

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

ZESTY.AI, INC.

Petitioner,

v.

AON RE, INC.

Patent Owner.

Case No. IPR2025-01357

U.S. Patent No. 10,650,285

PATENT OWNER'S PRELIMINARY RESPONSE

TABLE OF CONTENTS

I. INTRODUCTION	1
II. BACKGROUND	5
A. The '285 Patent.	5
B. The Petition and the Prior Art Cited by Petitioner.	7
III. CLAIM CONSTRUCTION	16
IV. LEVEL OF ORDINARY SKILL IN THE ART	16
V. ARGUMENT.....	17
A. The Petition relies on expert testimony in an improper attempt to gap fill the absence of any disclosure in Gross concerning two separate machine learning classifiers.....	17
1. Dr. Forsyth’s declaration reveals an improper hindsight bias.	19
2. Gross’s disclosure does not support Petitioner’s obviousness arguments.....	25
B. The Petition fails to even attempt to explain why and how a POSITA would combine facial recognition feature extraction algorithms with Gross.....	29
C. The Petition fails to even attempt to explain why and how a POSITA would combine Jafri’s passing reference to “a hybrid neural network solution” with Gross.....	34
D. Petitioner’s inconsistent claim construction positions undermine its ability to carry its burden.....	38
VI. CONCLUSION	41

Patent Owner Aon Re, Inc. (“PO”) respectfully submits this Preliminary Response to Petitioner’s Zesty.ai, Inc.’s (“Petitioner”) Petition (the “Petition”).

I. INTRODUCTION

Petitioner has fallen far short of meeting its burden and the Petition should be denied. The Petition relies heavily on Gross as its primary reference, which is directed to identifying dilapidated homes that present real estate and/or renovation opportunities—and Gross is a fundamentally different system compared to that disclosed and claimed in challenged U.S. Patent No. 10,650,285 (the “ ’285 patent”). See Ex. 1005. Gross relies largely on human coders and reviewers to tag images of homes with information concerning property “attributes.” Gross includes no ability for a user to even request information concerning a specific property, much less a specific property characteristic and the condition of such a specific property characteristic.

In contrast, the ’285 patent discloses and claims a system that does exactly what Gross does not: allows a user to query a specific property in order to gain information about the condition of a specific property characteristic (e.g., the condition of the roof). The claims of the ’285 patent recite an advance over the prior art in the form of an improved computer architecture that improves the speed, efficiency, and accuracy of the computers that execute the claimed inventions. These improvements result in large part from a tiered structure of machine learning

classifiers (the claimed “first machine learning classifier” and “second machine learning classifier”), each trained to separately identify different specific information about a specific property characteristic and its condition at a specific property. The system disclosed and claimed in the ’285 patent is thus fundamentally different from Gross. Given that, it is not surprising that Petitioner failed to carry its burden in at least five independent ways, any one of which is sufficient to result in denial of institution.

First, for the key recitation of a claimed “second machine learning classifier,” Petitioner admits (at 29) that “Gross does not explicitly disclose its condition qualifiers are classified via a different machine learning classifier than was used to identify attributes[.]” As such, Petitioner argues that it would be obvious to “separate” Gross’s “Classifier Engine 150” into two separate classifiers (as the ’285 patent does), one trained to classify property characteristics and another trained to identify the condition of the classified characteristic. Petitioner does not rely on any patent or publication as disclosing such “a second machine learning classifier,” but instead relies entirely on expert testimony from Dr. Forsyth in an attempt to fill the gap Petitioner admits is present in its cited prior art.

Petitioner’s attempt to supply a missing claim element through expert testimony fails because Dr. Forsyth’s declaration reveals a clear hindsight bias. Dr. Forsyth proposes a modification to Gross that substantially tracks the preferred

embodiment of the '285 patent, rather than any prior art disclosure—again, Petitioner presents no such disclosure. In context, it is apparent that Dr. Forsyth used the '285 patent itself as a roadmap for his proposed modification of Gross. The law forbids such a hindsight-based obviousness argument.

Second, as cover for his road-mapping based on the '285 patent, Dr. Forsyth points to various portions of Gross, searching in vain for disclosure to support Petitioner's proposed modification. For example, Dr. Forsyth modifies a sentence in Gross with a deceptive ellipsis to suggest that Gross discloses the notion of using “multiple classifiers” in a tiered machine learning architecture. However, as Petitioner admits, Gross does not disclose two independently trained classifiers trained to identify different property information (e.g., a property characteristic and property condition) from the same image as recited in the claims of the '285 patent. The actual disclosure of Gross refers to multiple classifiers operating in different ways to identify the **same** information as part of determining an average confidence interval—not the tiered machine learning architecture of the '285 patent.

Third, for the claimed “feature” extraction, for each challenged claim, Petitioner relies on a single reference obviousness argument based on Gross. In order to do so, Petitioner attempts to rely on material allegedly incorporated by reference from a survey paper discussing facial recognition technology (Jafri) with Gross's embodiments that allow a user to identify real estate and renovation opportunities.

Petitioner fails to even attempt to explain why a POSITA would be motivated to look to facial recognition technology or how a POSITA would reasonably expect to be successful in making the combination. This is not just a case where Petitioner's motivation and expectation of success arguments are not persuasive; those arguments are just not in the Petition. Petitioner and its expert Dr. Forsyth assume no such explanation is necessary, and that, of course, is not the law. This evidentiary shortcoming requires denial of institution.

Fourth, for the claimed “first machine learning classifier,” Petitioner again attempts to rely on Jafri, this time for its passing reference to a “hybrid neural network solution” for facial recognition. Here again, the Petition fails to offer *any* analysis at all concerning why a POSITA would be motivated to combine some unspecified “hybrid neural network solution” mentioned at a high level in a facial recognition technology survey paper with Gross, or how a POSITA would reasonably expect to be successful in making that combination. The law demands more. Moreover, Gross does not even incorporate Jafri's mention of a “hybrid neural network solution” by reference, contrary to Petitioner's argument. As such, Petitioner could not properly rely on this alleged “hybrid neural network solution,” even if it had set forth some analysis of motivation and expectation of success.

Fifth and finally, Petitioner relies on a construction of the term “feature” in this proceeding that is inconsistent with its construction of the same term “feature”

recited in U.S. Patent No. 11,030,491 (the “’491 patent”), which Petitioner challenges in a related proceeding (IPR2025-01360). Fatally, Petitioner provides no acknowledgement or explanation for this apparent inconsistency. Petitioner fails to do so despite the fact that the ’491 patent is in the same family as the ’285 patent and shares a substantially similar specification in relevant respect. Petitioner’s inconsistent positions fail to comply with 37 C.F.R. § 42.104(b)(3) and therefore undermine its ability to carry its burden here. Indeed, Petitioner itself disagrees with its own claim construction on which its Petition arguments are premised.

In sum, Petitioner does not meet its burden in establishing a reasonable likelihood of success that at least one challenged claim is unpatentable, and the Director should deny institution.

II. BACKGROUND

A. The ’285 Patent.

In a described embodiment, a user requests information concerning a specific property (e.g., by typing an address into a user interface). ’285 patent, Ex. 1001 at 13:60-67. The system then accesses an aerial image including a property using an “image acquisition engine 336.” *Id.* at 14:62-65. “[A]n image quality analysis and preparation engine 326 analyzes the acquired image(s) to confirm the acquired image(s) contains an adequately clear and detailed image of the property[.]” *Id.* at 15:14-17. A “feature identification engine 320” then “extracts features” from the

image that relate to a property characteristic from the image. *Id.* at 15:63-16:1. For example, a group of pixels of the digital image may include angles and outlines that digitally represent a roof. *Id.* at 8:26-30.

