

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.,

Petitioner,

v.

PERCEPTIVE AUTOMATA LLC,

Patent Owner.

Case No. IPR2025-01574

Patent No. 11,126,889

PATENT OWNER'S RESPONSE

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PATENT OWNER’S EXHIBIT LIST

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2001	Tesla February 1, 2022 IDS
2002	Tesla March 1, 2022 IDS
2003	Tesla March 4, 2022 IDS
2004	Tesla March 17, 2022 IDS
2005	Tesla March 18, 2022 IDS
2006	Tesla March 18, 2022 IDS
2007	Tesla March 21, 2022 IDS
2008	Tesla March 22, 2022 IDS
2009	Tesla March 22, 2022 IDS
2010	Tesla May 4, 2022 IDS
2011	Tesla May 10, 2022 IDS
2012	Tesla May 11, 2022 IDS
2013	Tesla May 11, 2022 IDS
2014	Tesla May 11, 2022 IDS
2015	Tesla May 12, 2022 IDS
2016	Tesla May 12, 2022 IDS
2017	Tesla May 13, 2022 IDS
2018	Tesla May 13, 2022 IDS
2019	Tesla May 25, 2022 IDS
2020	Tesla June 28, 2022 IDS
2021	Perceptive’s Original Complaint
2022	Tesla’s Motion to Dismiss
2023	Perceptive’s First Amended Complaint
2024	Tesla’s Motion to Stay
2025	Perceptive’s Opposition to Tesla’s Motion to Stay
2026	Tesla’s Reply in Support of Motion to Stay
2027	Perceptive’s Sur-Reply in Opposition to Motion to Stay
2028	Docket Sheet
2029	Motion for Protective Order
2030	Protective Order
2031	Operative Docket Control Order
2032	Perceptive’s Document Request Letter
2033	Perceptive’s First Set of Interrogatories
2034	Tesla’s First Set of Interrogatories
2035	Tesla’s Notice of Broadened Sotera Plus Stipulation

2036	Tesla's Initial and Additional Disclosures
2037	District Court Statistics on Post-Institution Motions to Stay Pending IPR
2038	District Court Time-to-Trial Statistics
2039	Declaration of Eli Saber, Ph.D.
2040	CV of Eli Saber, Ph.D.
2041	C. Aggarwal, "Neural Networks and Deep Learning", Springer ISBN 978-3-319-94462-3
2042	Kooij JFP, Schneider N, Flohr F, Gavrilă DM (2014) Context-based pedestrian path prediction. In: Proceedings of the European Conference on Computer Vision (ECCV). Berlin: Springer, pp. 618–633
2043	A. Zyner, S. Worrall, J. Ward and E. Nebot, "Long short term memory for driver intent prediction," 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, USA, 2017, pp. 1484-1489
2044	Deposition of Dr. Jason Janét

I. INTRODUCTION

Pursuant to 37 C.F.R. § 42.120, Patent Owner Perceptive Automata LLC (“Perceptive”) submits this Response to the Petition for *Inter Partes* Review (“Petition”) filed by Tesla, Inc. (“Tesla”) challenging claims 1-20 of U.S. Patent No. 11,126,889 (the “’889 patent”) (Ex. 1001).

The Petition presents four grounds of obviousness. Ground 1 relies on U.S. Patent Application Publication No. 2018/0373980 (“Huval”) (Ex. 1004) and U.S. Patent No. 10,496,091 (“Ross”) (Ex. 1005). Grounds 2-4 add International Publication No. WO2014/210334 (“Cox”) (Ex. 1006) and/or U.S. Patent Application Publication No. 2016/0162456 (“Munro”) (Ex. 1009) to the combination of Huval and Ross.

Tesla’s proposed combination of Huval and Ross does not teach several elements of the challenged claims—which is perhaps why Tesla attempts (unsuccessfully) to add additional references to Grounds 2-4. But, Tesla’s attempts to change its theories by adding in these additional references create additional flaws, including claim elements that are not met by the proposed combinations and lack of motivations to combine the references in the manner Tesla alleges.

Tesla’s attempt to combine Huval and Ross with Cox does not solve these problems. Cox discloses processes whose aim is to improve machine learning models for recognizing faces in images. In contrast, the ’889 patent claims concern

processes and systems for a different application of machine learning—specifically, predicting what road users (motorists, bicyclists, pedestrians, etc.) will do when navigating streets with an autonomous vehicle. As discussed below, Cox does not teach several elements of the challenged claims—most notably the requirements of generating and predicting “summary statistics describing the state of mind of the user in [an] image”—which is significant for the ’889 patent’s autonomous driving applications but not for face detection. While Tesla and its expert (inconsistently) point to myriad features of Cox as allegedly being summary statistics, each theory fails, which is fatal to Tesla’s Cox-based grounds. Tesla’s Cox-based grounds have additional shortcomings, including failure to properly consider the *Graham* factors and lack of motivation to combine Cox with the other references.

Tesla’s grounds that rely on Munro have similar deficiencies. Munro concerns natural language processing of documents, not any type of machine learning relating to images (for autonomous driving or otherwise). Despite Munro’s focus on a different field, Tesla incorrectly relies on its response aggregation process as supposedly teaching “summary statistics describing the state of mind of the user in [an] image”—an argument just as weak as it sounds on its face. Munro’s different focus also means that a POSITA would not have been motivated to combine it with Huval and Ross.

Finally, Tesla attempts to argue that many limitations of the challenged claims should not be given patentable weight in the invalidity analysis under the printed matter doctrine. Tesla’s arguments come woefully short on both the law and the facts and should be rejected.

Given the flaws in Tesla’s theories, the Board should conclude that challenged claims 1-20 are not unpatentable.

II. THE ’889 PATENT AND THE CHALLENGED CLAIMS

A. Overview of the ’889 Patent

The inventions disclosed and claimed in the ’889 patent generally relate to systems, computer-implemented methods, and computer readable media associated with controlling autonomous vehicles by “judging the behavior of people near a vehicle in a way that more closely resembles how human drivers would judge the behavior.” Ex. 1001, 3:50-53. The ’889 patent discloses an implementation for achieving this result by obtaining user responses of images displaying road scenes to determine a road user’s “state of mind—e.g. that a pedestrian is likely to cross the street or that an oncoming vehicle is unlikely to be willing to yield to the vehicle containing the sensor if the vehicle containing the sensor needs to turn.” *Id.* at 10:24-43; *see also id.* at 5:46-6:7, 9:1-10:5. The images of road users (e.g., motorists, cyclists, pedestrians) in a road scene can be captured by the autonomous vehicle and sent to a remote location for obtaining user responses and training a learning based

model. *Id.* at 7:45-8:8. Training dataset(s) comprising summary statistics of the user responses are used to train a learning based model so that the learning based model can predict whether a road user in a new image has a given “state of mind—e.g. that a pedestrian is likely to cross the street or that an oncoming vehicle is unlikely to be willing to yield to the vehicle containing the sensor if the vehicle containing the sensor needs to turn.” *Id.* at 10:24-43; *see also id.* at 6:44-7:25, 11:10-12:25. “The trained model or algorithm makes a prediction of what a pedestrian or other person shown in the ‘live data’ would do based on the summary statistics and/or training labels” *Id.* at 7:26-29; *see also id.* at 12:26-13:53. “The predictions produced by the trained model comprise a set of predictions of the state of mind of road users that can then be used to improve the performance of autonomous vehicles, robots, virtual agents, trucks, bicycles, or other systems that operate on roadways by allowing them to make judgments about the future behavior of road users based on their state of mind.” *Id.* at 7:38-44.

B. Claim Overview

Independent claims 1, 2, and 12 are reproduced below:

Claim 1	Limitations
1[pre]	A computer system comprising: a computer processor; and a non-transitory computer readable storage medium storing instructions that when executed by the computer processor cause the

	computer processor to perform steps of a computer-implemented method for controlling an autonomous vehicle based on a predicted state of mind of road users in a scene captured by a camera of the autonomous vehicle, the steps comprising:
1[a]	receiving a plurality of images displaying road scenes captured by one or more vehicles;
1[b]	receiving a plurality of user responses, each user response describing a state of mind of a road user displayed in one or more images;
1[c]	generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images;
1[d]	training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image;
1[e]	receiving, by an autonomous vehicle, a new image captured by a camera of the autonomous vehicle, the new image of a scene including a road user;
1[f]	predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image; and
1[g]	controlling the autonomous vehicle based on the prediction of the supervised learning based model.
Claim 2	Limitations
2[pre]	A computer-implemented method for controlling an autonomous vehicle based on a predicted state of mind of road users in a scene captured by a camera of the autonomous vehicle, the method comprising:
2[a]	receiving a plurality of images displaying road scenes captured by one or more vehicles;

2[b]	receiving a plurality of user responses, each user response describing a state of mind of a road user displayed in one or more images;
2[c]	generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images;
2[d]	training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image;
2[e]	receiving, by an autonomous vehicle, a new image captured by a camera of the autonomous vehicle, the new image of a scene including a road user;
2[f]	predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image; and
2[g]	controlling the autonomous vehicle based on the prediction of the supervised learning based model.
Claim 12	Limitations
12[pre]	A non-transitory computer readable storage medium storing instructions that when executed by a computer processor cause the computer processor to perform steps of a computer-implemented method for controlling an autonomous vehicle based on a predicted state of mind of road users in a scene captured by a camera of the autonomous vehicle, the steps comprising:
12[a]	receiving a plurality of images displaying road scenes captured by one or more vehicles;
12[b]	receiving a plurality of user responses, each user response describing a state of mind of a road user displayed in one or more images;
12[c]	generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images;

12[d]	training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image;
12[e]	receiving, by an autonomous vehicle, a new image captured by a camera of the autonomous vehicle, the new image of a scene including a road user;
12[f]	predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image; and
12[g]	controlling the autonomous vehicle based on the prediction of the supervised learning based model.

