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UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

Ex parte GUILLAUME DESJARDINS, RAZVAN PASCANU, RAIA THAIS HADSELL, JAMES KIRKPATRICK, JOEL WILLIAM VENESS, and NEIL CHARLES RABINOWITZ

Appeal 2024-000567
Application 16/319,040
Technology Center 2100

Before HUNG H. BUI, NABEEL U. KHAN, and JEREMY J. CURCURI,[1] *Administrative Patent Judges*.

BUI, *Administrative Patent Judge*.

DECISION ON REQUEST FOR REHEARING

Appellant[2] filed a Request for Rehearing ("Req. Reh'g") under 37 C.F.R. § 41.52(b) for reconsideration of our Decision on Appeal, mailed January 31, 2025 ("Decision"). In that Decision, we affirmed the Examiner's 35 U.S.C. § 103 rejection of claims 1–6 and 8–20 and issued a

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[1] Judge John F. Horvath retired from PTAB recently. For purposes of this rehearing, Judge Curcuri serves as Judge Horvath's replacement.

[2] "Appellant" herein refers to "applicant" as defined in 37 C.F.R. § 1.42. According to Appellant, DeepMind Technologies Limited is identified as the real party in interest. Appeal Br. 1.

new ground of 35 U.S.C. § 101 rejection of claims 1–6 and 8–20. We have considered Appellant's arguments presented in the Request for Rehearing but are not persuaded by Appellant's arguments. We have provided herein additional explanations, but decline to change our decision in view of Appellant's arguments.

ANALYSIS

The applicable standard for a Request for Rehearing is set forth in 37 C.F.R. § 41.52, which provide in relevant part, (1) § 41.52(a)(1): "[t]he request for rehearing must state with particularity the points believed to have been misapprehended or overlooked by the Board" and (2) § 41.52(b)(2): "[t]he request for rehearing must address any new ground of rejection and state with particularity the points believed to have been misapprehended or overlooked in entering the new ground of rejection and also state all other grounds upon which the rehearing is sought."

Appellant presents several arguments against the outstanding §101 rejection and the §103 rejections on the basis of points believed to have been misapprehended or overlooked in our Decision. Req. Reh'g 1–9.

A. 35 U.S.C. § 103 Rejections

First, Appellant argues "[t]he Board misinterprets the term 'parameter' as recited in the claims." *Id.* at 1–2. According to Appellant, the Board's interpretation of the term "parameters" as encompassing Mehanna's features as inputs to the machine learning models, or alternatively, Gordon's posterior distribution, is not reasonable because the Specification describes "parameters" as "**internal to the machine learning model**" and **"adjusted during training** to optimize performance," whereas Mehanna's features are "**input to the model**" and are "**not adjusted during**

training." *Id.* at 2 (citing Spec. ¶¶ 31–34, Figures 1–2; compared with Mehanna ¶ 6). As such, Appellant argues "a skilled person in the art would understand that parameters of a machine learning model refer to the internal variables (e.g., weights or biases in neural networks) that are adjusted during training and are not externally retrieved features [as disclosed by Mehanna]." *Id.* at 3.

Second, Appellant argues "[t]he Board mischaracterizes FIG. 1 and the Specification." *Id.* at 3–4. According to Appellant, "FIG. 1 does not show that parameters are input to a machine learning model" but instead, "shows trained parameter values 116 which are determined by the machine learning system 100 by **adjusting the parameter values during training** of the machine learning model 110." As such, Appellant argues "Mehanna fails to teach 'parameter' because its features, which the Examiner and the Board equate to the claimed parameters, are retrieved from **external** sources such as a 'user profile' or 'content items' and are **not adjusted** during training of a machine learning model." *Id.* at 4.