A machine learning classifier then determines the shape of the roof. *Id.* at 9:15-18. For example, “a gable roof 202*b* includes a central peak upon a generally rectangular outline[.]” *Id.* at 15:18-19. Another machine learning classifier analyzes the extracted features to determine the condition of the roof. *Id.* at 21:9-11. To determine roof condition, the system can “extract pixel intensity distributions.” *Id.* at 10:52-56. “[N]ewly constructed property features generally have sharp contrast and well-defined features” while “weathered or damaged property features can have softened edges, blurred contrasts, and asymmetrical patches of wear.” *Id.* at 10:56-60.

As the District of Delaware found in denying Petitioner’s motion to dismiss under 35 U.S.C. § 101, PO’s challenged “patents recite the patent-eligible arrangement of two independently trained classifiers to analyze property characteristics and conditions.” Ex. 2008 at 1. The District Court found that the allegedly representative claim 1 of the ’029 patent “recites a process with a distinctive structure: two separate and independently trained machine-learning classifiers that operate independently,” reciting a computer architecture that “is significant in the eligibility analysis.” *Id.* at 8-9. According to the District Court, the

“claim thus implements machine-learning technology in a specific way to address a practical technical problem: how to accurately and quickly assess the physical characteristics and condition of a property from an aerial image using machine learning models.” *Id.* at 9.

Ultimately, the District Court found:

Claim 1 is not particularly hard to understand; Aon does not pretend that it is. But intricacy must not be the principal measure of eligibility — why should elegant inventions be prejudiced? Claim 1 presents a targeted, technical solution to a specific problem and reflects more than a generic invocation of machine learning. Thus, it is directed to patent-eligible subject matter. And because Zesty has not shown that claim 1 is directed to an abstract idea, our *Alice* inquiry ends at step one. The motion to dismiss is denied.

Id. at 13.

B. The Petition and the Prior Art Cited by Petitioner.

The '285 patent includes three independent claims: 1, 9, and 16. The Petition presents two grounds: 1) Gross as a single reference obviousness argument (claims 1-7 and 9-22 and 2) Gross in combination with Davis (claim 8). Thus, Petitioner relies on Gross alone to argue that each of the three challenged independent claims are unpatentable as allegedly obvious.

Gross explains that “the main application is described in connection with assisting property seekers, real estate personnel and others to assess and develop

leads for real estate prospects for single family residences.” Ex. 1005, ¶0237. To that end, Gross explains that “[c]ompetition for housing stock is rapidly increasing in the United States” and that “[y]oung families have significant difficulties finding suitable existing homes for rent or purchase in many desirable areas.” *Id.*, ¶0003. According to Gross, “homes [that] are dilapidated or in poor condition” or homes that are “not even inhabited . . . would be excellent leads for housing opportunities but currently go undiscovered and thus unexploited due to inadequate research and assessment tools.” *Id.*, ¶0004.

For another use case, Gross references “a considerable market in the US for home improvement goods and services, such as for example, windows, landscaping, siding, paint, roofing, plumbing and similar products to name a few.” *Id.*, ¶0008. Gross explains that “to date such types of entities have not targeted groups of homes in a neighborhood by identifying common issues with structures that could induce or at least incentivize group purchasing behavior.” *Id.* Thus, another use of Gross’s system is for contractors to identify opportunities for seeking work.

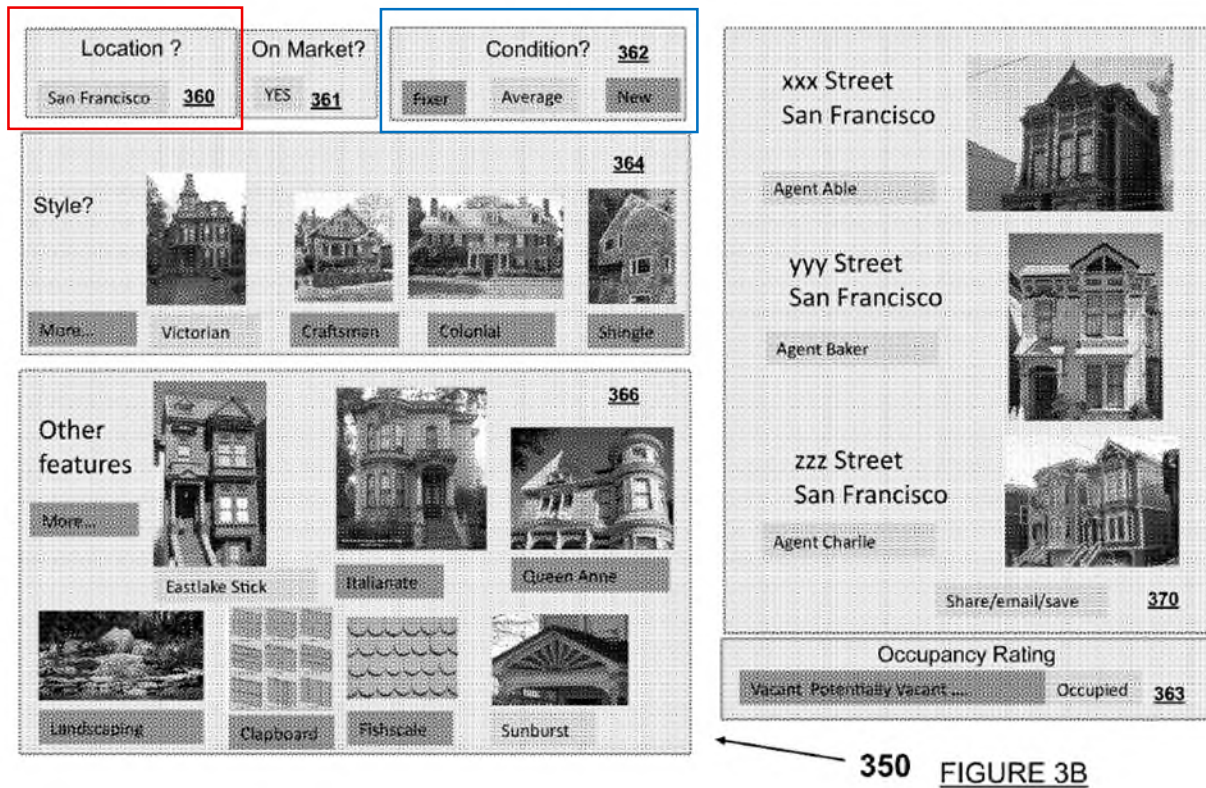
However, these use cases highlight the critical differences between Gross and the ’285 patent. Unlike the ’285 patent, Gross does not disclose an improved, two-tiered computer architecture for assessing the structural condition of a building at a specific property location. Instead, Gross discloses a system that allows home seekers and contractors to search geographic regions for opportunities. Gross

mentions the insurance field only in passing as a theoretical use case with no detail on how the disclosed system could be adapted for use in the insurance industry. *See id.*, ¶¶0237-38.

Gross discloses an “[i]mage database 142” that is comprised of images of buildings in a particular location. *See id.*, ¶0059. This image database allows a user to review images of homes that may be in need of improvement for the purpose of identifying real estate development opportunities. The “image database” “includes a current image of the structure in question which is in a form that can be analyzed for building elements.” *Id.* These images “can also include annotations [] identifying structure elements, defects, severity ratings, locations of identified defects, etc. as annotated automatically by a classifier and/or manually by a human operator.” *Id.*