III. LEVEL OF ORDINARY SKILL

Tesla alleges that a POSITA in the field of the '889 patent as of July 5, 2017 “would have had at least: (1) a bachelor’s degree in electrical engineering, computer engineering, computer science, or equivalent course work, with two to three years of work experience in computer vision, image/video processing, and/or machine learning; or (2) a master’s degree in electrical engineering, computer engineering, computer science, or equivalent course work, with a focus in computer vision, autonomous vehicles, and/or machine learning.” Pet. 16; *see also* Ex. 1003, ¶ 63. Neither Perceptive nor its expert (Dr. Saber) dispute this definition for purposes of resolving this IPR proceeding. Ex. 2039, ¶ 53.

Notably, Tesla does not allege that its expert (Dr. Janét) meets this definition, nor does Dr. Janét opine that he does. *See* Pet.; Ex. 1003. As such, Tesla has not established that Dr. Janét was a POSITA at the relevant time for purposes of this

proceeding and thus his opinions should not be given consideration. *See, e.g., Kyocera Senco Indus. Tools Inc. v. Int’l Trade Comm’n*, 22 F.4th 1369, 1377-78 (Fed. Cir. 2022) (finding abuse of discretion when ALJ admitted “testimony on any issue that is analyzed through the lens of” a POSITA when expert did not qualify as POSITA). In contrast, Dr. Saber not only meets this definition today, but he also met it in the July 2017 timeframe. Ex. 2039, ¶ 53.

IV. CLAIM CONSTRUCTION

Petitioner alleges that “there is no need for claim construction” in this proceeding. Pet. 16-17. Patent Owner submits that the Board need not construe any claim terms in a particular manner to conclude that the challenged claims are not unpatentable. *See Wellman, Inc. v. Eastman Chem. Co.*, 642 F.3d 1355, 1361 (Fed. Cir. 2011) (claims “need only be construed ‘to the extent necessary to resolve the controversy’”).

V. APPLICABLE LEGAL STANDARDS

A. Tesla’s Burden

As the petitioner, Tesla bears the burden of showing the unpatentability of the challenged claims by a preponderance of the evidence. *See* 35 U.S.C. § 316(e). This burden never shifts to Perceptive. *See Harmonic Inc. v. Avid Tech., Inc.*, 815 F.3d 1356, 1363 (Fed. Cir. 2016) (“[T]he Petitioner has the burden from the onset to show with particularity why the patent it challenges is unpatentable.”); *Amazon Web*

Services, Inc. v. Saint Regis Mohawk Tribe, IPR2019-00103, Paper 22 at 17 (PTAB May 10, 2019) (“The burden is on Petitioner, not the Board, to specify with particularity how [the prior art] teaches [various claimed features].”); *Liberty Mut. Ins. Co. v. Progressive Cas. Ins. Co.*, No. CBM2012-00003, Paper 8 at 14-15 (P.T.A.B. Oct. 25, 2012) (representative) (“[I]t is the responsibility of the Petitioner to clearly articulate [the proposed combination].”); 37 C.F.R. §§ 42.22(a)(2), 42.104(b)(4). The Petition must provide an understandable explanation of the element-by-element specifics of the patentability challenges. *See* 35 U.S.C. § 312(a)(3); 37 C.F.R. §§ 42.22(a)(2), 42.104(b)(3)-(4).

B. Obviousness in IPR Proceedings

Each of Tesla’s grounds relies on obviousness. Section 103 of the Patent Act provides that “[a] patent may not be obtained . . . if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains.” 35 U.S.C. § 103(a). If a single element of the claim is absent from the prior art, the claim cannot be considered obvious. *See CFMT, Inc. v. YieldUp Int’l Corp.*, 349 F.3d 1333, 1342 (Fed. Cir. 2003) (“[O]bviousness requires a suggestion of all limitations in a claim.”) (citing *In re Royka*, 490 F.2d 981, 985 (C.C.P.A. 1974)); *In re Rijckaert*, 9 F.3d

1531, 1534 (Fed. Cir. 1993) (reversing obviousness rejection where prior art did not teach all claim limitations)).

Further, “[b]ecause an *inter partes* review may only be requested ‘on the basis of prior art consisting of patents or printed publications,’ . . . expert testimony cannot take the place of disclosure from patents or printed publications.” *See* OFFICE PATENT TRIAL PRACTICE GUIDE at § I.G. “In other words, expert testimony may explain ‘patents and printed publications,’ but is not a substitute for disclosure in a prior art reference itself.” *Id.*; *see In re Kahn*, 441 F. 3d 977, 988 (Fed. Cir. 2006) (“[R]ejections on obviousness grounds cannot be sustained by mere conclusory statements; instead, there must be some articulated reasoning with some rational underpinning to support the legal conclusion of obviousness”).

C. The *Graham* Factors in IPR Proceedings

Obviousness is resolved on several factual determinations including: (1) the scope and content of the prior art, (2) any differences between the claimed subject matter and the prior art, and (3) the level of ordinary skill in the art. *See Graham v. John Deere Co.*, 383 U.S. 1, 17-18 (1966). These factors provide the threshold “background” for the obviousness determination, and without undertaking an analysis of the *Graham* factors, a proper obviousness determination cannot be made. *Id.* at 18 (“Under § 103, the scope and content of the prior art are to be determined; *differences between the prior art and the claims at issue are to be ascertained*; and

the level of ordinary skill in the pertinent art resolved. *Against this background, the obviousness or nonobviousness of the subject matter is determined.*") (emphasis added).

In view of this clear Supreme Court precedent, it is not surprising that IPR petitions "must address the *Graham* factors." *Eizo Corp. v. Barco N.V.*, No. IPR2014-00358, Paper 11 at 29-30 (P.T.A.B. July 23, 2014) (citing *Graham*, 383 U.S. at 17-18). For example, the Board faulted the petitioner in *Eizo* for failing to identify the differences between the claimed subject matter and the prior art. *Id.* at 29-30. In particular, the Board found insufficient the petitioner's "conclusory assertion" that "[t]o the extent [the first reference] may not explicitly teach" the limitation, the second reference "explicitly teaches this limitation." *Id.* at 30. The Board explained that "such an assertion fails to resolve the exact differences sought to be derived from" the second reference. *Id.* (finding that petitioner had not shown a reasonable likelihood of prevailing on that ground). Other Board decisions have reached the same result. *See, e.g., Moses Lake Indus., Inc. v. Enthone, Inc.*, No. IPR2014-00246, Paper 6 at 17 (P.T.A.B. June 18, 2014); *eBay, Inc. v. Paid, Inc.*, No. CBM2014-00125, Paper 15 at 21 (P.T.A.B. Sept. 30, 2014).

VI. THE CHALLENGED CLAIMS ARE NOT UNPATENTABLE UNDER GROUND 1

The Petition challenges claims 1-20 of the '889 patent as obvious over Huval and Ross. *See* Pet. 17-55. However, as discussed in detail below, the challenged

claims are not unpatentable in view of Huval and Ross not only because Huval and Ross fail to teach multiple elements of the challenged claims, but also because Tesla failed to consider or address the *Graham* factors in the Petition.¹

A. Huval and Ross

Huval and Ross relate to different machine learning systems, with different aims and different processes for generating training data and for training their neural networks. Huval describes a machine learning system that is designed to identify objects in images. *See* Ex. 1004, Abstract. To train its neural network to better identify objects in images, Huval describes a process whereby images are labeled by both human annotators (i.e., “manual” labels) and by its neural network (i.e., “automated” labels). *See id.*, [0008]-[0009]. Where the manual and automated labels for an object in an image differ, Huval describes a label conflict resolution process that involves showing human annotators the image and the manual and automated labels, and having the human annotators confirm which label is correct. *See id.* Huval then takes the results of these conflict resolution responses from the human

¹ In discussing the elements of the challenged claims that Huval and Ross do not disclose, Patent Owner references the Petition’s allegations for claim 2, because Tesla’s allegations for the corresponding elements of claims 1 and 12 merely refer back to its allegations for claim 2. *See* Pet. 51-55.

annotators and “average[s] or otherwise combin[es] responses . . . into a final manually-confirmed label for the optical image.” *Id.*, [0085]. This “final” label is then used as part of the training dataset to further train the neural network. *See id.*

Ross, by contrast, describes a machine learning system for a different set of tasks—specifically, predicting not only the intent of an object in an image (e.g., whether a pedestrian will enter a crosswalk at an intersection), but also the trajectory of that object, the time “when the action is likely to occur,” and “associated likelihood values” for those predictions. *See* Ex. 1005 at, e.g., 9:27-41. Ross accomplishes this using a training process that is vastly different from Huval’s. In Ross’s training process, the training data includes not only an image at one point in time, but also image/video data past that point in time that shows what actually occurred (e.g., whether the pedestrian actually entered the crosswalk or not). *See id.* at, e.g., 9:41-10:10. Ross describes looking past the point in time, determining what the object actually did, and that action is “marked as the correct intent” and used to further train the neural network. *See id.*

Despite the significant differences between these systems, Tesla proposes to cherry-pick features from Ross to add to Huval’s system. Critically, Tesla does not provide articulated reasoning for this combination, as it does not explain what exactly its proposed combination is, how the combined system would operate, and how a POSITA would have performed the combination. *See* Section VI.D, *infra*.

