IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

ZESTY.AI, INC.,
Petitioner

v.

AON RE, INC.,
Patent Owner

Case IPR2025-00XXX
U.S. Patent No. 11,195,058

PETITION FOR *INTER PARTES* REVIEW
OF U.S. PATENT NO. 11,195,058

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11. [1.10]: applying one or more property condition profiles of the set of property condition profiles to at least a portion of each image of the at least one image to classify a condition of the respective property feature, and 27

12. [1.11]: responsive to receiving the request, cause presentation of, for review by the user at the remote computing device, a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature..... 28

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1. [13.P]: A method for automatically assessing features of a property location comprising a structure, the method comprising:..... 31

2. [13.1]: receiving, from a user at a remote computing device via a network, a request comprising identification of a property location; 32

3. [13.2]: accessing, by processing circuitry, aerial imagery of the property location; 32

4. [13.3]: classifying, by the processing circuitry, a condition of one or more features of the property location, wherein classifying comprises, for each feature of the one or more features, identifying the respective feature from at least one image obtained from the aerial imagery, ... 32

5. [13.4]: applying one or more property characteristic profiles of a set of property characteristic profiles to at least a portion of each image of the at least one image to determine a plurality of characteristics of the respective feature, ... 32

6. [13.5]: wherein each property characteristic profile of the set of property characteristic profiles is developed through training one or more machine learning algorithms using first property images to identify one or more characteristics of at least one property feature of one or more property features, and a first characteristic of the plurality of characteristics comprises a type of material of the feature or a shape of the feature, and 32

7. [13.6]: applying one or more property condition profiles of a set of property condition profiles to at least a portion of each image of the at least one image to classify a condition of the respective property feature, ... 33

8. [13.7]: wherein each property condition profile of the set of property condition profiles is developed through training one or more machine learning algorithms using second property images to identify one or more conditions of at least one property characteristic of one or more property characteristics corresponding to a given feature or features of the one or more property features; and..... 33

9. [13.8]: responsive to receiving the request, causing presentation of, for review by the user at the remote computing device, a graphical user interface comprising

information regarding the plurality of characteristics and the condition of each feature of the at least one property feature. 33

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PETITIONER'S EXHIBIT LIST

Exhibit No.	Description
1001	U.S. Patent No. 11,194,058 to Okazaki ("'058 patent")
1002	Prosecution History of U.S. Patent No. 11,195,058 ("Prosecution History")
1003	Declaration of Dr. David A. Forsyth
1004	*Curriculum Vitae* of Dr. David A. Forsyth
1005	U.S. Publication No. 2015/0186953 to Gross et al. ("Gross")
1006	*Intentionally Left Blank*
1007	*Intentionally Left Blank*
1008	Jafri, *et al.*, "A Survey of Face Recognition Techniques," *Journal of Information Processing Systems*, Vol. 5, No. 2, June 2009, pp. 41-68 ("Jafri")
1009	U.S. Patent No. 8,078,436 to Pershing et al. ("Pershing")
1010	U.S. Patent No. 6,885,771 to Takahashi ("Takahashi")
1011	U.S. Publication No. 2009/0265193 to Collins et al. ("Collins")
1012	U.S. Publication No. 2015/0302529 to Jagannathan ("Jagannathan")
1013	U.S. Patent No. 4,941,122 to Weideman ("Weideman")
1014	U.S. Patent No. 8,995,757 to Ciarcia et al. ("Ciarcia")
1015	Redistricting Data Hub, "TIGER Boundary Files," accessible at https://redistrictingdatahub.org/data/about-our-data/tiger-boundary-files/ (last accessed July 10, 2025)
1016	Norman, J., "Origins of Google Earth," History of Information, accessible at https://www.historyofinformation.com/detail.php?entryid=3145 (last accessed July 13, 2025)
1017	Krizhevsky, *et al.*, "ImageNet Classification with Deep Convolutional Neural Networks," Communications of the ACM, Vol. 60, No. 6, May 2017
1018	Lin, *et al.*, "Network In Network," 2013

Exhibit No.	Description
1019	Bradski, "The OpenCV Library," accessible at https://www.drdobbs.com/open-source/the-opencv-library/184404319 (last accessed July 10, 2025)
1020	van der Walt, *et al*., "scikit-image: image processing in Python," *PeerJ*, June 2014
1021	"Cartographic Work in Japan 2000 – 2005," United Nations Economic and Social Council, June 2005
1022	Usery, *et al*., "Mapping Developments and GIS in the USGS, 1884-2009," International Cartographic Association, January 2009
1023	Novak, *et al*., "Anatomy of a Color Histogram," *Proceedings of the 1992 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, June 1992, pp. 599-605

Petitioner Zesty.ai, Inc. ("Petitioner") petitions for *inter partes* review, seeking cancellation of claims 1-20 of U.S. Patent No 11,195,058 ("the '058 patent," EX1001), assigned to Patent Owner Aon Re, Inc.