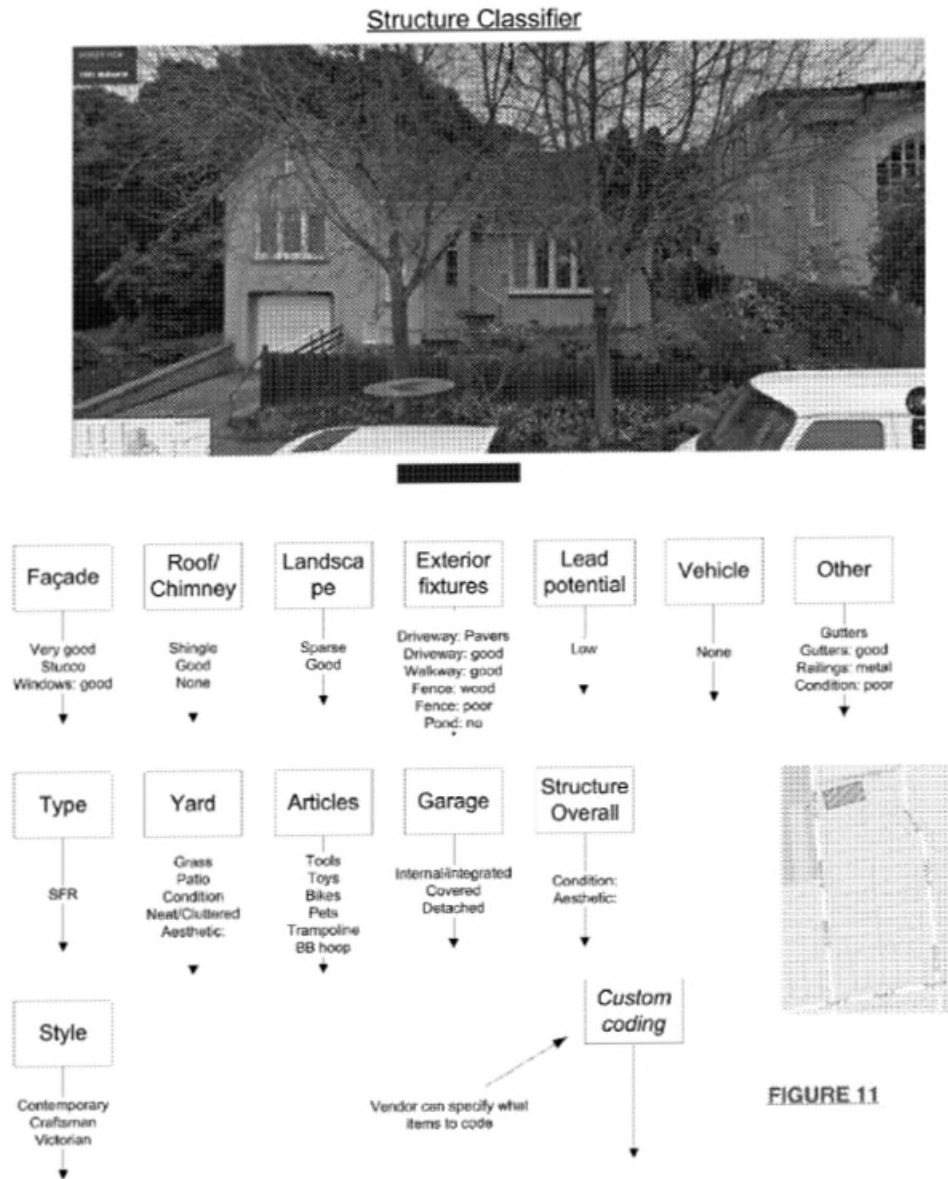
Later, Gross explains that humans are preferred for annotation of images: “To improve data accuracy it is expected that multiple human coders could be employed to review any particular structure. This will increase accuracy and coverage through crowdsourcing of such tasks. A voting algorithm can weigh the contributions from individual coders in assessing and attributing the presence of features, their type and condition.” *Id.*, ¶0145.

Gross discloses an “interactive interface 350” in Fig. 3B, which is reproduced below.



Consistent with the purpose of Gross's aspirational system, the interface includes drop down menus that allow the user to select a general geographic **location**, rather than a specific property address. Another drop down menu, allows the user to select the overall **condition** of the house, rather than the condition of a particular property characteristic of a particular property at a given address.

Petitioner relies (at 18) on Fig. 11 to argue that Classifier Engine 150 identifies property attributes and conditions:



However, there is no disclosure that the tagging in Fig. 11 is the result of any type of automated or machine learning process implemented by Classifier Engine 150. Instead, the description of Fig. 11 references a “human rater/coder” in paragraph 143 and “multiple human coders” in paragraph 145. The tagging in Fig. 11 was conducted by a human, not a machine learning classifier. Moreover, the

information shown in Fig. 11 is not searchable by the user. Rather, it appears the information included in Fig. 11—input by human coders—is used to determine the *overall* condition of a property in a geographic region that is targeted for real estate/renovation opportunities. See Ex. 1005, ¶0133 (discussing overall condition score that is presented to the user), ¶0099 (“The condition of the property can also be specified in query box 362 which may be presented in the form of a sliding scale, descriptors, etc. which permit a wide range of building stock to be searched, from ‘new’ all the way to ‘extreme fixer upper’ or some other similar moniker.”).

Indeed, Fig. 12 confirms that the tagging disclosed in Fig. 11 would be performed by humans—not an automated Classifier Engine 150. For example, as shown below, the figure includes **instructions** for a human reviewer to identify damage.

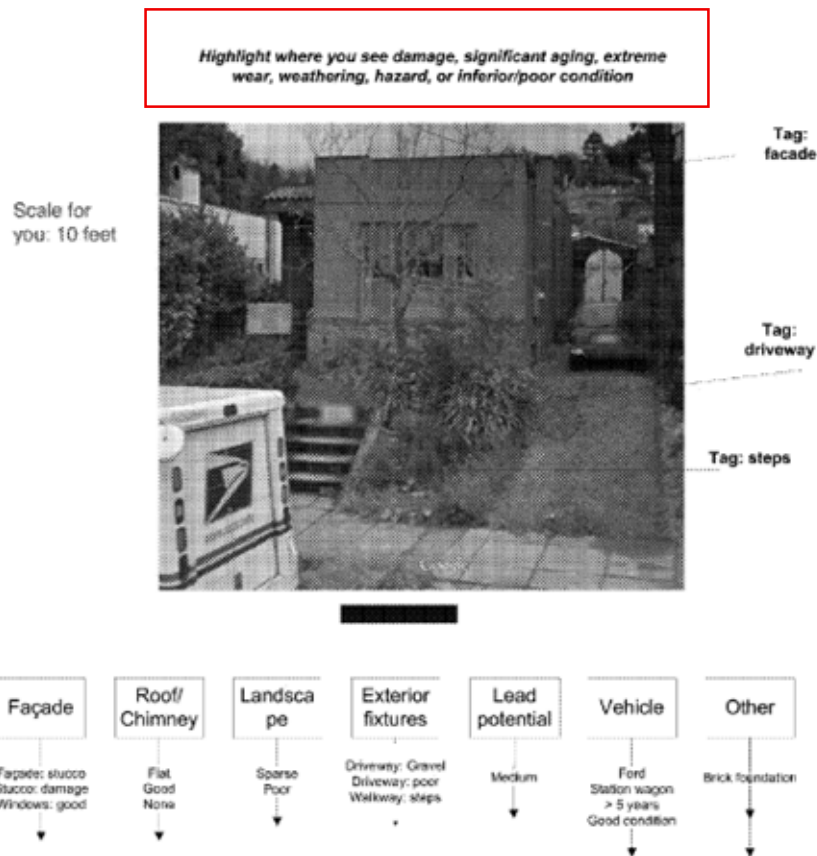


FIGURE 12



Gross mentions the use of a machine learning classifier as a future possibility, stating that “*it is expected* that with sufficient training an automated classifier *could* participate in the process, if not perform the entire process of classifying structural features.” *Id.*, ¶0145 (emphasis added). Thus, Gross does not disclose that the system discussed in the reference actually implemented the use of a machine learning classifier to identify attributes—much less a multi-tiered system of separate

classifiers each trained to identify different specific information about different specific things as part of an improved computer architecture.

Importantly, Gross himself appears to lack skill in the art of machine learning. Instead, his LinkedIn profile states that he is an “[e]xperienced inventor, prosecutor, negotiator and enforcer in all aspects of patent business, including strategic monetization of key portfolios in software, e-commerce, search, recommendations, Adtech, and social networking.” Ex. 2019 at 1. Consequently, Gross leaves the details of machine learning to others, disclosing very little about machine learning or how Gross’s so-called “Classifier Engine 150” would rely on machine learning techniques to identify real estate/renovation opportunities.