Moreover, the proposed combination of Ross and Huval fails to teach every element of the challenged claims.

B. Huval and Ross Do Not Teach “generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images”

Nothing in Huval or Ross teaches elements 1[c], 2[c], or 12[c], which each require “generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images.” The Petition alleges that Huval teaches this element in two ways, either through (i) “combin[ing] the labels by determining an ‘average’ to generate a final label for each image,” or (ii) “[t]he training set of Huval . . . includ[ing] the manual labels that are ‘packaged’ into the training set.” Pet at 33-34. Both of these theories fail.

Tesla’s first theory (Huval’s “combin[ing] the labels by determining an ‘average’”) misinterprets what Huval’s disclosure means by “averag[ing] or otherwise combin[ing] responses.” Pet. at 33; Ex. 1004, [0085]. Huval does not describe calculating a mean or other statistic, but instead describes “averag[ing] or otherwise combin[ing] responses . . . into a final manually-confirmed label for the optical image.” Ex. 1004, [0085]. In other words, the result of this averaging/combining process is not a statistic, but instead a “final manually-confirmed label.” Such labels are not “summary statistics of user responses” as

required by the challenged claims. Ex. 2039, ¶ 65. Huval’s example of this process, which describes “calculat[ing] a binary combination,” only further confirms this, as that binary combination is “either the manual label or the automated label” and is the binary combination of “a first conformation of one of the first manual label and the first automated label received from a first human annotator in the set; a second confirmation of one of the first manual label and the first automated label received from a second human annotator in the set; etc.” Ex. 1004, [0085]; Ex. 2039, ¶ 65. The result of that binary combination calculation is a final label, not a summary statistic of user responses as required by the challenged claims. Ex. 1004, [0085]; Ex. 2039, ¶ 65.²

Tesla’s second theory is that “[t]he training set of Huval comprises summary statistics of [the] user responses at least because it includes the manual labels that are ‘packaged’ into the training set and reflect the summarized statistics of the content of all accurate manual human labels that have been obtained and are used

² Moreover, Tesla’s attempt to compare Huval’s description of this averaging to the ’889 patent’s discussion of “measurements of the central tendency of the distribution of scores like the mean, median, or mode” is incorrect. *See* Pet at 34 (citing Ex. 1001, 10:60-67, 6:8-24). Nothing in the cited portions of Huval describes computing a mean, median, or mode of any figures. Ex. 2039, ¶ 66.

for training.” Pet. 34-35. This assertion is incorrect. As Dr. Saber explains, “[t]he fact that Huval teaches that the training set includes the images and their labels does not mean that the training set includes any kind of summary statistics.” Ex. 2039, ¶ 67. Nor is Tesla correct that “because these aggregated labels are a collection of measurements summarizing how data has been labeled, a POSITA would have recognized that these aggregated labels form statistics.” Pet. 35. Dr. Saber confirms that “the labels stored in Huval’s training set are merely the manual or automated labels for the content of the image (e.g., a car defined by a boundary box) and are not any kind of statistic, much less a summary statistic.” Ex. 2039, ¶ 67.

Tesla’s expert declaration adds nothing here, as its expert merely regurgitates the Petition’s allegations. *Compare* Pet. 33 with Ex. 1003, ¶¶ 91-95. *See Xerox Corp. v. Bytemark, Inc.*, IPR2022-00624, Paper 12 at 5 (P.T.A.B. Feb. 10, 2023) (affirming Board’s decision to “giv[e] little weight to Petitioner’s expert because the expert declaration merely offered conclusory assertions without underlying factual support and repeated, *verbatim*, Petitioner’s conclusory arguments”); *In re Ethicon, Inc.*, 844 F.3d 1344, 1348, 1352 (Fed. Cir. 2017) (concluding that the Board properly gave “little weight” to conclusory expert testimony of objective indicia); *TQ Delta, LLC v. Cisco Sys.*, 942 F.3d 1352, 1359 (Fed. Cir. 2019) (“This court’s opinions have

repeatedly recognized that conclusory expert testimony is inadequate to support an obviousness determination on substantial evidence review”).

Each of Tesla’s theories therefore fail, and Huval and Ross do not teach “generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images,” as required by elements 1[c], 2[c], and 12[c].

C. Challenged Dependent Claims

As discussed above, Huval and Ross do not teach every element of claims 1, 2, and 12. Each of the remaining challenged claims in Ground 1 depend from one of those independent claims, and Huval and Ross do not render them obvious for the same reasons.

D. A POSITA Would Not Have Been Motivated to Combine Huval and Ross in the Manner Tesla Alleges

As discussed above, Huval and Ross describe fundamentally different machine learning systems, with different goals, and with vastly different mechanisms for training their neural networks. Not only do Tesla and its expert fail to account for these differences, but they fail to explain why a POSITA would have been motivated to cherry-pick the identified features from Ross and add them to Huval, and they fail to explain how a POSITA could or would have implemented Ross’s features in Huval’s system. Tesla and its expert also fail to explain what their proposed modifications are or how the combined system would operate. As a result,

Tesla has not met its burden to provide “some articulated reasoning with some rational underpinning to support the legal conclusion of obviousness.” *In re Kahn*, 441 F. 3d at 988.

Tesla’s first proposed modification to Huval’s system in view of Ross is to have the “annotation labels provided by human annotators label observed road user actions in image data” instead of identifying and locating an object in the image. Pet. 20. Under this proposed modification, Huval’s system would be highly illogical, as its manual annotations would relate to observed road user actions but its automated labels would still relate only to the identification and location of objects in the image. Ex. 2039, ¶ 73. A POSITA would not have been motivated to make such a nonsensical modification to Huval. *Id.* Tesla also does not explain the significant redesign of Huval’s system that would be necessary to accomplish this modification, or how such a modification would impact Huval’s system as a whole. Ex. 2039, ¶¶ 73-74.

Moreover, the extent of Tesla’s proposed modification is unclear. Tesla does not articulate whether this proposed modification would be accomplished by using Ross’s process for labeling the image (i.e., by looking at image/video data past the particular point in time to determine what the road user did in a given scenario (*see* Ex. 1005, 9:41-10:10) or by using Huval’s existing process of relying on either a human or automated prediction or judgment as to what the road user will do based

on an image at a fixed point in time (*see* Ex. 1004, [0008]-[0009]). Ex. 2039, ¶ 74. If the combined Huval-Ross system uses Huval’s existing process, the prediction of road user actions will increase the occurrence of conflicts between the human and automated labels, requiring significant additional usage of the human annotation portals for label conflict resolution. Ex. 2039, ¶ 74. Huval specifically teaches away from requiring significant amounts of human annotation, as it drastically increases the cost of training and operating the system. *See* Ex. 1004, [0011] (“Similarly, manual labeling of features in optical data by one human annotator and subsequent checking of these labeled features by other human annotators . . . may further escalate costs to develop the training set, both in terms of human labor hours per label and transmission of the same optical data to multiple local computer systems.”). On the other hand, to use Ross’s process of looking past the particular point in time, “Huval’s system would have to be significantly reconfigured to provide the additional image/video data to make such a determination of what the road user in fact did.” Ex. 2039, ¶ 74. This would require significantly more storage space and processing power. *Id.* Tesla does not address these issues anywhere in its motivation to combine allegations. *See* Pet. 20-26.

Tesla’s second alleged modification (i.e., to modify Huval to both train its model with images labeled with observed road user actions and to have its model predict intents, trajectories, when such actions will occur, and associated likelihood

values) is equally unsupported. *See* Pet. 20. As discussed above, if a POSITA were to have implemented this change, conflicts between human and automated labels in Huval’s modified system would significantly increase, which would necessitate more human annotation for conflict resolution—something Huval expressly teaches away from doing. *See* Ex. 1004, [0011]; Ex. 2039, ¶¶ 74, 75. Moreover, to the extent Tesla proposes to implement this modification by using Ross’s process of looking at image/video data past the particular point in time in the image, Huval’s system would have to “have been significantly reconfigured to provide the additional image/video data to make such a determination of what the road user in fact did.” *Id.*

This is not a scenario where “there are a finite number of identified, predictable solutions” to address the shortcomings of Huval, nor does Tesla allege as much. *KSR Int’l Co. v. Teleflex Inc.*, 550 U.S. 398, 421 (2007). To the contrary, the solutions here are not identified, predictable, or even explained. Tesla thus has not met its burden. *In re Kahn*, 441 F. 3d at 988.

