MLA1**. *See, e.g.*, EX-1001 at 26:50-54; EX-2008 at ¶ 55.

The reason for having two machine learning algorithms that both receive training data and output instructions is that **MLA1** may create its instructions using a computationally intensive process to create highly accurate results, which can be fed to **MLA2** to create instructions using less complexity while still arriving at highly accurate results. EX-1001 at 16:12-44; EX-2008 at ¶ 57.

B. The Alleged Prior Art

Petitioner asserts the following grounds:

Ground I: Claims 1-4, 7-10, and 13-16 are anticipated by Ganin;

Ground II: Claims 16 and 19 are obvious over Ganin in view of Liu;

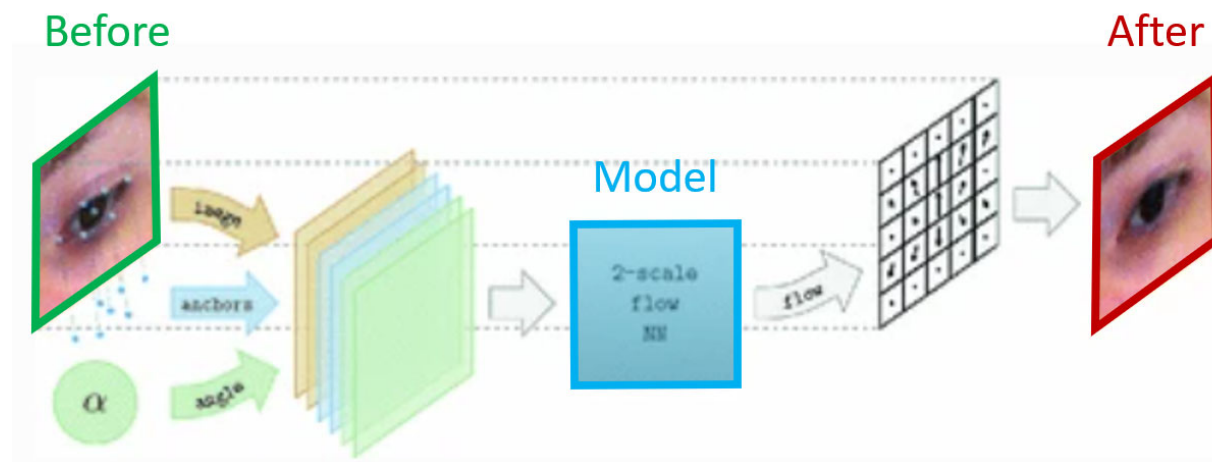
Ground III: Claims 1-3, 5-6, 8-14, and 16-19 are obvious over Chalom in view of Aslan;

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.

1. Ganin.

Ganin teaches, at best, a single machine learning algorithm. EX-2008 at ¶¶ 68, 77-103. 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-2008 at ¶ 79. 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 the after images that are images after exiting the fine module as shown below:



EX-1006 at Fig. 2 (annotated); EX-2008 at ¶ 79.

Ganin’s “coarse” step provides a coarse adjustment to the image. EX-2008 at ¶ 80. 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 p. 6 (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-2008 at ¶ 80. Only at the end of the second step does the system provide a usable, adjusted “after” image. EX-2008 at ¶ 80.

2. Chalom.

Chalom also teaches a single machine learning algorithm for gaze correction based on a camera’s location. EX-2008 at ¶ 71. The system includes a “random forest classifier” that determines which random forest to implement based on the camera’s angle. EX-1005 at 10:35-39; EX-2008 at ¶ 71. 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 10:35-64; EX-2008 at ¶ 71.

3. Aslan.

Aslan discloses a student-teacher model that can train two machine learning models. EX-1007 at ¶ 20; EX-2008 at ¶ 73. For the “student” and “teacher” to learn from one another, Aslan explains that the models “pass[] information” through “an

objective function.” EX-1007 at ¶ 28; EX-2008 at ¶ 73. 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-2008 at ¶ 73. To force the two models to agree, the objective function and its penalty term may be optimized. EX-1007 at ¶ 31; EX-2008 at ¶ 73.

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-2008 at ¶ 22. 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

As noted in the Institution Decision, neither party proposed constructions of any ’985 Patent claim terms. Institution Decision at 16. The Board will issue a final determination on claim construction “at the close of the proceeding, after any

hearing, based on all the evidence of record.” *Id.*

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

As explained in detail below, none of Petitioner’s grounds support a finding of anticipation or obviousness. RealD requests that the Board find each of claims 1-14 and 16-19 not unpatentable.

A. Ground I: Ganin Does Not Anticipate the Second Machine Learning Algorithm Elements of Claims 1-3, 5, 10, 12-14, and 18.

Ground I fails for two reasons: (1) Ganin does not disclose the “second machine learning algorithm” and related elements of independent claims 1 and 18; and (2) Ganin’s alleged algorithms do not use “the same training data” as also required by independent claims 1 and 18. Each of Ganin’s failures are explained in detail below.

1. Ganin does not disclose two machine learning algorithms as required by the independent claims.

The ’985 Patent claims all require two machine learning algorithms: a “first machine learning algorithm” and a “second machine learning algorithm.” EX-1001 at 26:45-57, 29:53-30:5 (elements 1[D]/18[D] and 1[E]/18[E]). Each of these algorithms receive the same training data. *Id.* (claiming a “first machine algorithm . . . using the training data” and a “second machine learning algorithm . . . using the same training data”). Ganin anticipates neither of these claimed features. EX-2008 at ¶¶ 69, 77-103.

At the most basic level, machine learning involves an algorithm that learns how to perform a task. *Id.* at ¶ 42. It learns by “training” on a large amount of sample data that represents the before and after of the task. *Id.* at ¶¶ 43-46. For example, if the machine learning algorithm’s task is to rotate an image by 90 degrees, the training data would include many samples of “before” (original, unrotated) images and “after” (final, rotated) images. *Id.* These sample “before” and “after” images (or “input” and “output” images) are called “training pairs.” In this way, the algorithm can learn how to instruct the system to take an unknown input and create an output that closely matches the training pairs. *See id.* The machine learning algorithm can measure how well it has learned the task with an error calculation called an “objective function.” *See id.* at ¶ 73. A typical objective function is called an “ l_2 -distance” that measures how far away the actual output is from the desired output present in the training pair. *Id.* at ¶ 99, n.1.

a) Ganin has one set of training data and therefore one machine learning algorithm.