Instead, Gross merely mentions in passing that “neural networks, etc., [] can be used to detect and extract features of such attributes” as part of training Classifier Engine 150. Ex. 1005, ¶0077. Gross provides no detail at all on how these supposed neural networks would be involved in training Classifier Engine 150. Notably, Gross does not state that “neural networks” are implemented in its disclosed system to *classify* property attributes—let alone explain how its system would implement “neural networks” to identify dilapidated homes that present real estate and renovation opportunities.

For its “feature extraction algorithms,” Gross relies entirely on a survey paper concerning *facial recognition* technology—A *Survey of Face Recognition*

Techniques, by Jafri et al.—rather than any of his own work. See *id.*, ¶0079. Conspicuously, Gross fails to explain how facial recognition feature extraction algorithms have any application whatsoever to identifying dilapidated homes. In turn, the Petition and Dr. Forsyth rely on Gross’s reference to Jafri—again without explaining how Jafri’s facial recognition survey paper has anything to do with Gross’s Classifier Engine 150, much less the system disclosed and claimed in the ’285 patent. On this point, Petitioner and Dr. Forsyth appear to assume that no motivation is needed where Jafri is allegedly incorporated by reference. But that is not the law as explained *infra*.

In fact, the Petition acknowledges (at 16) that Gross mentions “image processing and attribute classification techniques” only in connection with training the so-called “Classifier Engine.” Nonetheless, the Petition argues (*id.*) that these alleged “techniques” “were intended to also be utilized in [Gross’s] building attribute/condition assessment process.” According to the Petition (*id.*), it would have been obvious to combine “Gross’s disclosure of the image processing elements used to train the Classifier Engine” with Gross’s alleged “disclosure of image processing used in its building attribute/condition assessment process.”

Petitioner’s “reasoning” (at 16-17) for this combination is self-fulfilling: “image processing techniques used to train the Classifier to identify attributes/conditions would in fact have also been used when performing a property

assessment.” However, Gross’s discussion of Figs. 11 and 12 belie Petitioner’s argument. Any discussion of Classifier Engine 150 to identify attributes appears to have been aspirational, which explains the lack of technical detail in Gross and Petitioner’s attempted gap filling through conclusory expert testimony and unexplained references to a survey paper concerning facial recognition technology.

Gross’s system is simply far afield from that disclosed and claimed in the ’285 patent.

III. CLAIM CONSTRUCTION

In an *inter partes* review filed on or after November 13, 2018, claim terms are construed based on their ordinary and customary meaning. 37 C.F.R. § 42.100(b). Petitioner argues (at 10) that “all claim terms should receive their plain and ordinary meaning in the context of the ’285 patent specification.” Solely for purposes of this Preliminary Response, PO accepts Petitioner’s argument. If trial is instituted, however, and to the extent deemed necessary to resolve any dispute, PO reserves the right to propose more specific constructions of one or more claim terms.

IV. LEVEL OF ORDINARY SKILL IN THE ART

Petitioner defines (at 9) a person of ordinary skill in the art (“POSITA”) as an individual who “would have had a bachelor’s degree in Computer or Electrical Engineering or equivalent discipline, and approximately two years’ experience in image processing and machine learning. Additional education could substitute for

professional experience.” Because it does not affect the ultimate analysis at this time, PO takes no position with respect to Petitioner’s proposed level of ordinary skill in the art solely for the purposes of the institution decision.

V. ARGUMENT

A. The Petition relies on expert testimony in an improper attempt to gap fill the absence of any disclosure in Gross concerning two separate machine learning classifiers.

Element 1.5 recites “applying, by the processing circuitry, a second portion of the set of pixel groupings to a second machine learning classifier to determine a condition classification of the characteristic from a plurality of potential condition classifications of the characteristic.” Similarly, element 9.2 recites “a second machine learning analysis model trained to identify one or more property conditions” while element 16.6 recites “apply at least a portion of the one or more sets of pixel groupings corresponding to the respective feature to one or more second machine learning classifiers trained to identify a condition of the respective feature in view of at least a first characteristic of the one or more characteristics.” Thus, each independent claim recites a second machine learning classifier or second machine learning analysis model.¹

¹ Petitioner addresses element 1.5 at 26-30, and Petitioner relies (at 31, 35) on its discussion of element 1.5 for elements 9.2 and 16.6. Thus, PO focuses on Petitioner’s discussion of element 1.5.

Critically, Petitioner acknowledges (at 29) that “Gross does not explicitly disclose that its condition qualifiers are classified via a different machine learning classifier than was used to identify attributes.” In other words, Petitioner admits that Gross does not disclose a “first machine learning classifier” trained to identify property characteristics and a “second machine learning classifier” trained to classify the condition of a given property characteristic. Thus, Petitioner argues (*id.*) that a POSITA “would have found it obvious to separate the classifiers and would have been motivated to employ a second machine learning classifier to identify a property characteristic conditions[.]”

Notably, Petitioner does not cite any patent or printed publication that actually discloses the use of a “first machine learning classifier” and a “second machine learning classifier” (let alone classifiers trained to evaluate different things in an improved computer architecture). Instead, Petitioner relies on expert testimony in an attempt to fill gaps in the prior art. However, that expert testimony fails to fill those gaps as it suffers from two primary flaws.

First, given that Dr. Forsyth does not rely on any prior art that discloses the claimed two-tiered machine learning architecture, Dr. Forsyth resorts to hindsight using the ’285 patent as a roadmap for his obviousness arguments. The law does not permit the use of such hindsight in an obviousness analysis. Second, Dr. Forsyth rests his argument on a fundamental misrepresentation of Gross. Stripped of this

misrepresentation, Gross provides no basis for a POSITA to separate “Classifier Engine 150” to include two separately trained machine learning classifiers to identify different specific pieces of information concerning a property. Each of these flawed arguments are addressed in turn below, and each provide an independent basis for denial of institution.

1. Dr. Forsyth’s declaration reveals an improper hindsight bias.

Dr. Forsyth proposes modifying Gross to include a first classifier trained to identify features that represent property characteristics and a second classifier trained to identify conditions of those characteristics.” Ex. 1003, ¶90. According to Dr. Forsyth, “a POSA would have understood that separating these classification tasks allows for independent optimization of each classifier’s training parameters and training datasets. Doing so would lead to increased overall system accuracy compared to a single classifier attempting to perform two types of classification simultaneously.” *Id.*

Dr. Forsyth does not cite any prior art reference that discloses his envisioned system. Instead, Dr. Forsyth’s proposed system comes directly from the specification and claims of the ’285 patent itself, providing Dr. Forsyth with a roadmap to make his obviousness arguments. However, the Federal Circuit has “cautioned against ‘allowing the challenger to use the challenged patent as a roadmap to reconstruct the claimed invention using disparate elements from the prior

art—i.e., the impermissible *ex post* reasoning and hindsight bias that *KSR* warned against.” *Adapt Pharma Operations Ltd. v. Teva Pharms. USA, Inc.*, 25 F.4th 1354, 1381 (Fed. Cir. 2022). Dr. Forsyth has violated this settled legal principle.

Starting with Dr. Forsyth’s suggestion that a POSITA would separate Gross’s “classification tasks [] for independent optimization of each classifier’s training parameters and training datasets . . . to increase [] overall system accuracy compared to a single classifier attempting to perform two types of classification simultaneously,” it is apparent that Dr. Forsyth found this teaching in the ’285 patent rather than any cited prior art reference. *See* Ex. 1003, ¶90. For example, the ’285 patent explains that a “test was conducted using NIN deep learning algorithms to classify rooftop shape in two-dimensional aerial images including a mix of gambrel, gable, hipped, square, and flat roof shapes of assorted colors.” Ex. 1001 at 9:39-43. The test involved “2,250 sample images in a training dataset and 250 test images in a test dataset” and resulted in “an accuracy rate of 94%.” *Id.* at 9:51-55. This is shown in Fig. 2D reproduced below.