Tesla’s third proposed modification to Huval in view of Ross (i.e., to control an autonomous vehicle based on the predictions of the Huval-Ross combination) is flawed because it fails to account for the realities of operating such a system in an autonomous driving environment. Ex. 2039, ¶ 77. As Dr. Saber explains, “[a]utonomous vehicle systems must be robust enough and have enough processing

power to make such intent predictions and control the vehicle in very short amounts of time to allow the autonomous vehicle to react to the intent prediction in time (e.g., by steering/swerving, braking, etc.).” *Id.* Neither Tesla nor its expert explain how Huval’s model could be modified to make a multitude of predictions within the allotted amount of time to allow the system to control the autonomous vehicle—or even whether a POSITA would have had a reasonable expectation of success in doing so. *See id.*

In sum, Tesla’s vague allegations do not come close to satisfying its burden, and Tesla has failed to show that a POSITA would have been motivated to combine Huval and Ross in the manner Tesla and Dr. Janét allege. Thus, the challenged claims should be found not unpatentable under Ground 1.

VII. THE CHALLENGED CLAIMS ARE NOT UNPATENTABLE UNDER GROUND 2

Ground 2 of the Petition challenges claims 1-20 of the ’889 patent as obvious over Huval, Ross, and Cox. *See generally* Pet. 55-68. However, as discussed below, the challenged claims are not unpatentable over Huval, Ross, and Cox not only because the proposed combination fails to teach elements of the challenged claims, but also because Tesla did not properly analyze the *Graham* factors and because a POSITA would not have been motivated to combine Huval, Ross, and Cox in the manner Tesla alleges.

A. Cox

As stated above, Huval and Ross’s focus on object detection and prediction, respectively, in road scenes for autonomous vehicles. In contrast, Cox generally describes processes for improving machine learning systems for face detection in images. Ex. 1006, [0002] (describing “a machine-learning system trained to decide whether a face is present in an image will be given set of human-generated ‘ground truth’ labels that signal whether a human judged the image to contain a face or not”); *see also id.* (“In this case, the job of the machine-learning system is to emit analogous labels (for example, ‘face present’ and ‘face not present’) in response to new, previously unseen images.”). Cox uses this diametric “face present”/“face not present” example throughout its disclosure. *Id.* at [0002], [0008], [0010], [0012], [0013], [0016], [0017], [0026], [0029], [0033], [0039]-[0048], [0050], [0052]-[0056], Figs. 5, 6, 7, 9, 10, 11, 12 (all describing using Cox’s disclosure for face detection).

Cox explains that a limitation of machine learning at the time was “the unavailability of labeled data; it is difficult to provide an algorithm with enough labeled training data to achieve optimal performance.” *Id.*, [0003]. As Cox explains, “[w]ithout sufficiently large datasets, machine-learning algorithms tend to ‘overfit’ the data, adapting to spurious structure present in the training set that is not representative of the larger distribution of all examples in the real world.” *Id.*

To address the stated issue, Cox describes using “psychometric data” as an input in the machine learning system, in addition to the human annotations of the image. *See id.* at [0005]-[0010]. This psychometric data includes information about how long the human viewed the image before providing his or her response. *See id.* As Cox describes, this information can be used to determine the degree of “penalization” for misclassifying the image (i.e., indicating that the image contains a face when it does not, or vice versa), because “greater penalties may be introduced for misclassification . . . of examples that are easily classified by humans” and “lesser penalties may be introduced for misclassification of examples that are relatively more difficult for humans to classify.” *See id.*, [0005]. These penalties are used in a “human-weighted loss function” to train the model, with the aim of improving its accuracy. *See id.*, [0005]-[0010].

Because of the fundamental differences between Huval and Ross, on one hand, and Cox, on the other hand, a POSITA would not have been motivated to combine Huval, Ross, and Cox, particularly in the manner Tesla alleges. Further, given Cox’s fundamentally different purpose, Tesla’s attempts to use Cox to cure the shortcomings of Huval and Ross fall woefully short of meeting Tesla’s burden.

B. Huval, Ross, and Cox Do Not Teach “generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images”

As discussed in Section VI.B above, the combination of Huval and Ross does

not teach elements 1[c], 2[c], or 12[c], which each require “generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images.” For these elements, Tesla switches its theory from Ground 1 to Ground 2, here relying instead on several features from Cox to attempt to satisfy these elements. Each of Tesla’s theories again fail.

Psychometric data: Tesla first alleges that Cox’s psychometric data meets the claimed requirement of “summary statistics of user responses.” Pet. 63. Cox expressly describes its psychometric data as “includ[ing] or consist[ing] essentially of (i) response time for classifying one or more features, (ii) accuracy of feature classification, and/or (iii) presentation time of one or more training objects.” Ex. 1006, [0008]. Neither “response time” (i.e., the amount of time it takes a particular user to annotate a particular image), “accuracy of feature classification” (i.e., whether the particular user’s annotation of a particular image is correct), nor “presentation time” (i.e., the amount of time the particular image was displayed to the particular user) is a summary statistic of any kind. Instead, as Dr. Saber explains, “each piece of psychometric data relates to a particular annotator’s labeling of a particular image.” Ex. 2039, ¶ 90.

Nowhere does the Petition or Tesla’s expert declaration point to any disclosure in Cox of preparing any summary statistics from Cox’s psychometric

data. *See* Pet. 63-64; Ex. 1003, ¶ 160. Instead of showing that the reference itself contains the necessary disclosure, which cannot be done, Tesla and its expert allege without any explanation that Cox’s psychometric data as a whole “summarizes statistics on how human annotators annotated training images.” Pet. 63; Ex. 1003, ¶ 160. But Tesla’s identification of the entire psychometric dataset (i.e., every annotator’s response time to every image, the accuracy of every response, and the presentation time of every image to every annotator) is not a summary. Ex. 2039, ¶ 90.³ It is merely a set of data.

Tesla’s expert declaration adds nothing to the analysis here, as Dr. Janét merely regurgitates the allegations in the Petition. *Compare* Pet. 63-64 with Ex.

³ Moreover, Tesla’s effort to compare Cox’s psychometric data to the ’889 patent specification’s description of summary statistics (Pet. 63-64) is inaccurate. The specification indicates that summary statistics can “be associated with a [] central tendency, variance, skew, kurtosis, scale, or histogram. For example, the amount of time users took to input their responses can be characterized in terms of central tendency, variance, skew, kurtosis, scale, histogram.” Cox’s psychometric dataset is not a central tendency, variance, skew, kurtosis, scale, or histogram. Ex. 2039, ¶¶ 92, 93.

1003, ¶ 160. *See Xerox*, Paper 12 at 5; *Ethicon*, 844 F.3d at 1348, 1352; *TQ Delta*, 942 F.3d at 1359.

Item-response curves: Tesla next alleges that Cox’s “item-response curves” can constitute the claimed “summary statistics of user responses.” Pet. 64. Cox’s only descriptions of item-response curves is that they are one of several “well-known techniques . . . for measuring human performance” that “may be used as additional streams of input in accordance with embodiments of the present invention” (Ex. 1006, [0006]) and that “[t]he psychometric data may be displayed to analyze, e.g., . . . an item response curve 370 for each of the training objects (i.e., the presented image)” (*id.*, [0029]; *see also* Fig. 3). However, the challenged claims specifically require “generating a training dataset comprising summary statistics of user responses,” and nowhere does Cox describe including item-response curves in the training dataset. Ex. 2039, ¶ 95. Neither Tesla nor its expert address this requirement, other than to summarily allege that “the item response curve would be included as part of training data for the Huval-Ross model.” *See* Pet. 64; Ex. 1003, ¶ 161. However, despite Tesla and its expert’s citation to wide swaths of Huval’s disclosure, nothing in those cited portions describes including item-response curves in the training dataset. Ex. 2039, ¶ 96.

Here too, Tesla’s expert declaration adds nothing to the analysis, as Dr. Janét merely regurgitates the allegations in the Petition. *Compare* Pet. 64 *with* Ex. 1003,

¶ 161. *See Xerox*, Paper 12 at 5; *Ethicon*, 844 F.3d at 1348, 1352; *TQ Delta*, 942 F.3d at 1359.

“distribution of data and labels”: Tesla next alleges that Cox’s “distribution of data and labels” can constitute the claimed “summary statistics of user responses.” Pet. 65; Ex. 1003, ¶ 162. Cox’s lone mention of a “distribution of data and labels” is a reference to “the joint distribution of data and labels $P(x, y)$ ” when discussing a “recognition function.” Ex. 1006, [0035]. Nothing in Cox teaches generating a “distribution of data and labels” for user responses. Ex. 2039, ¶ 98. Tesla offers no explanation for how this “distribution of data and labels” meets this element of the challenged claims. *See* Pet. 65; Ex. 2039, ¶ 98.

Here too, Tesla’s expert declaration adds nothing to the analysis, as Dr. Janét merely regurgitates the allegations in the Petition. *Compare* Pet. 65 with Ex. 1003, ¶ 162. *See Xerox*, Paper 12 at 5; *Ethicon*, 844 F.3d at 1348, 1352; *TQ Delta*, 942 F.3d at 1359.