A POSITA can easily tell how many tasks (and how many machine learning algorithms) are present in a system by looking at the training data. *See* EX-2008 at ¶¶ 85-87. If there is one set of training data, then there is one task. *See id.* If there are two different sets of training data, then there are two different tasks. *See id.* If, as Petitioner contends, a system includes **two different** tasks performed by **two different** machine learning algorithms, then there must be **two different** sets of

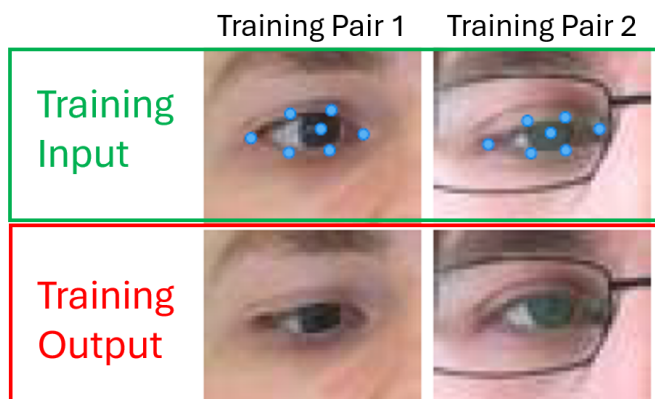
training data. *See id.* Otherwise, the system cannot learn both tasks because it does not know what the desired output of each one should look like. *See id.* at ¶ 87. This is one reason why Ganin cannot anticipate the two machine learning algorithm requirement of the '985 Patent's independent claims. *Id.* at ¶¶ 85-87.

In Petitioner's view, Ganin teaches the '985 Patent's two machine learning algorithm claim elements through: (1) a "coarse" machine learning algorithm for performing a "coarse" image adjustment and (2) a "fine" machine learning algorithm for performing a "fine" image adjustment. Petition at 5. This is wrong because there is only one set of training data and therefore Ganin cannot train two different algorithms to perform two different tasks (i.e., a coarse adjustment and a fine adjustment). EX-2008 at ¶¶ 85-87.

If Ganin taught a "coarse" machine learning algorithm, it would need to provide training data with a "coarse" input image and a "coarse" output image. Likewise, for a "fine" machine learning algorithm, Ganin would need to provide training data with a "fine" input image and a "fine" output image. Petitioner's expert concedes this point. EX-2009 at 106:1-21 (testifying that "if you want to optimize the flow of the first model, the coarse module, . . . you have to give the ground truths there, too.")). There is no such thing in Ganin. Rather, Ganin discloses a single machine learning algorithm with one set of training data to perform one task.

Ganin's training data makes this clear. Ganin Figure 4 shows a training pair

for two people where the top image is an “input image with superimposed feature points on top” and the bottom image is the “output image:”



EX-1006 at Figure 4; EX-2008 at ¶ 86.

Ganin describes its training data as a training “pair”—meaning there is only a single input image (green) and a single output image (red) per pair. EX-1006 at Figure 4; *id.* at 4¹ (“The model is trained on pairs of images corresponding to eye appearance before and after the redirection.”); *id.* at 5 (“At training time, our dataset allows us to mine pairs of images . . . The head pose, the lighting, and all other

¹ To avoid confusion from Petitioner’s replacement of EX-1006 with a “corrected” EX-1006, RealD maintains the original page numbering scheme. A reference to a particular page of EX-1006 reflects the original page number at the top of each page. For example, a reference to page 4 equates to pdf page 10 as noted in the footer of EX-1006.

nuisance parameters are [] the same between the two images in the pair. . . . The resulting image pair serves as a training example for the learning procedure (Figure 4-Right).”).

In sum, Ganin only describes a training “pair” with one input and output, not a training “quad” with a coarse input, a coarse output, a fine input, and a fine output as would be necessary to train a coarse machine learning algorithm and a fine machine learning algorithm. EX-2008 at ¶ 87. Ganin therefore discloses **one** machine algorithm and cannot anticipate the “second machine learning algorithm” elements 1[E] and 18[E] of the ’985 Patent. *Id.*

b) Ganin has one objective function and therefore one machine learning algorithm.

As explained above, a machine learning algorithm can assess its performance using an objective function. Section V.A.1. Ganin provides one objective function that assesses one output (*i.e.*, redirected gaze image), and thus uses only one machine learning algorithm. More specifically, Ganin’s objective function provides only one “ l_2 -distance,” which is a measure of how good the algorithm is at taking the input image and creating the output image. EX-1006 at 8. Ganin has 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 its fine module. EX-2008 at ¶¶ 94-95. Petitioner’s expert concedes this point as well. EX-1003 at ¶ 116 (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). Ganin’s objective function also confirms that Ganin uses one machine learning algorithm and not two as required by the ’985 claims. EX-2008 at ¶ 102.

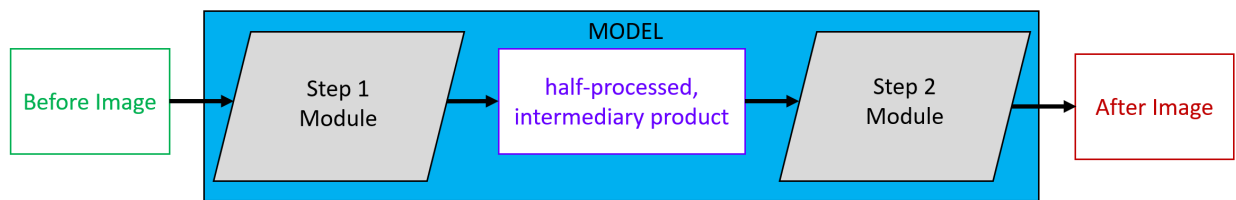
c) Ganin’s text repeatedly states it includes one machine learning algorithm, not two.