Third, Appellant argues "[t]he Board overlooked Appellant's arguments in the Appeal Brief regarding the limitation [A2] of 'approximating a probability that the first value of the parameter after the training on the first machine learning task is a correct value of the parameter given the first training data used to train the machine learning model on the first machine learning task' as required by claim 1 and erred finding that Gordon teaches this limitation." *Id.* at 4–5. According to Appellant, "even if a 'feature' in Mehanna could be interpreted as a 'parameter' in claim 1 (which Appellant does not concede), nowhere does Mehanna teach or suggest that the measure of the feature's importance '**approximat[es] a**

probability that the first value of the parameter after the training on the first machine learning task is a correct value of the parameter given the first training data used to train the machine learning model on the first machine learning task' as required by claim 1. *Id.* at 5. Likewise, Gordon's posterior distribution "does not teach or suggest the specific approximation recited in limitation [A2], either structurally or functionally, as required by the claims." *Id.* at 7.

However, Appellant's arguments are repetitive and fundamentally misapprehend our Decision and Judge Horvath's concurrence because Mehanna (including [1] the disputed interpretation of Mehanna's "features" as input to its machine learning model and [2] the alleged view of Appellant's Figure 1 and Specification) was not needed to support the Examiner's obviousness determination relative to the relevant part of limitation [A2] of Appellant's claim 1. For example, we explained:

> Nevertheless, for purposes of completeness, we are persuaded that Mehanna does not teach or suggest relevant part of limitation [A2] of claim 1: "approximating a probability that the first value of the parameter after the training on the first machine learning task is a correct value of the parameter given the first training data used to train the machine learning model on the first machine learning task." <u>However, Gordon teaches a machine learning algorithm configured to compute an approximation of a posterior distribution over possible values of the plurality of parameters.</u> Final Act. 13 (citing Gordon ¶¶ 14, 46). An approximation of a posterior distribution is commonly known by those skilled in the art as representing "a probability that the current value is a current value of the parameter." Spec. ¶¶ 49–50.
>
> <u>Based on the teachings of Gordon and the commonly known "approximation of a posterior distribution" (Spec. ¶¶ 49–50), a skilled artisan would understand that Gordon (rather than</u>

> <u>Mehanna) teaches or suggests the relevant part of limitation [A2] of claim 1.</u>

Decision 15 (emphases added).

Judge Horvath's concurrence also explained:

> As the Examiner correctly finds, Gordon teaches limitation [A1]. *See* Final Act 13 (citing Gordon ¶ 14); Gordon ¶ 14 (disclosing for a "[g]iven set of training data d=(x,y), Bayes' rule expressions may be obtained for computing a posterior distribution p(w|d, h)" and that "[t]his Bayesian model represents a wide variety of machine learning tasks"). Thus, Gordan also teaches limitation [A2] because, according to Appellant's own Specification, Gordon's posterior distribution *is* a measure of the importance of a trained parameter that expresses the probability that the trained parameter has a correct value (i.e., that it has been correctly trained).

Decision 29–30 . Judge Horvath's concurrence only disagreed with the majority's interpretation of the term "parameters" recited in Appellant's claim 1. Nevertheless, that disagreement was deemed moot because (1) Mehanna was no longer needed to support the obviousness rejection, and (2) Gordon (rather than Mehanna) was then relied upon to teach or suggest the relevant part of limitation [A2] of claim 1.

For these reasons, Appellant has failed to identify any issue we misapprehended or overlooked in determining that the Examiner did not err as to the 35 U.S.C. § 103 rejection before us in the appeal.

B. <u>35 U.S.C.§ 101 Rejection</u>

Appellant requests a rehearing not on the basis of any points believed to have been misapprehended or overlooked by our Decision, but on the basis of Appellant's continued disagreement regarding "specific technical improvements in the field of machine learning" which integrate the alleged abstract idea "into a practical application" under the 2019 Revised Guidance, Step 2A. Req. Reh'g 7–9. In particular, Appellant argues:

> the claimed invention provides specific technical improvements in the field of machine learning by enabling a single model to be sequentially trained on multiple tasks while maintaining acceptable performance on each task. This is achieved without the need to store or maintain separate models for each task, thereby significantly reducing system complexity and storage requirements. Instead of requiring multiple sets of parameters – one for each task – the system retains a single set of parameters, which is adjusted during training on a new task using an objective function that incorporates a penalty term reflecting the importance of parameters to previously learned tasks. This training strategy allows the model to preserve performance on earlier tasks even as it learns new ones, directly addressing the technical problem of "catastrophic forgetting" in continual learning systems.