“End-of-test statistics”: Finally, Tesla alleges that Cox’s “end-of-test statistics” can constitute the claimed “summary statistics of user responses.” Pet. 65; Ex. 1003, ¶ 162. However, Cox’s only description of these end-of-test statistics is that they “may be displayed to the annotators 160 via display module 167.” Ex. 1006, [0048]; *see also* Fig. 8A. Nothing in Cox teaches that these end-of-test statistics would be included in the training dataset. Cox does not describe the contents of these

end-of-test statistics, an issue which alone is fatal to Tesla’s argument. Indeed, the mere statement that these statistics “may be displayed to the annotators,” and Figure 8A’s illegible content, conveys nothing about the content of those statistics. *See id.* at [0048], Fig. 8A. And, nothing about that description suggests that these end-of-test statistics would be included in the training dataset. Ex. 2039, ¶ 102.

Because Dr. Janét’s declaration again regurgitates the Petition’s allegations, his opinions do not impact this result. *Compare* Pet. 65 with Ex. 1003, ¶ 162. *See also Xerox*, Paper 12 at 5; *Ethicon*, 844 F.3d at 1348, 1352; *TQ Delta*, 942 F.3d at 1359. Moreover, at deposition, Dr. Janét confirmed that he could not discern the contents of Figure 8A and that Cox does not describe the content of these end-of-test statistics. Ex. 2044, pp. 160-164.

Moreover, in addressing independent claims 1 and 12 for Ground 2, the Petition does not make any substantive argument or even cross-reference its Ground 2 discussion for independent claim 2. *See* Pet. 68. Instead, Tesla refers back to its discussion of independent claim 2 from Ground 1. *Id.* Thus, Tesla cannot rely on any disclosure from Cox as part of any theory with respect to independent claims 1 and 12 for Ground 2. *Harmonic*, 815 F.3d at 1363; *Amazon*, Paper 22 at 17; *Liberty Mut.*, Paper 8 at 14-15; 37 C.F.R. §§ 42.22(a)(2), 42.104(b)(3)-(4). As discussed in Section VI.B above, the combination of Huval and Ross does not disclose the “[c]” elements

of the challenged independent claims. The Board should find independent claims 1 and 12 not unpatentable under Ground 2 for those same reasons.

C. Challenged Dependent Claims

As discussed above, Huval, Ross, and Cox do not teach every element of claims 1, 2, and 12. Each of the remaining challenged claims in Ground 2 depend from one of those independent claims, and Huval, Ross, and Cox do not render them obvious for the same reasons.

D. Tesla and its Expert Fail to Analyze the *Graham* Factors, As Required for a Proper Obviousness Analysis

Despite having an obligation to do so, the Petition fails to consider the *Graham* factors in its obviousness analysis. In fact, in discussing Ground 2, the Petition is contradictory, because in the same paragraph the Petition alleges that “[t]he Huval-Ross combination renders obvious the Challenged Claims,” it also alleges the following:

Huval and Ross are further combined with Cox regarding the following limitations in Ground 2: (1) generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images; (2) training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image; and (3) predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image.

Pet. 55; *see also* Ex. 1003, ¶ 143 (same).

This express failure to account for the differences between the challenged claims and the art is not only precisely what *Graham* requires but it is also what the Board has repeatedly required from a petitioner in past decisions. *Graham*, 383 U.S. at 17-18; *see Eizo*, Paper 11 at 29-30 (concluding petitioner “fail[ed] to resolve the exact differences sought to be derived from” the second reference when petitioner alleged that “[t]o the extent [the first reference] may not explicitly teach” the limitation, the second reference “explicitly teaches this limitation”); *see also Moses Lake*, Paper 6 at 17; *eBay*, Paper 15 at 21.

E. A POSITA Would Not Have Been Motivated to Combine Huval, Ross, and Cox in the Manner Tesla Alleges

As discussed in Section VI.D above, a POSITA would not have been motivated to combine Huval and Ross in the manner Tesla and its expert allege. This analysis is equally applicable to Tesla and Dr. Janét’s allegations with respect to Ground 2. Ex. 2039, ¶ 108. Moreover, Tesla and Dr. Janét’s proposed addition of Cox to the combination of Huval and Ross introduces new flaws, and a POSITA would not have been motivated to combine Cox with Huval and/or Ross.

As discussed above, Cox is generally directed to determining the presence or absence of a face in images, whereas Huval and Ross relating to identifying objects in images and predicting what an object in a road scene will do, respectively. As Dr. Saber explains, Cox’s machine learning system is specifically designed for the tasks

it is intended to accomplish, including the design of the network architecture, the regularization methodology applied, and the selection of the particular loss function employed (a human weighted loss function instead of a hinge loss function). Ex. 2039, ¶¶ 109-114; *see also* Ex. 2042 at 1; Ex. 2043 at 1 (both explaining unique challenges to autonomous vehicle system design). Given that Huval and Ross’s systems are designed for completely different purposes than those of Cox, Huval and Ross’s systems require different system designs with different training and validation processes and different datasets. *Id.* Tesla and its expert do not address these differences, and do not articulate how the proposed combination would function in view of these differences. Thus, Tesla has not supplied the requisite articulated reasoning with rational underpinnings in its obviousness assertions. *In re Kahn*, 441 F. 3d at 988.

In addition, each of Tesla’s proposed modifications to Huval and Ross in view of Cox fails to provide a proper motivation to combine. A POSITA would not be motivated to combine Huval and Ross in view of Cox as suggested by Tesla for several reasons.

First, Tesla proposes to modify Huval and Ross such that “Cox’s psychometric data is generated from the Huval-Ross combination’s human annotator response labels and used for model training.” Pet. 57. However, as discussed above (*see* Section VI.D), Huval and Ross each already describe processes for training their

models, and neither Tesla nor its expert explain what the addition of Cox’s psychometric data to Huval and Ross adds to its training process or how they propose to use Cox’s psychometric data in the training process. Ex. 2039, ¶ 116.

This situation is similar to *Kinetic Concepts, Inc. v. Smith & Nephew, Inc.*, in which the Federal Circuit held that there was no motivation to combine two references. 688 F.3d 1342, 1369 (Fed. Cir. 2012). There, the defendant proposed combining two wound-care patents to invalidate a patent related to treating a wound with negative pressure. One of those references disclosed “treating or healing of wounds,” and the other disclosed “a seal capable of maintaining negative pressure.” *Id.* The Court observed that “both of these references independently accomplish similar functions, namely, draining fluids.” *Id.* The Court held that, “[b]ecause each device independently operates effectively, a person having ordinary skill in the art, who was merely seeking to create a better device to drain fluids from a wound, would have no reason to combine the features of both devices into a single device.” *Id.* The same is true here. Huval and Ross each already describe processes for training their models, and a POSITA would have had no reason to combine them with Cox.

Second, Tesla alleges proposes to modify Huval and Ross such that “Cox’s distribution of data and labels (e.g., statistics) and other statistical information are generated from the Huval-Ross combination’s human annotator response labels and used for model training.” Pet. 57. However, as discussed above, Cox only mentions

a “distribution of data and labels” once and it does not describe using it for training a model. Ex. 1006, [0035]. Thus, Tesla has not met its burden because it has not explained how it proposes to use this “distribution of data and labels” in training the model, or even what Tesla means by “other statistical information.” Ex. 2039, ¶ 117; *see Harmonic*, 815 F.3d at 1363; *Amazon*, Paper 22 at 17; *Liberty Mut.*, Paper 8 at 14-15; *see also In re Kahn*, 441 F. 3d at 988.

Third, Tesla proposes to modify Huval and Ross such that “[t]he training of the Huval-Ross model would have included comparing the predicted intents to the human labeled training data to identify prediction errors and optimize the Huval-Ross model such that the prediction errors are minimized.” Pet. 57-58. However, Huval and Ross each already teach processes for identifying prediction errors and optimizing the model to minimize prediction errors. *See, e.g.*, Ex. 1004, [0008]-[0009], [0073]-[0098], Figs. 1, 3; Ex. 1005, 9:41-10:10. Thus, a POSITA would not have been motivated to combine Huval and Ross with Cox for this purpose. *Kinetic Concepts*, 688 F.3d at 1369.

For these reasons, Tesla has failed to show that a POSITA would have been motivated to combine Huval, Ross, and Cox in the manner Tesla and Dr. Janét allege, and the challenged claims should be found not unpatentable under Ground 2 for this reason.

VIII. THE CHALLENGED CLAIMS ARE NOT UNPATENTABLE UNDER GROUND 3

Ground 3 of the Petition challenges claims 1-20 of the '889 patent as obvious over Huval, Ross, and Munro. *See generally* Pet. 68-74. However, as discussed below, the challenged claims are not unpatentable over Huval, Ross, and Munro not only because those references fail to teach all elements of the challenged claims, but also because of a lack of motivation to combine Huval, Ross, and Munro in the manner Tesla alleges.⁴

A. Munro

In contrast to Huval, Ross, and the '889 patent, Munro is generally directed to natural language processing. Instead of being concerned with analyzing the contents of an image for a given purpose (i.e., identifying an object in an image as in Huval, or determining the intent of a road user in an image as described in the '889 patent), Munro is directed to improving processes for analyzing the content of documents. *Compare, e.g.*, Ex. 1004, [0008]-[0009], Ex. 1005, 1:7-26 *and* Ex. 1001, 1:19-53 *with, e.g.*, Ex. 1009, Abstract, [0003], [0004]; *see also* Ex. 2039, ¶¶ 121-124.