Since Ganin’s technical discussion relates to one algorithm, it should be unsurprising that Ganin repeatedly refers to its algorithm in the singular. *See, e.g.*, EX-1006 at 2, 4, 5, and 8 (emphasis added); *see also* EX-2008 at ¶ 88. For example, Ganin states as follows:

- “[a]ll these operations are performed in a feed-forward manner . . . **the resulting neural network** can synthesize images with manipulated gaze.” EX-1006 at 1.
- “**a** new deep feed-forward **architecture** [] combines several principles of operation . . .” *Id.* at 2.
- “[t]he proposed system takes [various] input[s] . . . and sends them to **the multi-scale neural network** . . .” *Id.* at 4 (Figure 2).
- “**3. The Model**” *Id.* at 4 (heading).
- “[i]n this section, we discuss **the architecture** of our deep model . . . **The model** is trained on pairs of images . . .” *Id.* at 4.
- “[t]he task of **the network** is therefore the prediction of the warping field.” *Id.*
- “[a]ll operations . . . are implemented in **a single feed-forward architecture** . . .” *Id.*
- “[t]he **model** was trained end-to-end . . .” *Id.* at 8 (emphasis added to all).

Ganin’s *single* algorithm uses a two-step process, but this is not the same as

having *two* machine learning algorithms. EX-2008 at ¶ 78. As an illustration, consider a single algorithm that adjusts a headshot image. *Id.* at ¶ 83. In step one, the algorithm blurs the background. *Id.* In step two, the algorithm takes the partially-processed image and adjusts for lighting in the foreground. *Id.* Between steps one and two, there is no completed output, no corrected image. *Id.* There is simply a half-processed, intermediary product as shown below in purple:

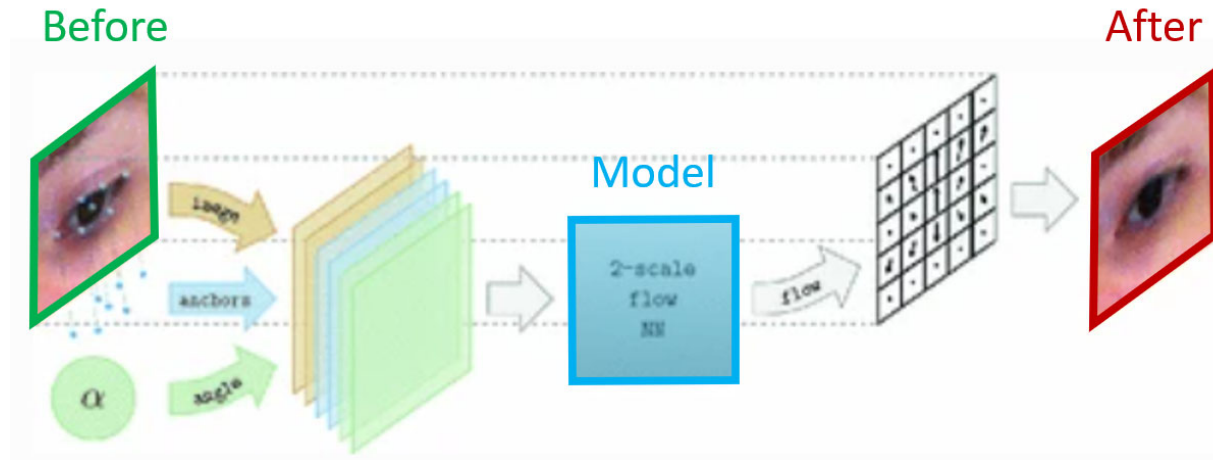


Id. at ¶¶ 82-83.

In this two-step model (shown in blue) there is one set of training data. *Id.* It provides the before images (green) and the after images (red), but not any of the half-processed, intermediary products between the two steps (shown in purple). *Id.* at ¶¶ 82-84.

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 ¶¶ 79-80. 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-2008 at ¶ 79. Taking the headshot example again, Ganin’s “coarse” step provides a coarse adjustment to the image. EX-2008 at ¶ 80. Then that semi-adjusted image is 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.* 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-2008 at ¶ 79.

As explained above, Ganin provides a “training pair” of one before and one after image. EX-2008 at ¶ 79. The before image (in green) is the input with an off-camera gaze. *Id.* It is sent to one algorithm (shown in blue as the “2-scale flow N[eural] N[etwork]”), and the after image (in red) is the final, adjusted image with the corrected gaze. *Id.*

Ganin does not teach or disclose any “coarse” before images, “coarse” after images, “fine” before images, or “fine” after images. *Id.* at ¶¶ 85, 87. Petitioner’s expert admits this is true, 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. This is a critical distinction because it means that Ganin has one machine learning algorithm and not two. EX-2008 at ¶ 87.

In summary, Ganin teaches **one** set of training data, **one** training to complete **one** task, **one** objective function, and thus **one** machine learning algorithm. *Id.* at ¶ 77-103. As a result, Ganin does not disclose the second machine algorithm element as claimed in independent claims 1 and 18. *Id.* at ¶¶ 77-103.

d) Petitioner’s conclusory expert testimony that Ganin discloses two algorithms cannot support a finding of anticipation.

Petitioner’s unsupported conjecture that a POSITA “could” infer that Ganin discloses two algorithms cannot provide substantial evidence of anticipation. *See* EX-1003 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 . . .”). To establish anticipation, “[t]he mere fact that a certain thing may result from a given set of circumstances is not sufficient.” *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" be stretched beyond reason to include two machine learning algorithms, Petitioner fails to establish anticipation.

2. Ganin does not disclose first and second machine learning algorithms that use "the same training data" as required by the independent claims.

The '985 independent claims all recite a "first machine algorithm . . . using the training data" and a "second machine algorithm . . . **using the same training data** as the first machine learning algorithm." EX-1001 at 26:45-53, 29:53-60 (claim elements 1[D]/[E] and 18[D]/[E]) (emphasis added). Ganin does not disclose this element, nor can Petitioner's unsupported expert testimony establish otherwise.

a) Petitioner's interpretation of Ganin requires two different sets of training data rather than "the same training data" as required by the '985 claims.