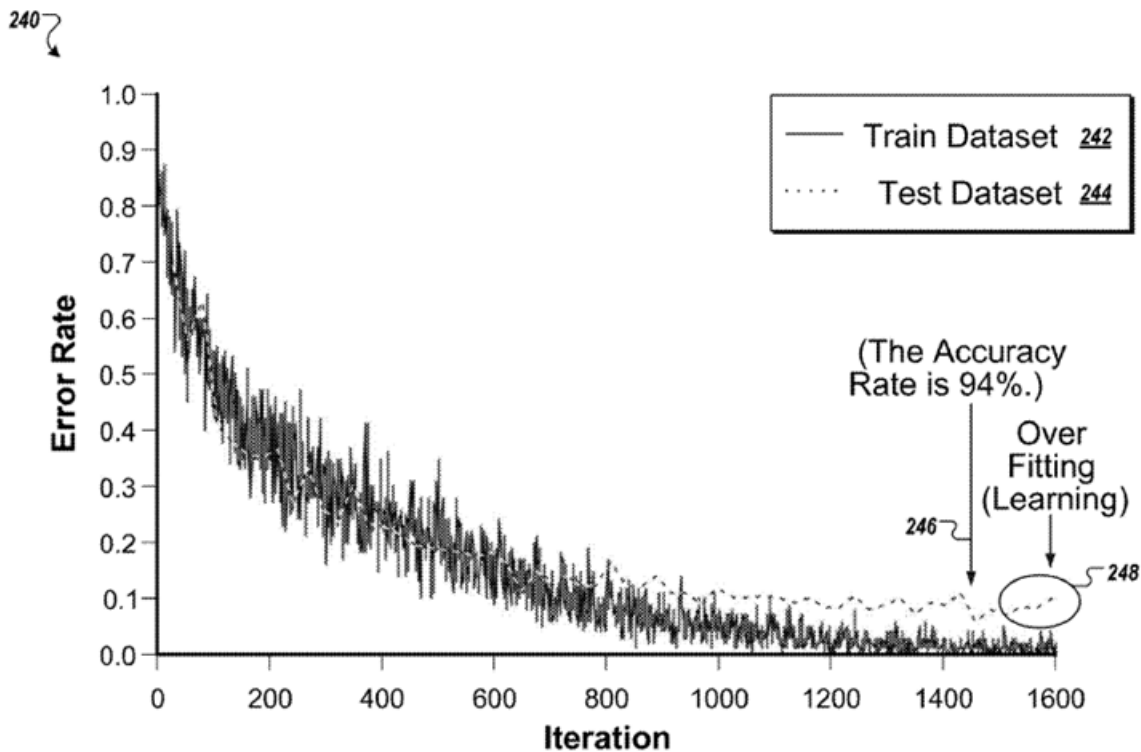


FIG. 2D

As another example of the '285 patent's disclosure of improved accuracy through the implementation of separately trained machine learning classifiers, the '285 patent explains that "individual condition profiles 114 can be generated for each property characteristic (e.g., profiles specific to gabled, gambrel, flat, hipped, square, etc.)" and that "in certain embodiments, individual condition profiles 114 can be generated for combinations of property characteristics (e.g., a gabled, shingled roof, a gabled, clay tiled roof, a gabled, metal roof, etc.) to **increase accuracy** rate based upon pixel densities corresponding to the combined characteristics." *Id.* at 12:7-15 (emphasis added). The '285 patent then further

explains that “[m]any combinations of characteristics of property features may be used singly or in combination to generate a condition profile 114 designed to **accurately** identify the condition of the corresponding property feature.” *Id.* at 12:15-18 (emphasis added). Thus, Dr. Forsyth’s opinion tracks the disclosure of the ’285 patent—a telltale sign of hindsight bias.

As another example of hindsight bias, Dr. Forsyth asserts that a POSITA would modify Gross’s so-called “Classifier Engine” to include “a first classifier trained to identify features that represent property characteristics” Ex. 1003, ¶90. Dr. Forsyth does not cite any prior art disclosure for this proposition. Instead, his assertion again tracks the specification of the ’285 patent.

For example, as to roof shape, the ’285 patent explains:

In an illustrative example, turning to FIG. 2A, extracted ***angular and outline features of aerial images 204 may be used to classify a roof shape 202*** of the particular property location 102*b*. In a first example, a gable roof 202*b* includes a central peak upon a ***generally rectangular outline***, as depicted in corresponding aerial image 204*b*. A gambrel roof 202*a* includes these features of the gable roof 202*b* but, as illustrated in aerial image 204*a*, the gambrel roof additionally includes a “skirt” region surrounding the central gable-shaped portion. ***The “skirt” region can be identified, in part, based upon its corner edges*** extending from the four corners of the gable-shaped portion. A hipped roof 202*c*, as shown in aerial image 204*c*, includes a central peak and ***two opposing triangular ends*** extending from either end of the central

peak. ***The central peak forms a top edge of two trapezoidal sections.***

A square roof 202d, in contrast, has no central peak. Instead, as illustrated in aerial image 204d, the square roof includes ***four triangular portions*** meeting at a central point. Finally, a flat roof 202e, as shown in aerial image 204e, is represented by ***a substantially flat surface outlined by a rectangle.***

Ex. 1001 at 9:15-35 (emphasis added).

Thus, the '285 patent discloses a first machine learning classifier that is trained to identify features that represent property characteristics, which matches exactly Dr. Forsyth's hindsight proposal. The Petition invites error by using the '285 patent as a roadmap in a hindsight-laden obviousness argument.

Dr. Forsyth's argument with respect to characteristic condition classification suffers from the same hindsight bias. As to this point, Dr. Forsyth asserts that it would have been obvious to modify Gross to include "a second classifier trained to identify conditions of those characteristics." Ex. 1003, ¶90. Dr. Forsyth does not cite any prior art disclosure for this proposition. Instead, this again tracks the specification of the '285 patent.

With respect to condition classification, the '285 patent discloses:

In an illustrative example, turning to FIG. 2B, examples of condition characteristics of aerial images of hipped rooftops and corresponding example histograms generated through ***machine learning analysis of pixel intensity are presented.*** For example, a set of good condition

aerial images 210*a* through 214*a*, are presented alongside corresponding good condition histograms 210*b* through 214*b*. The good condition histograms 210*b* through 214*b*, in an illustrative embodiment, illustrate probability ***metrics of grayscale color distribution***, where a respective maximum value 210*c* through 214*c* demonstrates the peak probability of grayscale color distribution of a good condition roof. The values, for example, can range from 0 (total black) to 255 (total white).

Conversely, a set of poor condition aerial images 216*a* through 220*a*, are presented alongside corresponding poor condition histograms 216*b* through 220*b*. The poor condition histograms 216*b* through 220*b*, in an illustrative embodiment, illustrate probability metrics of ***grayscale color distribution***, where a respective maximum value 216*c* through 220*c* demonstrates the peak probability of grayscale color distribution of a good condition roof. The maximum values 216*c* through 220*c* corresponding to the poor condition rooftops 216*a* through 220*a* are markedly lower than corresponding maximum values 210*c* through 214*c* of good condition rooftops 210*a* through 214*a*. In addition, a width of the distributions of the poor condition histograms 216*b* through 220*b* may be markedly wider than a width of the distributions of the good condition histograms 210*b* through 214*b*. ***As can be seen of the aerial images of the poor condition rooftops 216*a* through 220*a*, the color distribution is patchy and bleached out, while the edges of the rooftops have lost their crisp lines. Conversely, looking to the aerial images of the good condition rooftops 210*a* through***

214a, the rooftops are more substantially uniform in color with crisp lines on the edges.

Ex. 1001 at 11:14-50 (emphasis added); *see also id.* at 10:52-60 (“Using machine learning for analysis, for example, the system can extract pixel intensity distributions of previously identified property features of the aerial image of the particular property location 102b. In some examples, newly constructed property features generally have ***sharp contrast and well-defined features*** in machine learning image analysis. Conversely, weathered or damaged property features can have ***softened edges, blurred contrasts, and asymmetrical patches of wear.***”) (emphasis added).