⁴ In discussing the elements of the challenged claims that Cox and Munro do not disclose, Patent Owner references the Petition's allegations for claim 2, because Tesla's allegations for the corresponding elements of claims 1 and 12 merely refer back to its allegations for claim 2. *See* Pet. 74.

B. Huval, Ross, and Munro Do Not Teach “training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image”

Nothing in Huval, Ross, and Munro teaches elements 1[d], 2[d], or 12[d], which each require “training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image.” With respect to these elements, Tesla alleges that, “[a]s combined, the training of the Huval-Ross model would have been performed as discussed in [Ground 1, element 2[d]], except the training data includes the generated summary statistics as taught by Munro” and that “the model is trained on such training data in the same manner discussed in [Ground 1, element 2[d]].” Pet. 73.

At the outset, Tesla does not make clear what it means by “generated summary statistics as taught by Munro.” *Harmonic*, 815 F.3d at 1363; *Amazon*, Paper 22 at 17; *Liberty Mut.*, Paper 8 at 14-15. As best the Petition can be understood, Tesla proposes to modify Huval and Ross in view of Munro to include “tallies of the number of annotators who classified the behavior or activity in the images as having various labels in their responses” and to store these tallies in Huval’s training data. *See* Pet. 72-73. However, the “tallies” the Petition refers to from Munro are part of an “aggregation process” that is used to “analyze[] all of the annotations made to a single document to determine whether said document may be reliably annotated for

use in training the natural language model.” Ex. 1009, [0140]. Nothing in Munro suggests that its tallies “describ[e] the state of mind of the user in the image,” nor does anything in Munro teach storing the result of that aggregation process (or any tally generated as part of or as a result of that process) in any training dataset. Ex. 2039, ¶ 128. Indeed, nothing in Munro suggests that its tallies have anything to do with an image, because Munro’s disclosure concerns analysis of documents, not images. *See* Ex. 1006, [0140]; Ex. 2039, ¶ 128. In addition, as Munro expressly states, this aggregation process is intended to determine whether a given document should remain in the training data—a process wholly different than “generating summary statistics describing the state of mind of the user in the image based on the received responses from the plurality of human observers.” *See* Ex. 1009, [0140]; Ex. 2039, ¶ 128.

Because Dr. Janét’s declaration again regurgitates the Petition’s allegations, his opinions do not impact this result. *Compare* Pet. 73 with Ex. 1003, ¶ 183. *See also* *Xerox*, Paper 12 at 5; *Ethicon*, 844 F.3d at 1348, 1352; *TQ Delta*, 942 F.3d at 1359.

The combination of Huval, Ross, and Munro therefore fails to teach “training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image,” as required by elements 1[d], 2[d], and 12[d].

C. Huval, Ross, and Munro Do Not Teach “predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image”

Nothing in Huval, Ross, or Munro teaches elements 1[f], 2[f], or 12[f], which each require “predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image.”

With respect to this element, the entirety of the Petition’s allegations claim that: “Huval, Ross, and Munro teach element 2[f]. As combined, the Huval-Ross trained model would have operated on new images to determine the actions and possible intents of vehicles, bicyclists, and pedestrians in the images, teaching element 2[f] for the same reasons as discussed in [Ground 1, element 2[f]].” Pet. 74. As best the Petition can be understood, Tesla alleges that “determin[ing] the actions and possible intents of vehicles, bicyclists, and pedestrians in the images” constitutes the claimed “predicting . . . summary statistics describing a state of mind of the road user in the new image.” *See id.* However, neither “actions” nor “possible intents” are any kind of statistic, much less a summary statistic of any kind. Ex. 2039, ¶ 141. Nowhere here or in its cross-referenced discussion of Ground 1 does Tesla explain how actions or possible intents constitute a summary statistic. *Harmonic*, 815 F.3d at 1363; *Amazon*, Paper 22 at 17; *Liberty Mut.*, Paper 8 at 14-15. In sum, the vague and conclusory allegations of Tesla do not come close to satisfying its burden. CITE.

Dr. Janét’s declaration regurgitates the Petition’s allegations here too, his opinions thus add nothing. *Compare* Pet. 74 with Ex. 1003, ¶ 185. *See also Xerox*, Paper 12 at 5; *Ethicon*, 844 F.3d at 1348, 1352; *TQ Delta*, 942 F.3d at 1359.

D. Challenged Dependent Claims

As discussed above, Huval, Ross, and Munro do not teach elements of claims 1, 2, and 12. Each of the remaining challenged claims in Ground 3 depend from one of those independent claims, and Huval, Ross, and Munro do not render them obvious for the same reasons.

E. Tesla and its Expert Fail to Analyze the *Graham* Factors, As Required for a Proper Obviousness Analysis

Additionally, the Petition fails to consider the *Graham* factors in its obviousness analysis. As with Ground 2, the Petition’s discussion of Ground 3 is contradictory, because in the same paragraph the Petition alleges that “[t]he Huval-Ross combination renders obvious the Challenged Claims” but goes on to allege that:

Huval and Ross are further combined with Munro regarding the following limitation in Ground 3: generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images. As discussed below, this limitation is explicitly taught by Munro, and it would have been obvious to combine Munro’s relevant teachings with Huval and Ross.

Pet. 68-69; *see also* Ex. 1003, ¶ 172 (same).

This express failure to account for the differences between the challenged claims and the art is not only precisely what *Graham* requires but it is also what the Board has repeatedly required from a petitioner in past decisions. *Graham*, 383 U.S. at 17-18; *see Eizo*, Paper 11 at 29-30; *see also Moses Lake*, Paper 6 at 17; *eBay*, Paper 15 at 21.

F. A POSITA Would Not Have Been Motivated to Combine Huval, Ross, and Munro in the Manner Tesla Alleges

Setting aside the fact that Huval, Ross, and Munro fail to teach elements of the challenged claims and Tesla's failure to analyze the *Graham* factors, Ground 3 suffers from an additional flaw in that a POSITA would not have been motivated to combine Huval, Ross, and Munro in the manner Tesla and Dr. Janét allege.

As discussed above, Munro relates to a different field than Huval and Ross, in that Munro relates to natural language processing of documents. *Compare, e.g.*, Ex. 1004, [0008]-[0009], Ex. 1005, 1:7-26 *with, e.g.*, Ex. 1009, Abstract, [0003], [0004]; *see also* Ex. 2039, ¶¶ 121-124. As Dr. Saber explains, the differences between the fields of Huval/Ross and Munro go far beyond just the types of inputs they consider and include fundamental differences in what they aim to accomplish, the technological processes used to process those inputs, and the form of their outputs. Ex. 2039, ¶¶ 129-135. Nothing in the Petition or Dr. Janét's declaration acknowledges much less accounts for these fundamental differences. *See* Pet. 69-72; Ex. 1003, ¶¶ 175-179. Critically, these differences relate directly to Tesla's proposal

to combine Huval, Ross, and Munro, because Munro’s aggregation process (which is the crux of Tesla’s proposed combination) relates specifically to an issue in natural language processing, i.e., whether a “document may be reliably annotated for use in training the natural language model.” Ex. 1009, [0140].

As Dr. Saber explains, “[m]achine learning for natural language processing and object recognition in images . . . both aim to identify patterns in data, but they operate very differently on distinctively different types of data.” Ex. 2039, ¶ 130. “NLP models often use techniques such as transformers and language embeddings to capture semantic relationships and focus on understanding, interpreting, and/or generating human language and human language models, where data (words and sentences) is sequential and context-dependent.” *Id.* As a result, “[i]f two identical or nearly identical documents receive different labels (i.e. are annotated differently by human observers), the model is essentially being given contradictory instructions.” *Id.* “For this reason, dataset curators frequently try to identify and remove inconsistently labeled documents (i.e. inconsistent annotations), because the disagreement is often viewed as evidence that somebody made a mistake or that the labeling guidelines were not followed consistently.” *Id.*

On the other hand, object recognition models like those used in autonomous driving “process[] visual data, identifying and classifying objects within images based on spatial patterns, shapes, colors, and textures.” Ex. 2039, ¶ 131. “While NLP

models often use techniques such as transformers and language embeddings to capture semantic relationships, object recognition models typically employ convolutional neural networks (CNNs) to learn visual features that are not sequential as one would expect with text sentences.” *Id.*

Given these fundamental differences, “[i]f an autonomous-vehicle developer were to discard every example on which annotators disagreed, many of the most important real-world situations that could raise potential ambiguity would disappear from the training data.” Ex. 2039, ¶ 133. “Rather than treating the disagreement as error to be eliminated, autonomous machine learning designers may use it to estimate uncertainty, build probabilistic models, and/or identify scenarios that deserve special attention during training.” *Id.*, ¶ 134. In NLP model training, “inconsistent labels often suggest that the dataset is teaching the model conflicting rules.” *Id.* “On the other hand, in autonomous-driving prediction tasks, inconsistent labels may instead reveal that the presented scenarios often raise ambiguity and hence a competent model should learn to reason about that uncertainty rather than ignore it.” *Id.*

Given these fundamental differences between the NLP systems and object recognition models, a POSITA would not have been motivated to combine them in the manner Tesla suggests. The lack of any motivation to combine Huval, Ross, and

Munro is an independent reason that the challenged claims are not unpatentable under Ground 3.