As explained in detail in Section V.A.1 above, even if Ganin were to deploy a coarse machine learning algorithm and fine machine learning algorithm, Ganin would necessarily require two different sets of training data. EX-2008 at ¶¶ 85-87. Ganin's coarse module would need coarse input/output training pairs to learn what the coarse module's output should be. EX-2008 at ¶¶ 95-98. And Ganin's fine module

would need fine input/output training pairs to learn what the fine module’s output should be. *Id.* Having fine training pairs and coarse training pairs means the training data across both the coarse and fine algorithms are different.² Therefore, Ganin does not teach using the same training data for both the first and second machine learning algorithms as required by the ’985 claims. EX-2008 at ¶¶ 85-87, 94-103.

b) Petitioner’s unsupported expert testimony about Ganin’s training data cannot support a finding of anticipation either.

Recognizing this training data issue, Petitioner states—without any support whatsoever—that a POSITA “can” provide separate, distinct training data to both the coarse and fine modules. EX-1003 at ¶ 116. Petitioner’s expert goes further, noting that Ganin “does not necessarily” provide the algorithm’s desired output (i.e., ground truth) to only the fine warping module. This is improperly “fraught with hindsight bias.” *See TQ Delta, LLC v. Cisco Sys.*, 942 F.3d 1352, 1358-60 (Fed. Cir. 2019) (rejecting the adoption of “[c]onclusory expert testimony [because it] does not qualify as substantial evidence.”). Further, because Petitioner’s testimony is also speculative and hypothetical, it cannot constitute substantial evidence to establish anticipation. *See Finnigan*, 180 F.3d at 1365; *Bettcher*, 661 F.3d at 640 (holding that

² RealD disputes that Ganin teaches fine and coarse training pairs for all the reasons set forth above.

“[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*, IPR2013-00071, Paper 103 at 21.

But, even more importantly, Petitioner’s admission proves that Ganin, at best, uses two different sets of training data rather than the “same training data” required by the ’985 claims. *See* Section V.A.1 above. Ganin therefore does not anticipate the ’985 Patent’s second machine algorithm that uses “the same training data” as the first machine algorithm.

3. Ganin does not disclose the features of dependent claims 2, 3, 5, 10, or 12-14.

Dependent claims 2, 3, 5, 10, and 12-14 all depend—directly or indirectly—from independent claim 1 and are therefore not unpatentable for the same reasons discussed in detail above in Sections V.A.1 – V.A.2.

B. Ground II: Independent Claims 16 and 19 are Not Rendered Obvious by the Combination of Ganin and Liu.

Ganin does not anticipate the “second machine learning algorithm” or “same training data” elements recited in claims 1 and 18. *See* Section V.A above. These elements are also present in independent claim 16 and 19, 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 these elements. *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.

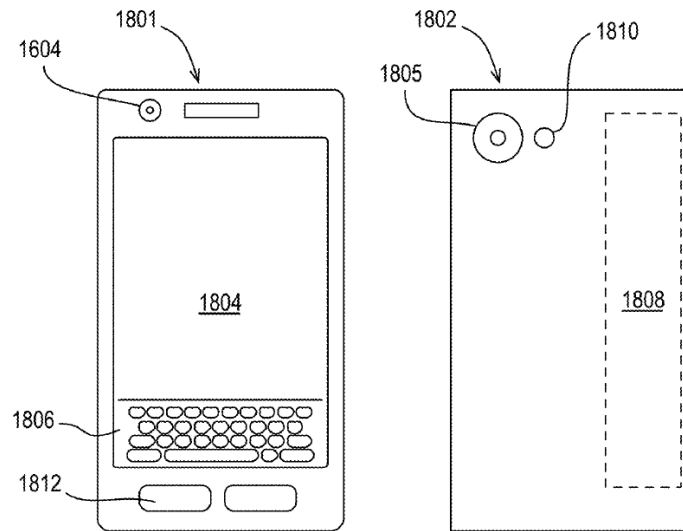
C. Ground III: Petitioner Cannot Combine Chalom and Aslan as It Suggests, Nor is there any Motivation to Do So.

Chalom alone does not disclose the ’985 claim elements, so Petitioner is forced to combine Chalom with Aslan. Petition at 56; *see also* EX-1003 at ¶ 209. Petitioner alleges that a POSITA would be motivated to make this combination because of “accuracy and/or efficiency gains.” Petition at 42. This is incorrect as explained in detail below.

1. Petitioner’s alleged motivation rests on the incorrect assumption that Chalom is not a limited-resource, low-power environment.

Petitioner’s expert was apparently led to combine Aslan with Chalom “because Chalom is not considering limited resources and low power.” EX-2009 at 154:12-155:4. She repeatedly testified that Chalom “did not mention limited resources” and for that reason Chalom “requires different techniques which Aslan solves . . .” *Id.* at 156:6-19; *see also id.* at 159:2-12 (testifying that Chalom has “no limit on resources . . . There’s no limit on resources. But if you want to limit to low power and have limited resources for mobile, then you have to seek to improve on Chalom in order to have that.”). In short, Petitioner’s expert opined that a POSITA would look to Aslan because Chalom uses “different techniques” that cannot function in a lower power, mobile device scenario.

This is incorrect. EX-2008 at ¶¶ 116-117. Chalom explicitly states that its system works in a limited-resource environment, including on a mobile device with low power (i.e., a small battery). *Id.* at ¶¶ 117. Chalom’s “limited resource” system is perhaps best illustrated by Figure 18 and the related description:



EX-1005 at Figure 18.