Here again, Dr. Forsyth’s suggestion concerning dividing Gross’s “Classifier Engine 150” into a separate condition classifier tracks the ’285 patent specification’s disclosure of a second machine learning classifier that relies on texture, color, surface artifacts—yet another telltale indication of improper hindsight bias. Petitioner’s reliance on Dr. Forsyth’s flawed opinion in an attempt to supply the missing “second machine learning classifier” in Gross fails.

2. Gross’s disclosure does not support Petitioner’s obviousness arguments.

As cover for a clear hindsight bias discussed *supra*, Dr. Forsyth attempts to support his opinion that it would be obvious to modify Gross to include a “second machine learning classifier” as claimed in the ’285 patent by pointing to various sections of Gross—again a prior art reference that by Petitioner’s own admission (at

29) does not include the claimed “second machine learning classifier.” None of these sections provide a basis for Dr. Forsyth’s proposed system as discussed below.

First, Dr. Forsyth argues that “Gross explicitly discloses that ‘it may be useful to employ multiple classifiers ... to identify the attributes and classify the structure.’” Ex. 1003, ¶88 (alterations in original) (emphasis added). However, as shown by the yellow highlighting, Dr. Forsyth relies on selectively placed ellipsis to modify Gross’s actual disclosure. The text that Dr. Forsyth and Petitioner omits makes clear that Gross’s “multiple classifiers” are in fact classifiers theoretically trained to identify the *same* information.

Specifically, the full sentence in Gross states: “For better accuracy it may be useful to employ multiple classifiers trained with different algorithms **to give a combined or averaged score** to identify the attributes and classify the structure.” Ex. 1005, ¶0080 (emphasis added). Gross does not disclose the use of one classifier to classify a property attribute and then another separately trained classifier to classify the condition of the property attribute.

Rather, Gross’s theoretical “multiple classifiers” each attempt to identify the same information in different ways with the idea being that the scores can be averaged as a form of confidence interval concerning the identification of the same information. Again, this is fundamentally different from the ‘029 patent, a key feature of which is having a second classifier within the computer architecture that

classifies different information as compared to the first classifier. This explains Petitioner’s admission (at 29) that “Gross does not explicitly disclose its condition qualifiers are classified via a different machine learning classifier than was used to identify attributes.” Petitioner’s attempt to find some basis in Gross for its proposed modification fails.²

Second, Dr. Forsyth further argues that “Gross further discloses examples of using a classifier to identify conditions, such as ‘damaged/exposed roof elements’ and ‘exposed broken—façade,’” citing to paragraphs 85 and 91 of Gross. Ex. 1003, ¶88. But in these paragraphs, Gross identifies “[e]xamples of the types of attributes and conditions that can be used for training *the* classifier”—a reference to a *single* classifier. Ex. 1005, ¶0084 (emphasis added); *see also id.*, ¶0123 (referring to simultaneous coding of “block 701” for both property attribute and condition), ¶0127 (“If Classifier Engine 150 identifies an attribute, condition, and location with an acceptable confidence in block 701”). Dr. Forsyth’s reliance on paragraphs discussing a single classifier simply confirms Petitioner’s reliance on Dr. Forsyth’s testimony in an attempt to gap fill.

² For clarity, PO does not argue that averaging the scores of different algorithms that classify the same thing is outside the scope of the first or second machine learning classifier as claimed. Instead, PO’s point is that Gross’s disclosure of such averaging relates to algorithms trained to identify the same information from an image in different ways. Gross does not disclose the multi-tiered machine learning architecture claimed in the ’285 patent.

Third, Dr. Forsyth argues that Gross “discloses that different classifiers could be customized for different purposes by claiming, ‘an electronic classifier *customized* for a vendor ... as corresponding to said individual building *elements, types* and/or *associated conditions*,’” citing not to the written description in Gross but to a dependent claim (that was never allowed). Ex. 1003, ¶88 (alteration in original). That claim recites: “26. The method of claim 25 wherein said query engine uses an electronic classifier customized for a vendor generating said query which is based on products or services calculated by a computing system as corresponding to said individual building elements, types and/or associated conditions.” Ex. 1005, cl. 26. This simply does not disclose a second machine learning classifier trained to classify the condition of an already classified property characteristic as Petitioner contends. Again, Petitioner relies on Dr. Forsyth in an attempt to gap fill a “second machine learning classifier” that is not present in Petitioner’s cited art.

Fourth, Dr. Forsyth argues that a POSITA “would have been motivated to employ a second machine classifier to identify a condition classification because Gross explicitly suggests that different classifiers can be used and that classifiers can be customized for different purposes.” Ex. 1003, ¶90. However, as explained above, that is simply not what Gross says; indeed, this argument relies on Dr. Forsyth’s misleading ellipsis.

Fifth, Dr. Forsyth next argues that a POSITA “would recognize that the reason Gross suggests using different classifiers is so that they would then ‘be trained with different algorithms’ and ‘additional data’ that optimize and focus on identification of property characteristic conditions, which would improve accuracy of the classification.” *Id.* However, as explained above, to the extent Gross discloses “different algorithms” in paragraph 80, Gross refers to algorithms that operate in different ways to identify the same information—not algorithms trained to identify different things. This is the same disclosure Petitioner omitted with its selective ellipsis, which does not provide a basis for Petitioner’s proposed modification.

B. The Petition fails to even attempt to explain why and how a POSITA would combine facial recognition feature extraction algorithms with Gross.

Element 1.2 recites “extracting, by the processing circuitry, one or more features of a plurality of features from the aerial image.” Similarly, element 9.3 recites “extract a set of image-related features from an aerial image, wherein the set of image-related features represent the property feature” while element 16.2 recites “extract a plurality of pixel groupings from the aerial and/or terrestrial imagery, wherein the plurality of pixel groupings includes a respective set of pixel groupings

representative of each feature of one or more features of the property.” Thus, each independent claim recites extraction of features from an aerial image.³

For each of these recitations, Petitioner argues (at 22) that “Gross further notes that feature extraction algorithms are well-known in the art and a suitable example that can be used in its embodiments is set forth in [Jafri]” and further that “Gross, through the incorporated Jafri material, additionally discloses *features represented by a set of pixel groupings* through Jafri’s description of a recognition system that detects ‘prominent facial landmarks (i.e., the eyes, nose, and mouth)’ to track those *features*.” Thus, the Petition relies on Jafri in an attempt to supply missing “feature extraction” details for Gross’s cited embodiments. However, the Petition fails to even attempt to identify a motivation to combine with the requisite expectation of success. This is not simply a case where Petitioner’s motivation and expectation of success arguments are unpersuasive—there is simply no argument on either point in the Petition.