Id. at 8 (emphasis added). According to Appellant, by implementing the training steps recited in claim 1,

> the claimed subject matter provides technical improvements over conventional systems by addressing challenges in continual learning and model efficiency by reducing storage requirements and preserving task performance across sequential training. Further, the claimed subject matter improves the functioning of the computer by requiring less memory and storage capacity to perform the tasks.

Id. at 9.

We disagree. As previously discussed in our Decision, limitations [A]–[D] of Appellant's claim 1 are considered part of "a mathematical concept/calculation" to train a machine learning model, identified as an abstract idea, similarly to the claims in *Gottschalk v. Benson*, 409 U.S. 63, 67 (1972). A claim for a new abstract idea is still an abstract idea. *See Synopsys, Inc. v. Mentor Graphics Corp.*, 839 F.3d 1138, 1151 (Fed. Cir. 2016). "No matter how much of an advance in the finance field the claims recite, the advance lies entirely in the realm of abstract ideas, with no plausibly alleged innovation in the non-abstract application realm." *See SAP Am., Inc. v. Investpic, LLC*, 898 F.3d 1161, 1163 (Fed. Cir. 2018).

As recently explained by the Federal Circuit in *Recentive Analytics, Inc. v. Fox Corp.*, 134 F.4th 1205, 1212 (Fed. Cir. 2025), the requirements that the machine learning model be "iteratively trained" or dynamically adjusted in the machine learning training are incident to the very nature of machine learning and, as such, do not represent a technological improvement.

There is no evidence in the record (e.g. the Specification or the claims) to support any specific means or method that solves a problem in an existing technological process. *Koninklijke KPN N.V. v. Gemalto M2M GmbH*, 942 F.3d 1143, 1150 (Fed. Cir. 2019). Instead, the only thing Appellant's claims disclose about the use of "a [single] machine learning model" in a new environment or a new field of use, i.e., "on multiple machine learning tasks" such that "once the model has been trained, the model can be used for each of the multiple tasks with an acceptable level of performance" for each task. Spec. ¶¶ 6, 21. However, "[a]n abstract idea does not become nonabstract by limiting the invention to a particular field of use or technological environment." *Intellectual Ventures I LLC v. Capital One Bank (USA)*, 792 F.3d 1363, 1366 (Fed. Cir. 2015).

For these reasons, we decline to change our decision rejecting claims 1–6 and 8–20 under 35 U.S.C. § 101 as directed to non-statutory subject matter.

DECISION

We have considered the new arguments raised by Appellant in the Request, but find none of these arguments persuasive that our original Decision misapprehended or overlooked in entering the new ground of rejection. It is our view, Appellant has not identified any points the Board misapprehended or overlooked. We decline to grant the relief requested. This Decision on Appellant's "**REQUEST FOR REHEARING**" is deemed to incorporate our earlier Decision by reference. *See* 37 C.F.R. § 41.52(a)(1).

Outcome of Decision on Rehearing:

Claims	35 U.S.C. §	Reference(s)/Basis	Denied	Granted
1–6, 8–20	101	Eligibility	1–6, 8–20	
1, 2, 4, 9, 15, 17–20	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna	1, 2, 4, 9, 15, 17–20	
3, 14	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna, Aslan	3, 14	
6, 10–12	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna, Cao	6, 10–12	

5, 8, 13, 16	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna, Sinyavskiy	5, 8, 13, 16	
Overall Outcome			1–6, 8–20	

Final Outcome of Appeal after Rehearing:

Claim(s) Rejected	35 U.S.C. §	Reference(s)/Basis	Affirmed	Reversed	New Ground
1, 2, 4, 9, 15, 17–20	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna	1, 2, 4, 9, 15, 17–20		
3, 14	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna, Aslan	3, 14		
6, 10–12	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna, Cao	6, 10–12		
5, 8, 13, 16	103	Marcheret, Jamaluddin, Rousset, Gordon, Mehanna, Sinyavskiy	5, 8, 13, 16		
1–6, 8–20	101	Eligibility			1–6, 8–20
Overall Outcome			1–6, 8–20		1–6, 8–20

DENIED
37 C.F.R. § 41.50(b)