IX. THE CHALLENGED CLAIMS ARE NOT UNPATENTABLE UNDER GROUND 4

Ground 4 of the Petition challenges claims 1-20 of the '889 patent as obvious over Huval, Ross, Cox, and Munro. *See generally* Pet. 75-78. However, as discussed below, the challenged claims are not unpatentable over Huval, Ross, Cox, and Munro not only because Huval, Ross, Cox, and Munro fail to teach elements of the challenged claims, but also because Tesla fails to analyze the *Graham* factors and fails to articulate a valid motivation to combine Huval, Ross, Cox, and Munro in the manner Tesla alleges.⁵ Indeed, a POSITA would not be motivated to combine the references in the manner proposed by Tesla.

⁵ In discussing the elements of the challenged claims that Huval, Ross, Cox, and Munro do not disclose, Patent Owner references the Petition's allegations for claim 2, because Tesla's allegations for the corresponding elements of claims 1 and 12 merely refer back to its allegations for claim 2. *See* Pet. 78.

A. Huval, Ross, Cox, and Munro Do Not Teach “training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image”

Nothing in Huval, Ross, Cox, or Munro teaches elements 1[d], 2[d], or 12[d], which each require “training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image.” With respect to these elements, Tesla alleges the following:

As combined, the training of Huval-Ross model would have been performed as discussed in [element 2[d] – Ground 1] and [element 2[d] – Ground 2], except the training data includes the generated summary statistics as taught by Munro, and the Huval-Ross model is trained on such training data in the same manner discussed in [element 2[d] – Ground 1] and [element 2[d] – Ground 2].

Pet. 76-77. Tesla’s limited, cross-referenced allegations are entirely unclear. In particular, it is impossible to discern Tesla’s theory regarding what the combined Huval-Ross model is configured to predict. In discussing element 2[d] in Grounds 1 and 2, Tesla alleges that “Huval’s model is configured to predict a ‘set of possible intents or hypotheses identifying possible next actions . . . , a given point in time when the action is likely to occur, and associated likelihood values’ for road users . . . displayed in input image data.” Pet. 38, 65-66. Here in Ground 4, however, Tesla appears to allege that “the training data includes the generated summary statistics as

taught by Munro,” i.e. the tallies from Munro’s aggregation process. Pet. 76-77. It is unclear whether Tesla alleges that the model would be configured to predict those tallies, whether those tallies are merely used in the training to “compar[e] the predicted intents to the human labeled training data to identify prediction errors and optimize the Huval-Ross model” (Pet. 66), or both. *Harmonic*, 815 F.3d at 1363; *Amazon*, Paper 22 at 17; *Liberty Mut.*, Paper 8 at 14-15. Tesla’s vague allegations fail to discharge its burden. Additionally, Tesla’s allegations are deficient for several reasons.

First, Munro does not teach configuring a model to predict its tallies. Instead, as discussed above, the purpose of Munro’s aggregation process is to “analyze[] all of the annotations made to a single document to determine whether said document may be reliably annotated for use in training the natural language model.” Ex. 1009, [0140]. Nothing in Munro teaches storing the result of that aggregation process (or any tally generated as part of or as a result of that process) in any training dataset. Ex. 2039, ¶ 151. Moreover, nothing in Huval, Ross, or Munro teaches a model that is configured to predict such tallies, as required by the challenged claims. *Id.* Instead, the purpose of that aggregation process in Munro is to determine if the document should be excluded from the dataset for training the natural language model. Ex. 1009, [0140]; Ex. 2039, ¶ 151.

Second, Munro does not teach that its tallies are used to “identify prediction errors and optimize the Huval-Ross model.” *See* Pet. 66. Instead, Munro’s tallies are used to determine whether a given document should be excluded from the training set. Ex. 1009, [0140]. Nothing about Munro’s aggregation process identifies prediction errors—in fact, as Dr. Saber explains, “it is designed to excuse prediction ‘errors’ by ‘determin[ing] whether said document may be reliably annotated for use in training the natural language model.” Ex. 2039, ¶ 152. Similarly, Munro’s process does not optimize the machine learning model but instead enhances the quality of the training dataset used to train the model. *Id.*

The combination of Huval, Ross, Cox, and Munro therefore fails to teach “training, using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image,” as required by elements 1[d], 2[d], and 12[d].

B. Huval, Ross, Cox, and Munro Do Not Teach “predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image”

Nothing in Huval, Ross, Cox, or Munro teaches elements 1[f], 2[f], or 12[f], which each require “predicting, by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image.” For these elements, Tesla alleges that “[a]s combined, the Huval-Ross model would have operated on new images to determine the actions and

possible intents of vehicles, bicyclists, and pedestrians in the images.” Pet. 77. But as discussed above with respect to Ground 3, determining actions and possible intents of vehicles, bicyclists, and pedestrians is not predicting summary statistics, as such actions/intents are not summary statistics. *See* Section VIII.C.

C. Challenged Dependent Claims

As discussed above, Huval, Ross, Cox, and Munro do not teach every element of claims 1, 2, and 12. Each of the remaining challenged claims in Ground 4 depend from one of those independent claims, and Huval, Ross, Cox, and Munro do not render them obvious for the same reasons.

D. Tesla and its Expert Fail to Analyze the *Graham* Factors, As Required for a Proper Obviousness Analysis

Also, the Petition fails to consider the *Graham* factors in its obviousness analysis. As with Grounds 2 and 3, the Petition’s discussion of Ground 4 is contradictory, because in the same paragraph the Petition alleges that “[t]he Huval-Ross combination renders obvious the Challenged Claims,” it goes on to allege that:

Huval, Ross, and Cox are further combined with Munro regarding the following limitation in Ground 4: generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images.

Pet. 75; *see also* Ex. 1003, ¶ 190 (same).

This express failure to account for the differences between the challenged claims and the art is not only precisely what *Graham* requires but it is also what the

Board has repeatedly required from a petitioner in past decisions. *Graham*, 383 U.S. at 17-18; *see Eizo*, Paper 11 at 29-30; *see also Moses Lake*, Paper 6 at 17; *eBay*, Paper 15 at 21.

E. A POSITA Would Not Have Been Motivated to Combine Huval, Ross, Cox, and Munro in the Manner Tesla Alleges

Finally, a POSITA would not have been motivated to combine Huval, Ross, Cox, and Munro in the manner Tesla alleges.

As discussed in Section VI.D above, a POSITA would not have been motivated to combine Huval and Ross. Also, as discussed in Section VII.E above, a POSITA would not have been motivated to modify Huval and Ross in view of Cox. Finally, and as discussed in Section VI.F above, a POSITA would not have been motivated to modify Huval and Ross in view of Munro. All of those reasons apply equally to Tesla's flawed, hindsight-driven effort to combine all four references. Ex. 2039, ¶ 163.

Therefore, the lack of any motivation to combine Huval, Ross, Cox, and Munro is an independent reason that the challenged claims are not unpatentable under Ground 4.

X. TESLA FAILED TO SHOW THAT CERTAIN LIMITATIONS ARE PRINTED MATTER NOT ENTITLED TO PATENTABLE WEIGHT

Tesla asserts that the challenged claims include limitations that are not entitled to patentable weight under the printed matter doctrine.⁶ To prevail on this assertion, Tesla must make two showings. First, Tesla must show that the claim limitations constitute printed matter. Second, even if the claim limitations recite printed matter, Tesla must show that the limitations are *not* functionally or structurally related to the physical substrate holding the printed matter. Only if Tesla makes both showings are the claim limitations not given patentable weight in the invalidity analysis. As set forth below, Tesla has not, and cannot, meet its burden on either prong of the printed matter test. *See FanDuel, Inc. v. Interactive Games LLC*, 966 F.3d 1334, 1341 (Fed. Cir. 2020) (“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.”); *Lowry*, 32 F.3d at 1584 (“Even assuming, arguendo, that data objects and data structures are analogous to printed matter . . . the burden of establishing the absence of a novel, nonobvious functional relationship rests with the PTO.”).

⁶ The printed matter doctrine is disfavored, “stand[ing] on questionable legal and logical footing.” *In re Lowry*, 32 F.3d 1579, 1583 (Fed. Cir. 1994) (citing *In re Gulack*, 703 F.2d 1381, 1385 n.8 (Fed. Cir. 1983)).