Chalom explains that its “system 1700 may be embodied in varying physical styles or form factors[,]” including a “small form factor device 1800.” *Id.* at 22:33-37. As Figure 18 shows, that device has a “camera 1805 . . . integrated into [the] back 1802,” a “camera 1604 integrated into the front 1801,” and “a mobile power source or supply, such as one or more batteries.” *Id.* at 23:16-19, 22:40-45. Chalom goes to great lengths explaining that its system may operate on mobile devices like “cellular telephone[s],” “smart device[s],” or “wearable computers.” *Id.* at 22:40-61, 19:1-14, 3:4-10; *see also* EX-2008 at ¶¶ 117. Chalom also works with a “graphics

processing unit (GPU)” and can incorporate “wireless HDMI[] and/or wireless HD compliant techniques.” EX-1005 at 19:65-20:6. So Chalom provides high quality images. EX-2008 at ¶¶ 116-117.

Contrary to Petitioner’s allegations, Chalom discloses a high-quality, real-time machine learning algorithm that performs perfectly well in a limited power, mobile device scenario. EX-2008 at ¶¶ 116-117. The alleged deficiencies that would cause a POSITA to combine Aslan with Chalom are therefore nonexistent, and Petitioner’s motivation to combine must be rejected. *Id.*

2. Petitioner’s alleged “accuracy and/or efficiency gains” do not motivate a POSITA to combine Chalom and Aslan.

Nothing in Chalom indicates it is inaccurate or inefficient, and thus there is no reason to look to Aslan—and add another machine learning algorithm—to correct these falsified problems with Chalom. EX-2008 at ¶¶ 105-115.

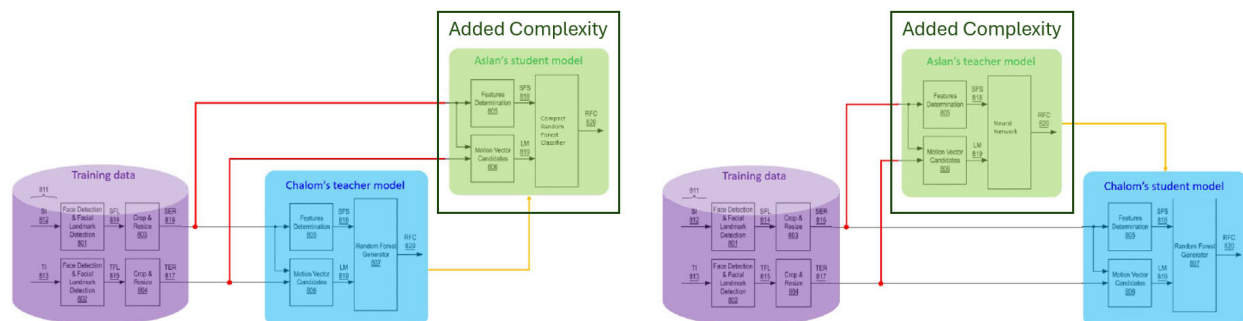
First, as a general principle, adding another machine learning algorithm does not improve accuracy. *Id.* at ¶¶ 108-112. Nor would a POSITA jump to this conclusion (except with the impermissible hindsight employed by Petitioner). *Id.* Instead, a POSITA would improve accuracy in other ways, none of which involve adding another algorithm. *Id.* at ¶ 111. For example, a POSITA would improve an algorithm’s accuracy by increasing the size/diversity of the training data or by changing certain features of the algorithm, such as its parameters or resolution. *Id.* at ¶¶ 108, 111-112.

Petitioner’s expert agrees. When asked how to improve a poorly functioning machine learning algorithm, Petitioner’s expert listed several options but none of them were to add another algorithm. She proposed (1) “running the training process through more iterations” (EX-2009 at 97:17-98:2); (2) “restarting the training with different . . . weight[s]” (*id.* at 98:3-7); (3) changing or tuning “the model hyperparameters” (*id.*); (4) “adding more layers” to the machine learning algorithm (*id.*); and (5) “using the right objective function” (*id.* at 99:18-24). Petitioner’s expert also admitted “it’s a no-brainer that you need a good training set to start that’s representative of your task.” *Id.* at 99:13-17. This is true. If the training data is not of sufficient quantity or diversity, then the algorithm will be poorly trained and give inaccurate results. EX-2008 at ¶ 108. Adding a second algorithm does not provide better training data or add different weights, hyperparameters, layers, or objective functions. *Id.* Thus, a second algorithm would not improve accuracy. *Id.*

If a POSITA were truly concerned with improving Chalom’s accuracy, they would exercise one of the many other options on which both parties’ experts agree, such as ensuring adequate training data and adding sufficient structure, weights, and parameters to the first (and only) machine learning algorithm. *Id.* at ¶ 111. The alleged inaccuracies of Chalom therefore do not motivate a POSITA to look to Aslan or a second machine learning algorithm for a solution. *Id.* at ¶¶ 104-112.

Second, Petitioner’s proposed combination does not result in improved

efficiency or accuracy. EX-2008 at ¶ 113. It does the exact opposite by increasing complexity with more or larger models (which reduces efficiency) and by teaching incorrect gaze correction parameters (which reduces accuracy). The goal of efficiency is poorly served by adding a teacher-student relationship into a single algorithm system. EX-2008 at ¶¶ 113-115. Said another way, a teacher-student system would add complexity by adding more algorithms as shown below:



See Petition at 46-47 (annotated); see also EX-2008 at ¶¶ 113-115. Chalom alone would have the components highlighted in purple and blue above, but Aslan's teacher-student element increases complexity by adding another model (in green) on top of the one presented in Chalom (in blue). *Id.* The inevitable consequence of adding another model here is to add complexity, which drives down efficiency. *Id.*

Moreover, there is no basis to conclude that Aslan's student model would be smaller or more compact (i.e., more efficient). According to Petitioner, Chalom's teacher model and Aslan's student model both get the same training data. Petition at 46. They also both "hav[e] one set of features determination module 805 and motion vector candidates module 806." *Id.* Yet Petitioner argues that the same input and the

same construction would yield a complex, larger model in some instances and a smaller, more compact model in other instances. Petitioner is wrong. If a POSITA desired a more efficient way to deploy Chalom, they would reduce the size of the model by having fewer trees and branches, or compress the model by selecting the most probable trees and branches. EX-2008 at ¶¶ 113-115. This is precisely what Chalom suggests. *Id.* at ¶ 115 (citing EX-1005 at 15:4-7). There is no reason to look for a second algorithm, or a teacher-student system, to improve the efficiency of Chalom. *Id.* at ¶¶ 113-115.