I. INTRODUCTION

The '058 patent issued without a single rejection based on prior art. It claims nothing more than well-known concepts of using standard image processing and known machine learning techniques to identify features (e.g., a roof) from an image of a property, determine characteristics of the feature (e.g., a "tile" roof), and classify a condition of the feature (e.g., new, damaged). The claimed property assessment concepts were known to anyone who ever performed such an assessment of a property. In fact, property assessment was performed manually—either by manually reviewing images or by inspecting the property in person—long before the '058 patent proposed applying standard image processing and known machine learning techniques to automate the process. *See, e.g.*, EX1005, ¶6 (describing prior art systems to assess buildings, including a manual inspection form "used to assess a risk of damage to a house as a result of physical disturbance, such as wind, earthquakes, etc."); EX1005, ¶7 (describing prior art camera system for surveying property). And the '058 patent admits the use of machine-learning analysis was "well-established and popular" and relies only on existing machine learning capabilities—it does not advance this technology, or even describe it in

any detail. *See* EX1001, 8:11-35. Indeed, the independent claims merely implement the age old property assessment practice using generic computing components that employ conventional image processing technique and the well-known existing machine learning capabilities to classify the property features and conditions. EX1003, ¶¶45-49.

In fact, the sole reference asserted herein—Gross—renders obvious all of the challenged claims. This Petition is supported by the declaration of Dr. David Forsyth (EX1003), an expert in the fields of image processing and computer vision, which is a field of artificial intelligence that enables computers to derive and analyze information from images and videos similar to how the human mind would analyze this information. Dr. Forsyth's testimony confirms that all challenged claims are unpatentable.

Accordingly, the Board should institute review and cancel all claims of the '058 patent.

II. MANDATORY NOTICES (37 C.F.R. § 42.8(A)(1))

REAL PARTY-IN-INTEREST: The real party-in-interest is Zesty.ai, Inc.

RELATED MATTERS: The '058 patent is at issue in *Aon Re, Inc. v. Zesty.ai, Inc.*, Case No. 1:25-cv-00201 (D. Del.), filed February 19, 2025.

In addition, Petitioner is concurrently filing petitions for *inter partes* review of the following related U.S. patents, each of which is also at issue in the above-

captioned district-court litigation proceeding:

- U.S. Patent No. 10,529,029 (IPR2025-00XXX);
- U.S. Patent No. 10,650,285 (IPR2024-00XXX);
- U.S. Patent No. 11,030,491 (IPR2024-00XXX).

LEAD AND BACK-UP COUNSEL: Under 37 C.F.R. §§ 42.8(b)(3) and 42.10(a), Petitioner appoints **Daniel S. Block** (Reg. No. 68,395) as lead counsel, and **Jennifer Meyer Chagnon** (Reg. No. 55,440) and **Justin D. Wang** (Reg. No. 81,975) as back-up counsel, all at the address: Sterne, Kessler, Goldstein & Fox PLLC, 1101 K Street, NW, 10th floor, Washington, DC, 20005, phone (202) 371-2600, and facsimile (202) 371-2540.

SERVICE INFORMATION: Petitioner consents to electronic service by email at: **dblock-PTAB@sternekessler.com, jchagnon-PTAB@sternekessler.com, jwang-PTAB@sternekessler.com,** and **PTAB@sternekessler.com**.

III. GROUNDS FOR STANDING (37 C.F.R. § 42.104(A))

The undersigned and Petitioner certify that the ’058 patent is available for *inter partes* review and that Petitioner is not barred or estopped from requesting *inter partes* review of any ’058 patent claim on the grounds herein.

IV. IDENTIFICATION OF THE CHALLENGE (37 C.F.R. §42.104(B))

A. Identification of Prior Art

The ’058 patent’s earliest possible priority date is September 23, 2016.

Without conceding that this is the correct priority date, the reference relied upon herein is prior art as of September 23, 2016.

Gross (EX1005) was filed on September 26, 2014 and published on July 2, 2015. Gross is prior art under at least 35 U.S.C. § 102(a)(1).

Gross is analogous art in the same field and reasonably pertinent to the problems of the ’058 patent. EX1003, ¶50. Gross was not previously before the Office.

B. Grounds Summary

Petitioner requests *inter partes* review based on the ground summarized below.