A. The Claim Limitations At Issue Are Not Printed Matter

A claim limitation is printed matter “*only* if it claims the content of information.” *In re DiStefano*, 808 F.3d 845, 848 (Fed. Cir. 2015) (emphasis added). Stated differently, “printed matter must be matter claimed *for what it communicates*.” *Id.* at 850 (emphasis added). To be considered printed matter, the claimed information must be “useful and intelligible only to the human mind.” *Lowry*, 32 F.3d at 1583 (citations omitted). “[P]rinted matter cases have no factual relevance where ‘the invention as defined by the claims *requires* that the information be processed not by the mind but by [a] computer.” *Id.* (emphasis in original).

Cases finding printed matter illustrate these requirements. Limitations covering markings on the face of a game die were found to be printed matter. *In re Marco Guldenaar Holding B.V.*, 911 F.3d 1157, 1161 (Fed. Cir. 2018). This is because “[e]ach die’s marking or lack of marking communicates information to participants indicating whether the player has won or lost a wager” *Id.* Limitations covering markings on a vascular access port were found to be printed matter. *C R Bard Inc. v. Angiodynamics, Inc.*, 979 F.3d 1372, 1381 (Fed. Cir. 2020). The markings’ purpose was to inform a medical provider that the vascular access port was suitable for a particular type of procedures, and thus “directed to *the content of the information conveyed*.” *Id.* at 1381-82 (emphasis added). Limitations covering “identifying marks” on meat were found to be printed matter. *In re McKee*, 64 F.2d

379, 379-80 (CCPA 1933). The markings’ purpose was to inform a person of the origin of the meat or its producer. *Id.* Limitations covering a prescription label were found to be printed matter. *King Pharms., Inc. v. Eon Labs., Inc.*, 616 F.3d 1267, 1279 (Fed. Cir. 2010). The label’s instructions advised a patient to take a prescription with food. *Id.* The common thread in these cases is that the printed matter communicated specific information to a human.

Cases refusing to find a claim limitation to be printed matter are also instructive. Limitations covering a data structure including a plurality of attribute data objects stored in memory were not found to be printed matter. *Lowry*, 32 F.3d at 1583. The limitations at issue did not “claim merely the information content of a memory.” *Id.* Moreover, the Federal Circuit refused to extend the printed matter doctrine to information stored in memory, which was processed by a computer rather than conveyed to a human being. *Id.* A limitation of “selecting a first element from a database including web assets authored by third party authors and web assets provided to the user interface from outside the user interface by the user” was not found to be printed matter. *DiStefano*, 808 F.3d 848-851. The Federal Circuit found that the limitation did not claim the *content* of information. *Id.* at 851 (“Although the selected web assets can and likely do communicate some information, *the content of the information is not claimed.*”) (emphasis added).

Here, Tesla identifies fourteen claim limitations and alleges that they constitute printed matter. Pet. 79-80. Tesla’s allegations are conclusory and lack any meaningful analysis. Tesla never explains how any of those limitations claim the content of information, as required by Federal Circuit precedent. For example, Tesla generically asserts that “each [limitation] recites a data element [] and then defines that data element based on its content.” *Id.* at 80. But this allegation is plainly false as none of the limitations claim content. None of the limitations recite “matter claimed for what it communicates.” *DiStefano*, 808 F.3d at 850.

For example, the first claim limitation identified by Tesla is “a plurality of images displaying road scenes.” While the claimed “images” are defined as “displaying road scenes,” the claim limitation does not attempt to claim specific content. The modifier “displaying road scenes” merely describes the *types* of images stored and used in the computer-implemented method. The limitation “a plurality of user responses, each user response describing a state of mind of a road user displayed in the one or more images” is similar. Nothing in this limitation defines or claims specific content of the “user responses.” The modifier “describing a state of mind of a road user displayed in the one or more images” merely describes the *type* of responses that will be received.

The remaining limitations are similar in that they do not describe or claim specific content. Instead, they merely describe the types of information involved in

the computer-implemented method. These limitations are very different from those found to constitute printed matter for their communicative content, such as markings on a die that inform a game participant if they won, markings on a medical device that indicate to a doctor the device's suitability for a particular procedure, markings on meat to identify the meat's origin, or instructions on a prescription label to take a drug with food. *See supra*. Simply put, the limitations here bear no resemblance to those found to constitute printed matter.

Tesla also failed to address that several claim elements recite information that is not “useful and intelligible only to the human mind.” *Lowry*, 32 F.3d at 1583 (citations omitted). For example, Tesla claims that “summary statistics” are printed matter. But claim 2 is a “computer-implemented method” that involves “generating a training dataset comprising summary statistics” and training a model using the “training dataset.” The claimed summary statistics are never communicated to a person. *See id.* (rejecting application of printed matter doctrine to information processed by a computer). Here, the claimed information is used by a computer system to perform computational functions, not by a human reader to receive a message.

Accordingly, Tesla has not met its threshold burden of showing that the claim limitations recite printed matter.

B. The Alleged Printed Matter Is Functionally Related to the Substrate

Even if Tesla were to prevail on its claim that the limitations constitute printed matter, it cannot prevail on the second prong of the printed matter test. Printed matter is given patentable weight if the “claimed informational content has a functional or structural relationship to the substrate.” *DiStefano*, 808 F.3d at 850. A limitation deemed to be printed matter is entitled to patentable weight if it is “interrelated with the rest of the claim.” *Praxair Distrib., Inc. v. Mallinckrodt Hosp. Prods. IP Ltd.*, 890 F.3d 1024, 1032, 1035 (Fed. Cir. 2018) (“By interrelating the claimed information regarding correlations between nitric oxide, LVD, and pulmonary edema with the concrete step of discontinuing treatment of the information . . . the printed matter . . . has a functional relationship to the rest of the claim[,] giving the printed matter patentable weight.”). The Federal Circuit further “consider[s] whether the printed matter merely informs people of the claimed information, or whether it instead interacts with the other elements of the claim to create a new functionality in a claimed device or to cause a specific action in a claimed process.” *C R Bard Inc.*, 979 F.3d at 1381.

Cases finding that printed matter is entitled to patentable weight illustrate the requisite functional relationship. In *In re Miller*, the court reversed a finding of printed matter regarding “measuring indicia” and a “legend” printed on the side of a volumetric measuring device. 418 F.2d 1392, 1395-96 (CCPA 1969). These

limitations were given patentable weight because the indicia and legend enabled a user to measure specific volumes accurately and were thus integral to the functionality of the measuring device. *Id.* In *Gulack*, a claim limitation capturing a sequence of digits (“plurality of individual digits”) printed on an endless wrist band (“educational and recreational mathematical device”) constituted printed matter. 703 F.2d 1381, 1385 (Fed. Cir. 1983). Nevertheless, “the sequence deserved patentable weight because the informational content of the sequence (what numbers were represented) was functionally related to the endless-band physical structure of the substrate.” *DiStefano*, 803 F.3d at 850 (citing *Gulack*, 703 F.2d at 1385).

Here, Tesla has not, and cannot, demonstrate that the cited limitations are *not* functionally related to the substrate. Tesla asserts, in conclusory fashion, that “[t]he above printed matter limitations do not have any such functional relationship with the ‘substrate,’ which in this case is computer memory.”⁷ Pet 81. But this allegation

⁷ Tesla fails to explain why the alleged substrate is “computer memory.” Assuming Tesla is correct, this is reason enough to disregard Tesla’s printed matter challenge. *See Lowry*, 32 F.3d at 1583 (“[T]he Board erroneously extended a printed matter rejection under sections 102 and 103 to a new field in this case, which involves information stored in a memory. . . . The printed matter cases have no factual

is not true at all. For example, claim 2 is a “computer-implemented method” where “a plurality of user responses” are used to generate “a training dataset comprising summary statistics of user responses.” The “training dataset” is used to train an AI “model.” The “model” is then used to “predict[] . . . summary statistics describing a state of mind of the road user” in a new image. Each of the challenged limitations participates directly in this sequence of operations. The information is not merely stored in memory or presented to a user; it drives the generation of training data, the training of the model, and the ultimate prediction produced by the claimed method. The challenged limitations are therefore functionally intertwined with the operation of the claimed process. One would be hard pressed to find limitations more fundamentally related to the function of the computer-implemented method. Indeed, removing the challenged limitations would fundamentally alter how the claimed method operates. That is the hallmark of a functional relationship under Federal Circuit precedent.

In sum, the challenged claim limitations do not comprise printed matter. Even if they did, any alleged printed matter is still entitled to patentable weight.

relevance where ‘the invention as defined by the claims requires that the information be processed not by the mind but by a machine, the computer.’”) (citations omitted).

XI. CONCLUSION

For the foregoing reasons, Patent Owner respectfully requests that the Board find all challenged claims of the '889 patent not unpatentable.

Dated: June 29, 2026

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CERTIFICATE OF COMPLIANCE WITH WORD COUNT

Pursuant to 37 C.F.R. § 42.24(d), I certify that this Patent Owner's Response complies with the type-volume limits of 37 C.F.R. § 42.24(b)(1) because it contains 13,176 words, excluding the parts of this Patent Owner's Response that are exempted by 37 C.F.R. § 42.24(a), according to the word processing system used to prepare this Patent Owner's Response.

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CERTIFICATE OF SERVICE

The undersigned certifies that the foregoing Patent Owner's Response was served on June 29, 2026, to Lead and Back-up Counsel for Petitioner at the service address provided in Petitioner's Mandatory Notices:

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