Petitioner's combination also does not increase accuracy since it would result in horizontal gaze correction parameters being taught to vertical gaze correction models and vice versa. *Id.* at ¶ 113. Chalom's users may be looking below, above, right, or left of the camera, so Chalom employs different models, each one to correct for a different potential gaze direction. EX-1005 at 5:37-50, 10:7-64. If the camera is to the left of the device screen, then Chalom implements a left-to-right gaze correction. *Id.* at 10:40-64. On the other hand, if the camera is above the device screen, then Chalom implements a down-to-up gaze correction. *Id.*; *see also* EX-2008 at ¶ 113. Petitioner's alleged system would decrease accuracy by, for instance, putting the **upward** gaze correction model into a teacher-student relationship with the **left or right** gaze correction models. *Id.* The results would be extremely poor because the upward gaze correction model would seek to correct the gaze upward,

not left or right. *Id.* Because Petitioner’s motivation requires more complexity to arrive at less accurate results, a POSITA would not look to alter Chalom with Aslan’s teacher-student model. *Id.* at ¶¶ 113-115.

3. Chalom’s motion vector fields do not lend themselves to combination with Aslan.

Finally, a POSITA would not be motivated to combine Chalom and Aslan simply because they both operate on images. Petition at 43. Rather, a POSITA would recognize that these systems use different techniques for different outcomes, and thus do not support combination. Here Chalom performs a gaze correction task, while Aslan performs an image classification task. *Id.* To correct gaze, Chalom uses motion vector fields that represent two-dimensional displacement vectors for a pixel in an image. EX-2008 at ¶ 119. The motion vector field tells the system how much to shift an image’s pixel in the x and y directions to correct the image. *Id.* To accomplish this shift, systems usually require interpolation techniques and express the vector using decimal numbers (e.g., dx=13.5 pixels and dy=12.6 pixels). *Id.*

In contrast, Aslan simply classifies an image using a class or label typically represented as an index number (e.g., class = 1, class = 2). *Id.* As one example, Aslan may take an image and determine if it is a cat or dog, and assign it a class (e.g., class 1 for dog, class 2 for cat). EX-1007 at ¶¶ 2, 32; *see also id.* at ¶ 25 (explaining that the classification task can have “more than two possible outputs (e.g., labeling images a ‘cat,’ ‘dog,’ ‘duck,’ ‘penguin,’ and so on).”).

Chalom's motion vector fields are therefore not a class or label, and a POSITA would not combine Chalom and Aslan as Petitioner suggests. EX-2008 at ¶¶ 118-120. As noted above, motion vector fields and classes/labels are vastly different in structure and function. *Id.* Petitioner's expert agrees. EX-2009 at 199:8-200:19. Hence, motion vector fields do not represent classes or labels and cannot form a basis or way of combining Chalom and Aslan. EX-2008 at ¶ 117. For the same reasons, finding optimal motion vectors during runtime does not correspond to finding the best class/labels, and does not represent a classification process. *Id.* at ¶ 120. Petitioner's motivation for combining Chalom and Aslan therefore fails on multiple fronts. *Id.* at ¶¶ 105-120.

D. Ground III: Chalom-Aslan Does Not Disclose a Second Machine Learning Algorithm that Receives First Selection Instructions as Required by Claim 1.

Even if a POSITA was motivated to combine these references, Chalom-Aslan does not disclose a second algorithm that receives the first selection instructions as recited in '985 claim 1. More specifically, '985 claim 1 requires a "second machine learning algorithm . . . using . . . the first reference data." EX-1001 at 26:50-53. That "first reference data comprise[s] first editing instructions . . . **and first selection instructions.**" *Id.* at 26:58-60 (emphasis added). Thus, the second machine learning algorithm must also receive and use the first machine learning algorithm's **selection** instructions, not only the editing instructions.

This conclusion is mandated by the plain and ordinary meaning of the term “and.” “And” is conjunctive, not disjunctive. *SIMO Holdings Inc v. Hong Kong uCloudlink Network Tech. Ltd.*, 983 F.3d 1367, 1376-78 (Fed. Cir. Jan. 5, 2021); *Leseman, LLC v. Stratasys, Inc.*, 730 F.Appx. 912, 915 (Fed. Cir. Apr. 18, 2018); *SuperGuide Corp. v. DirecTV Enterprises, Inc.*, 358 F.3d 870, 886 (Fed. Cir. Feb. 12, 2004). As a result, the second machine learning algorithm must use both the first editing instructions **and the first selection instructions**, just as the claim recites.

The Petition is silent on this requirement. There is a complete absence of allegation, much less proof, that Chalom-Aslan’s alleged second machine learning algorithm receives and uses the first **selection** instructions. Petitioner argues that Chalom-Aslan’s “trained teacher model” is the alleged “first selection instructions.” Petition at 58-59. But Petitioner fails to state how or if the second machine learning algorithm uses Chalom-Aslan’s “trained teacher model” as is required by ’985 claim 1. *Id.* 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. Thus, Petitioner alleges that the “trained teacher model” is equivalent to the claimed “first selection instructions,” but fails to address whether that “trained teacher model” is provided to the second machine learning algorithm as required by claim 1.

This absence of proof requires that Petitioner’s Chalom-Aslan combination

fail without reaching the merits of '985 claim 1. *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.”). As such, '985 Patent claim 1 is not unpatentable in view of Chalom-Aslan.

E. Ground III: Chalom-Aslan Fails to Disclose a Second Machine Learning Algorithm that Uses First Reference Data as Recited in Claim Elements 1[E], 16[E], 17[E], 18[E], and 19[E].

Each of the challenged independent claims require a second machine learning algorithm that uses the 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-2008 at ¶¶ 104-120.