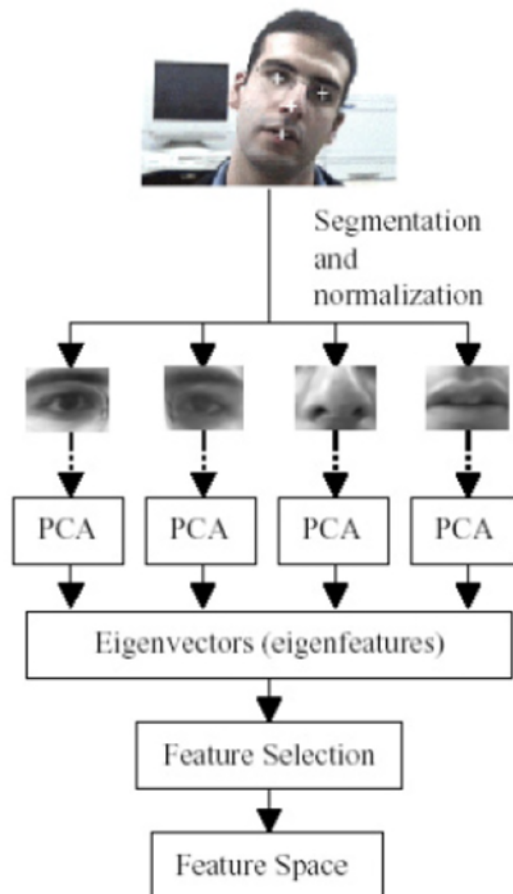
Nor does Dr. Forsyth offer any testimony on these points. Instead, Dr. Forsyth largely mimics the Petition: “Gross further notes that feature extraction algorithms are well-known in the art and a suitable example that can be used in its embodiments

³ Petitioner addresses element 1.2 at 20-23, and Petitioner relies (at 32, 34) on its discussion of element 1.2 for elements 9.3 and 16.2. Thus, PO focuses on Petitioner’s discussion of element 1.2.

is set forth in ‘*A Survey of Face Recognition Techniques* by Jafri’ (EX1008), which I understand from counsel is incorporated by reference into Gross. [. . .] Gross, through the incorporated Jafri material, additionally discloses *features represented by a set of pixel groupings* through Jafri’s description of a recognition system that detects ‘prominent facial landmarks (i.e., the eyes, nose, and mouth)’ to track those *features*.” Ex. 1003, ¶75.

Dr. Forsyth then provides an “example” with reference to Fig. 19 of Jafri that, according to Dr. Forsyth “illustrates pixel groupings around the nose, eye, and lips,” which figure is reproduced below.⁴ *See id.*

⁴ In fact, Fig. 19 is not even Jafri’s own work but instead is a figure from yet another reference discussing facial recognition from video (titled “A Framework for Face Recognition from Video Sequences Using GWN and Eigenfeature Selection”), which Petitioner did not even submit as an exhibit—a type of multi-layered incorporation by reference based on a reference that is not even of record here. *See* Ex. 1008 at 64 n.207. And yet again, neither the Petition nor Dr. Forsyth even attempt to identify a motivation to combine techniques from a paper—which is not even of record here—discussing facial recognition from video sequences with Gross’s embodiments.



Entirely missing from Dr. Forsyth’s discussion of Fig. 19 is any attempt to explain why a survey paper that discusses ways to identify a face has any relevance to property characteristic condition classification—much less a legally sufficient obviousness argument. Again, no motivation is mentioned at all. Nor is the required expectation of success.

Instead, Petitioner and Dr. Forsyth seem to assume that because Jafri is allegedly incorporated by reference, they need not address the legal requirements for an obviousness argument. But that is not the law. Indeed, the Federal Circuit has been clear that “[w]hether . . . combining disclosures from multiple references [or],

combining multiple embodiments from a single reference, or selecting from large lists of elements in a single reference, there must be a motivation to make the combination and a reasonable expectation that such a combination would be successful, otherwise a skilled artisan would not arrive at the claimed combination.” *In re Stepan*, 868 F.3d 1342, 1346 n.1 (Fed. Cir. 2017). Petitioner thus failed to offer a legally sufficient obviousness argument.

Compounding Petitioner’s failure to even attempt a legally sufficient obviousness argument is the fact that Jafri itself criticizes the very automated feature extraction the Petition argues would have been a “suitable example” to be used in Gross. Specifically, Jafri states (Ex. 1008 at 43): “In general, current algorithms for automatic feature extraction do not provide a high degree of accuracy and require considerable computational capacity;” *see also id.* at 45 (referring to “the difficulty of automatic feature detection”). Neither the Petition nor Dr. Forsyth make any effort to address this teaching in Jafri that counsels against the very automatic feature extraction on which the Petition relies to argue that automatic feature extraction would have been obvious in view of Jafri. Petitioner’s failure to address Jafri’s teaching away further demonstrates that Petitioner did not even attempt to carry its burden on motivation to combine Jafri with Gross. *Henny Penny Corp. v. Frymaster LLC*, 938 F.3d 1324, 1332 (Fed. Cir. 2019).

C. The Petition fails to even attempt to explain why and how a POSITA would combine Jafri’s passing reference to “a hybrid neural network solution” with Gross.

Petitioner relies (at 26) on Jafri’s mention of a “hybrid neural network solution” in an attempt to find a “first machine learning classifier” in Gross. However, Petitioner has again failed to offer *any* argument that a POSITA would be motivated to make the combination of Jafri and Gross with the requisite reasonable expectation of success. Again, this is not a situation where Petitioner’s motivation to combine and expectation of success arguments are simply unpersuasive—they are entirely absent from the Petition. Compounding Petitioner’s evidentiary shortcoming is the fact that Jafri’s alleged “hybrid neural network solution” is not even incorporated by reference into Gross, making the material unavailable to Petitioner on the current record.

Element 1.4 recites “applying, by the processing circuitry, a first portion of the set of pixel groupings to a first machine learning classifier to determine a characteristic classification of the characteristic from a plurality of potential classifications of the characteristic.” Similarly, element 9.1 recites “a first machine learning analysis model trained to identify one or more property characteristics” while element 16.5 recites “apply at least a portion of the one or more sets of pixel groupings corresponding to the respective feature to one or more first machine learning classifiers trained to identify one or more characteristics of the respective

feature.” Thus, each independent claim recites a first machine learning classifier or analysis model.⁵

For each of these recitations, Petitioner argues (at 29) that “Gross—through the incorporated Jafri material—describes using ‘a hybrid neural network solution’ (i.e., a form of classifier) to analyze image patterns.” Thus, Petitioner relies on Jafri’s alleged mention of a “hybrid neural network solution” as the Petition’s first machine learning classifier.

As with Jafri’s alleged “feature extraction,” neither the Petition nor Dr. Forsyth make any effort to identify a motivation to combine Jafri’s mention of “a hybrid neural network solution” with Gross’s Classifier Engine 150 with the requisite reasonable expectation of success. *See In re Stepan Co.*, 868 F.3d at 1345–46 (“An obviousness determination requires finding both that a skilled artisan would have been motivated to combine the teachings of the prior art ... and that the skilled artisan would have had a reasonable expectation of success in doing so.”) (citations omitted).

Instead, Dr. Forsyth simply mimics the Petition and asserts: “Gross, through the incorporated Jafri material, also describes using ‘a hybrid neural network

⁵ Petitioner addresses element 1.4 at 24-26, and Petitioner relies (at 31, 35) on its discussion of element 1.4 for elements 9.1 and 16.5. Thus, PO focuses on Petitioner’s discussion of element 1.4.

solution’ (i.e., a form of classifier) to analyze image patterns.”⁶ Ex. 1003, ¶82. There is simply no argument in the Petition or Dr. Forsyth’s declaration that a POSITA would have been motivated to combine Jafri’s mention of “a hybrid neural network solution” with Gross, much less with the requisite reasonable expectation of success. This is insufficient to carry Petitioner’s burden.

Petitioner is also incorrect in asserting that Jafri’s mention of “a hybrid neural network solution” is incorporated by reference into Gross. “To incorporate material by reference, the host document must identify with *detailed particularity* what specific material it incorporates and *clearly indicate where* that material is found in the various documents.” *Zenon Env’t, Inc. v. U.S. Filter Corp.*, 506 F.3d 1370, 1378 (Fed. Cir. 2007). Petitioner has failed to meet this legal standard here, as Gross limits its alleged incorporation by reference of Jafri to “**feature extraction** algorithms”: “**Feature extraction algorithms** are well-known in the art, and examples of such that are suitable and/or can be adapted easily for use in the present embodiments is set out in literature such as *A Survey of Face Recognition Techniques*, by Jafri et al.

⁶ On this point, Jafri references another paper—which again is not of record here—by Lawrence. *See* Ex. 1008 at 49. Like the rest of Jafri, the cited portion says nothing about property characteristic classification and instead—like the rest of Jafri—is about a facial recognition paper. It provides little detail on the referenced “hybrid neural network solution.”

appearing in *Journal of Information Processing Systems*, Vol. 5, No. 2, June 2009 and incorporated by reference herein.” Ex. 1005, ¶0079 (emphasis added).

Gross does not state that Jafri is incorporated by reference for purposes of supplying a neural network to classify extracted features, much less with the requisite “detailed particularity.”⁷ And because Gross does not even state that it incorporates Jafri’s mention of a “hybrid neural network solution,” it certainly does not clearly indicate where the unincorporated material is found in Jafri.

In deciding whether material is properly incorporated by reference, “the standard of one reasonably skilled in the art should be used to determine whether the host document describes the material to be incorporated by reference with sufficient particularity.” *Zenon*, 506 F.3d at 1378–79. Despite this, Dr. Forsyth fails to offer necessary supporting testimony. Ex. 1003, ¶82. Instead, Dr. Forsyth appears to have simply assumed that Gross properly incorporated Jafri’s reference to “hybrid neural network[s]” based on a legal instruction from counsel. *Id.*, ¶75. There is simply no discussion in Dr. Forsyth’s declaration as to how a POSITA would identify Jafri’s

⁷ For clarity, PO does not argue that a “hybrid neural network” is not a type of machine learning classifier or that a neural network solution cannot be used to extract features. Instead, the point here is that it was Petitioner’s burden to explain why a POSITA would have understood Gross to incorporate Jafri’s mention of a “hybrid neural network solution” and/or to identify a motivation to do so with the requisite expectation of success. Petitioner’s failure to do so means that it has not carried even its initial burden at the institution stage.

mention of a “hybrid neural network solution” as being incorporated into Gross for use in classifying property attributes. Absent its attempted improper incorporation of Jafri’s mention of “hybrid neural network[s]” used in facial recognition applications, Petitioner has failed to identify a “first machine learning classifier” in view Gross.⁸

D. Petitioner’s inconsistent claim construction positions undermine its ability to carry its burden.

Petitioner has taken inconsistent claim construction positions as to the term “feature” between this proceeding and a related IPR (IPR2025-01360) where Petitioner challenges PO’s ’491 patent. To the extent Petitioner believes it is appropriate to construe the term “feature” to mean different things as between claims in the same family of patents, it was incumbent on Petitioner to explain why that should be the proper result in view of the maxim that a claim term should be construed consistently across a related family of patents where possible. *See Rexnord Corp. v. Laitram Corp.*, 274 F.3d 1336, 1342 (Fed. Cir. 2001); *NTP, Inc. v.*

⁸ For clarity, PO does not argue that a “hybrid neural network” is not a type of machine learning classifier or that a neural network solution cannot be used to extract features. Instead, the point here is that it was **Petitioner’s** burden to explain why a POSITA would have understood Gross to incorporate Jafri’s mention of a “hybrid neural network solution” and/or to identify a motivation to do so with the requisite expectation of success. Petitioner’s failure to do so means that it has not carried even its initial burden at the institution stage.

Research In Motion, Ltd., 418 F.3d 1282, 1293 (Fed. Cir. 2005) (abrogated on other grounds).⁹

In this IPR, element 1.2 recites “extracting, by the processing circuitry, one or more features of a plurality of features from the aerial image.” Further, as explained *supra* in Section V.B, elements 9.3 and 16.2 include a similar “extracting” limitation. As to this claim element, Dr. Forsyth testifies that the claim term “*feature* can [] have multiple meanings, depending on the context” and that “the claimed *features*, here, appear to follow the **computer vision meaning** of the term.” Ex. 1003, ¶71 (third emphasis added).

In IPR2025-01360, element 1.5 of the ’491 patent recites “extracting the respective feature from each image of at least one image of the one or more images.” In that proceeding, Dr. Forsyth provides a substantially similar explanation concerning the multiple potential meanings of the word “feature.” Ex. 2020, ¶65. However, Dr. Forsyth offers a different opinion on the construction of “feature”: “When referring to the claimed *features of a property location, property features*, and *respective feature from each image*, the ’491 patent uses the word *feature* in the second sense, **describing ‘property features’ as physical aspects, qualities, or**

⁹ For clarity, PO takes no position on whether it would be appropriate for “feature” to mean one thing in one patent and a different thing in another patent in the same family. The point here is that it was Petitioner’s burden to explain this inconsistency, and it has failed to do so.

facets of a property,” rather than according to the “computer vision meaning of the term.” *Id.* (bold, underlined emphasis added). Importantly, Dr. Forsyth fails to explain why “feature” should be construed in two different ways.

In other words, in this proceeding, Petitioner—without explanation—disagrees with its own construction for the term “feature” in a different proceeding directed to a patent in the same family. This presents two issues: (1) Petitioner’s disagreement with itself fails to comply with 37 C.F.R. § 42.104(b)(3); and (2) Petitioner’s disagreement with itself generally undermines its ability to carry its burden to win institution here.

As to the ***first*** issue, 37 C.F.R. § 42.104(b)(3) requires the petition to identify “[h]ow the challenged claim is to be construed.” Petitioner’s inconsistent positions demonstrate that Petitioner has not actually identified how the challenged claim is to be construed. Should it be construed as argued in its Petition? Or should it be construed as argued in its petition in IPR2025-01360? Indeed, Petitioner did not simply adopt PO’s yet-unserved claim construction positions from the district court. Instead, Petitioner disagrees with *its own construction* presented to the Board in IPR2025-01360 without explaining the apparent inconsistency. This fails to comply with Rule 42.104(b)(3).

As to the ***second*** issue, Petitioner’s inconsistent positions undermine its ability to carry its burden in this proceeding. In this proceeding, Petitioner bases its

arguments concerning Gross on its “computer vision” construction of the term “feature.” *See* Pet. 20-23 (relying on Dr. Forsyth’s construction in paragraph 71 of his declaration). Yet, Petitioner disagrees with its own construction of “feature” in IPR2025-01360. Petitioner cannot persuasively advocate for the construction of “feature” in this proceeding—on which its challenge is based—where it disagrees with itself in another proceeding. This is an independent issue on which the Board can find that Petitioner has not carried its burden to win institution in this proceeding.

VI. CONCLUSION

For the above reasons, Petitioner has not met its burden to institute the present Petition. Thus, Patent Owner respectfully requests that institution be denied.

Dated: November 4, 2025

Respectfully submitted,

GARDELLA ALCIATI P.A.

By: /Greg H. Gardella/
Greg H. Gardella (Reg. No. 46,045)
Email: ggardella@ga-iplaw.com
Michael J. Stimson (Reg. No. 45,429)
Email: mstimson@ga-iplaw.com
80 M Street SE, 1st Floor
Washington, D.C. 20003
Phone: 703-556-9600
Fax: 703-740-4541

*Attorneys for Patent Owner
Aon Re, Inc.*

WORD COUNT CERTIFICATE OF COMPLIANCE

Pursuant to 37 C.F.R. § 42.24(d), I hereby certify that the foregoing PATENT OWNER'S PRELIMINARY RESPONSE contains 8,533 words as measured by the word processing software used to prepare the document. This total does not include the table of contents, the caption page, any signature blocks, the certificate of service, or this certificate of word count.

Respectfully submitted,

Dated: November 4, 2025

By: /Greg H. Gardella/
Greg H. Gardella
GARDELLA ALCIATI P.A.

CERTIFICATE OF SERVICE

The undersigned certifies that a copy of the foregoing document, along with any supporting document(s), was served in its entirety by filing through the Patent Trial and Appeal Case Tracking System (P-TACTS) as well as providing a courtesy copy via e-mail to the following attorneys of record for the Petitioner listed below:

Lead Counsel: Daniel S. Block
dblock-PTAB@sternekessler.com

Back-up Counsel: Jennifer Meyer Chagnon
Justin D. Wang
jchagnon-PTAB@sternekessler.com
jwang-PTAB@sternekessler.com
PTAB@sternekessler.com

Dated: November 4, 2025

By: /Greg H. Gardella/
Name: Greg H. Gardella
GARDELLA ALCIATI P.A.