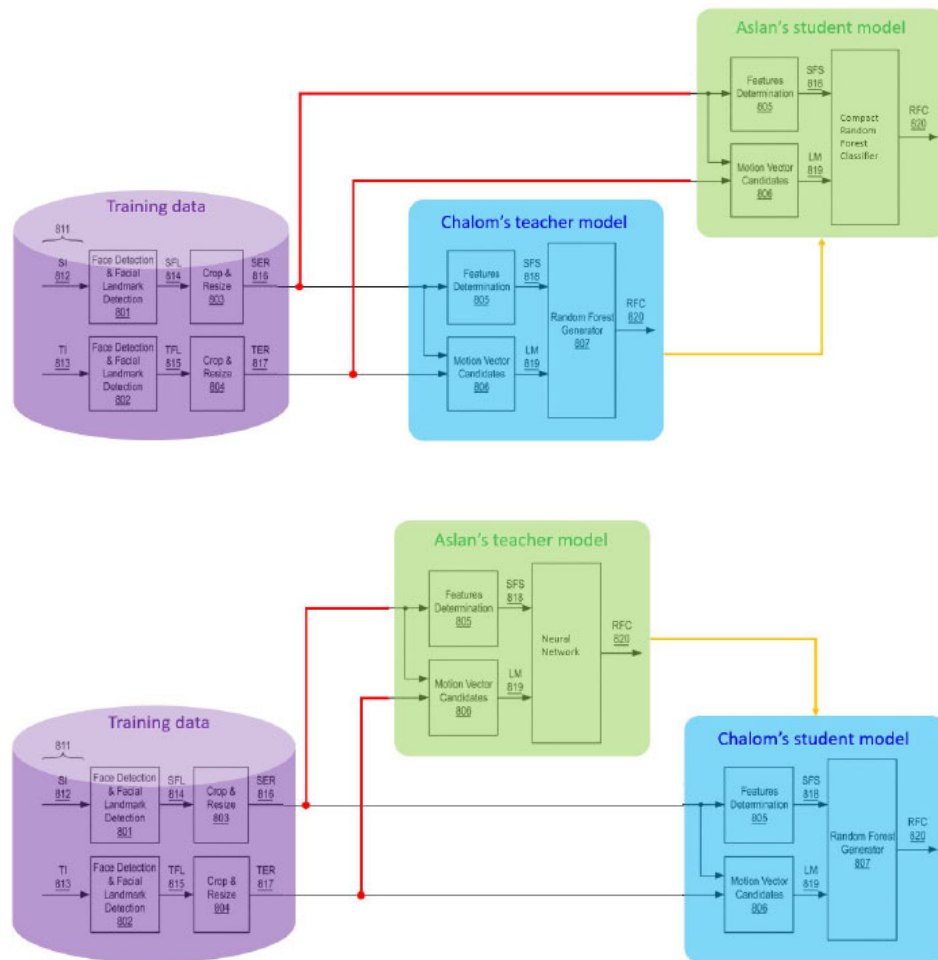
As an initial matter, Petitioner fails to sufficiently explain its Chalom-Aslan combination such that a POSITA could determine precisely what information passes between teacher and student models and how it operates. The Petition’s entire discussion of this portion of element 1[E] is as follows:

In the Chalom-Aslan system, the “task” is generating motion vector fields for gaze correction, and the teacher’s output, e.g., first editing instructions including motion vector fields, is used to train the student.

Petition at 58. This says nothing about where the “teacher’s output” (i.e., the alleged “first editing instructions” of the '985 Patent) enters the student model, how the “teacher’s output” is used by the student model, or how the “teacher’s output” results

in a smaller, more compact student model. EX-2008 at ¶¶ 122-129.

Petitioner’s original description of the combination likewise fails to provide any further detail. Petition at 46-47. There are simply two color-coded diagrams without any explanation of where the “teacher’s output” (the orange arrow below) enters the student model, how the student model uses the “teacher’s output” and in what capacity, or how the “teacher’s output” results in a smaller, more compact student model. EX-2008 at ¶¶ 122-129.



Petition at 46-47.

These are simply dead ends whose details are left to the imagination. *Id.*; *see also* EX-2008 at ¶¶ 122-129. To presume these missing details align with the claimed features of the '985 Patent is the definition of impermissible hindsight and should be rejected. *See, e.g., Insite Vision, Inc. v. Sandoz, Inc.*, 783 F.3d 853, 859 (Fed. Cir. 2015); *see also* MPEP § 2142 (“impermissible hindsight must be avoided”).

Without further detail, a POSITA is left to do as Petitioner commands: “follow the instructions provided in Aslan.” Petition at 45, 47. When a POSITA does so, they do not arrive at a combination that practices the '985 claims. Indeed, they arrive at a teacher-student system that exchanges an “objective function,” which cannot be the claimed “first reference data.” EX-2008 at ¶ 130-133; *see also* 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”).

The '985 Patent's editing instructions “adjust the digital representation of the head region” during runtime while Aslan's objective function is a performance measure used during training. Thus, they are not the same. EX-2008 at ¶¶ 131-133. This conclusion comports with both Aslan and Petitioner's expert. For example, Petitioner's expert explains that an objective function is a “performance measure” of an algorithm's “error” during training. EX-1003 at ¶¶ 23, 28. Similarly, Aslan's use of an “objective function” is in the context of training a machine learning model.

See, e.g., EX-1007 at Figure 7 (stating that “the objective function [is optimized] to train the multiple machine learning models . . .”). Aslan also describes its objective function as a “distance” term or error measurement repeatedly. *See id.* at ¶¶ 29, 31.

In summary, the information sent from teacher to student in Petitioner’s combination is an error assessment made during training of the algorithm. EX-2008 at ¶¶ 131-132. It is not the ’985 Patent’s editing instructions for adjusting the digital representation of the head region. *Id.* at ¶ 133. 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-2008 at ¶ 133.

To suggest otherwise, as Petitioner does, is to use impermissible hindsight. *See, e.g., Insite Vision*, 783 F.3d at 859; *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-2008 at ¶ 131. But in doing so, a POSITA would likewise adopt Aslan’s “objective function.” *Id.* This is different than the claimed editing instructions, as explained above, and suggesting otherwise relies on impermissible hindsight.

F. Chalom-Aslan Does Not Disclose First Reference Data and Second Reference Data that are Different as Required by Claim Elements 1[F], 16[F], 17[D], 18[D], and 19[D].

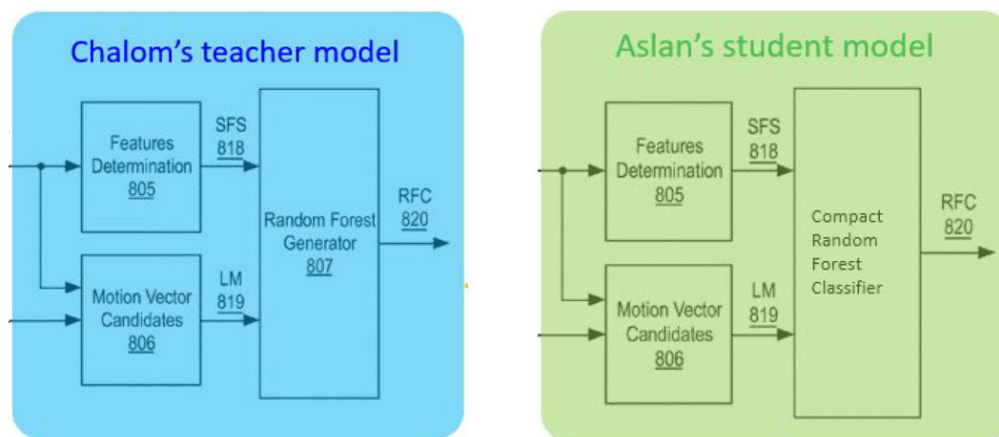
Each independent claim requires “first reference data” generated by the first machine learning algorithm and “second reference data” generated by the second machine learning algorithm. EX-1001 at 26:45-51, 28:55-58, 29:20-26, 29:53-59, 30:40-46. Thus, the ’985 claims require that the “first reference data” be different from the “second reference data” (hence the use of “first” and “second”). Petitioner ignores this distinction, suggesting a system that yields first and second reference data that are the same. Petitioner’s reasoning is flawed for the following reasons.

First, it is well settled that different terms connote different meanings. *See, MicroStrategy Inc. v. Business Objects Americas*, 238 F. App’x 605, 609 (Fed. Cir.

2007) (citing *CAE Screenplates Inc. v. Heinrich Fiedler GmbH & Co. KG*, 224 F.3d 1308, 1317 (Fed. Cir. 2000)). This remains true for terms like “first” and “second.” *See, e.g., 3M Innovative Properties Co. v. Avery Dennison Corp.*, 350 F.3d 1365, 1373 (Fed. Cir. 2003) (explaining that the terms “first pattern” and “second pattern” illustrated “the coexistence of two distinct patterns in the final product.”).

The ’985 terms “first reference data” and “second reference data” should also be given different meanings. EX-2008 at ¶¶ 136-137. Besides the use of the different monikers “first” and “second,” the ’985 specification confirms that the first and second reference data are different. *See, e.g.,* EX-1001 at 2:17-50; *see also* EX-2008 at ¶ 136. For example, the first reference data may be more detailed than the second reference data. EX-1001 at 22:14-17 (describing that MLA1 provides “more highly detailed reference data at the expense of higher computational demands, relative to the second machine learning algorithm MLA2.”). Or “the first selection instructions may be significantly more complex (e.g., involving linear algebra or other relatively computer intensive operations) than the second selection instructions (where the selection instructions may resemble a computationally straightforward look-up table, a combination of a look-up table and a tree structure, or similar).” *Id.* at 16:17-23. Thus, the first reference data are designed to be different from the second reference data for the purpose of striking the proper balance between accuracy and efficiency. EX-2008 at ¶ 136.

With this understanding, Petitioner’s Chalom-Aslan combination fails to disclose the claimed “first reference data” and “second reference data.” *Id.* at ¶¶ 135-137. This is because the Chalom-Aslan combination uses the same inputs, provided to the same modules, which would return the same outputs (i.e., the same “reference data”). *Id.* Petitioner concedes that its combination receives the same training data inputs at both the teacher model and the student model. Petition at 45. Petitioner also concedes that its combination uses the same features determination modules 805 and the same motion vector candidates modules 806:



Id. at 46; *see also id.* (stating that a POSITA would “hav[e] one set of features determination module 805 and motion vector candidates module 806 to provide [the data] . . . to both the teacher and student models.”). Here Chalom-Aslan also uses a random forest for both the teacher and student models. *Id.* As a result, the teacher model and student model would have the same outputs. EX-2008 at ¶ 135. Petitioner’s expert further confirmed this possibility in her deposition. EX-2009 at

120:7-14. This means that this combination of Chalom and Aslan yields the same reference data from both models rather than different “first reference data” and “second reference data” as required by the ’985 claims. *Id.* at ¶¶ 135-136.

For all the reasons noted above, the Petitioner fails to meet its burden under Ground III. *See also* EX-2001 at ¶¶ 97-111.

G. Ground IV: Claim 4 is Not 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* Section V.D above; *see also* EX-2008 at ¶¶ 104-137. Grau does not remedy the deficiencies of the Chalom and Aslan combination 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-2008 at ¶¶ 104-137. The Board should therefore not find claim 4 unpatentable.

H. Ground V: Claim 7 is Not 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* Section V.D above; *see also* EX-2008 at ¶¶ 104-137. Pace

does not remedy the deficiencies of the Chalom and Aslan combination 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-2008 at ¶¶ 104-137. The Board should therefore not find claim 7 unpatentable.

VI. CONCLUSION

RealD respectfully requests that the Board uphold the patentability of each of the challenged claim because Petitioner has failed to meet its burden on any of the Grounds.

Respectfully submitted,

Dated March 15, 2024

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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 Response to the Petition for *Inter Partes* Review of U.S. Patent No. 10,740,985 contains 8,121 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.

Respectfully submitted,

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CERTIFICATE OF SERVICE

A copy of Patent Owner's Response to the Decision granting *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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