Ground	Basis	Claims	References
1	§103	1-20	Gross

V. THE ’058 PATENT

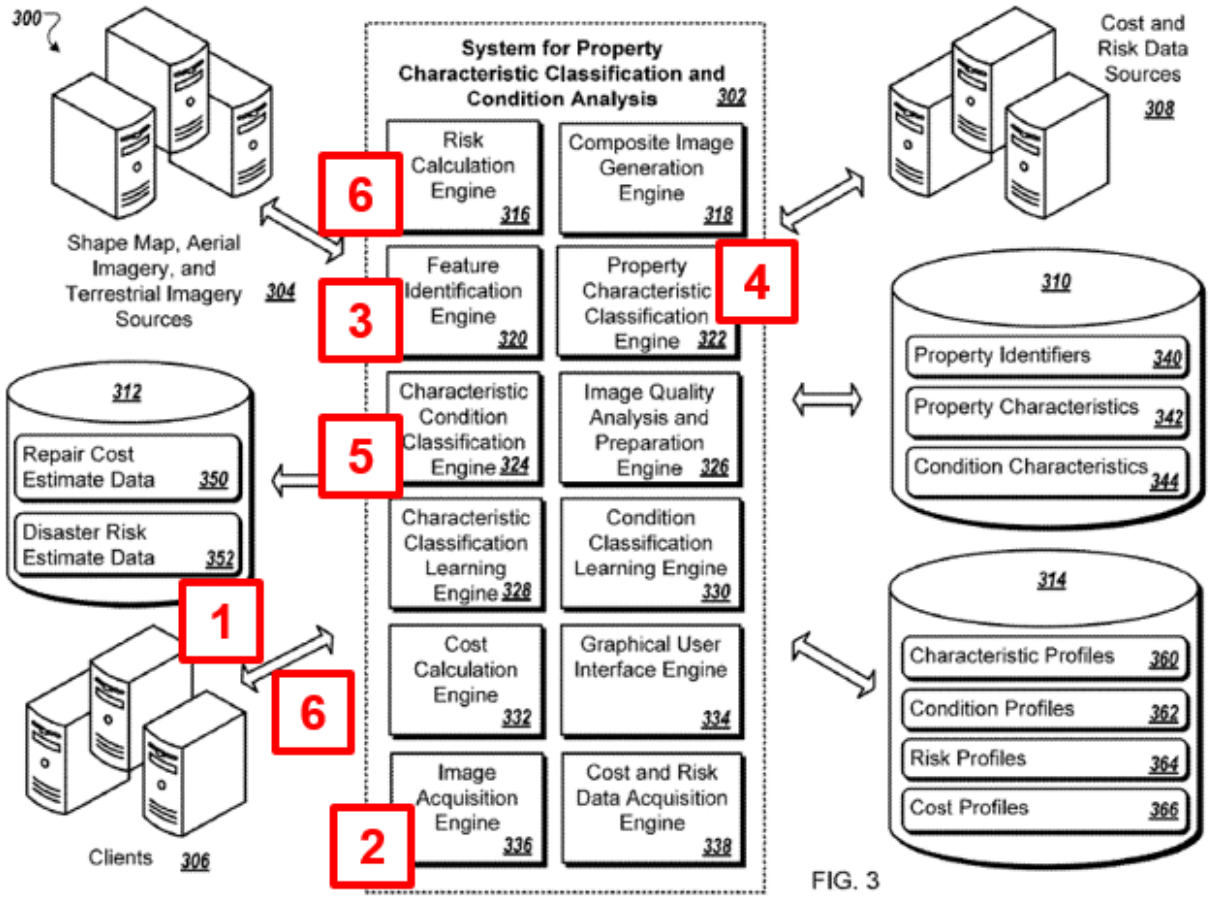
A. Summary of the ’058 Patent

The ’058 patent discloses techniques for analyzing aerial imagery to evaluate property characteristics and condition classifications. EX1001, Abstract. For example, this might include analyzing images to determine the maintenance levels of certain property features, such as the roof. EX1001, 1:41-46, 2:34-49. This information can then be used, e.g., to estimate the risk of damage in the event

of "disaster conditions, such as severe storms," to calculate repair costs, or to confirm a property has been repaired. EX1001, 2:42-49, 12:28-32 ("The types of disasters can include, in some examples, earthquake, hurricane, tornado, storm surge, fire, straight line winds, or explosion. The types and estimated severity of disasters, in some embodiments, may depend upon the particular property location.").

The '058 patent discusses applying "machine learning analysis" to "analyze aerial imagery and automatically extract characteristics of individual properties, providing *fast and efficient automated classification* of building styles and repair conditions," in order to perform risk evaluations. EX1001, 2:16–25, 34–42.[1] Figure 3 (annotated below) illustrates an exemplary embodiment of the '058 patent's alleged invention.

[1] Emphasis added throughout, unless otherwise noted.



EX1001, FIG. 3 (annotated).

The ’058 patent’s system operates in a series of steps, corresponding to numeric annotations in Figure 3 above. First, the system receives a request by “a user of a particular client computing system 306” to classify a property. EX1001, 13:65–14:1. The request “may include at least one property identifier 340” (e.g., address, geolocation coordinates) “as well as one or more property characteristics 342” (e.g., a “rooftop type”) (step “1”). EX1001, 14:1–14, 8:39–41. The system then obtains “imagery of the property from imagery source computing system(s) 304 using an image acquisition engine 336” (step “2”). EX1001, 15:1–4.

Upon obtaining the image(s), the system "extracts features from the property image(s) related to the identified property characteristics 342" via a "feature identification engine 320." EX1001, 16:4–6. "Features" (or "image-related features") can include, for example, angles, outlines, substantially homogenous fields (step "3"). EX1001, 8:31–35.

The system "classifies the property characteristic" via "a property characteristic classification engine 322," for example, into "a grouping, type, or other characterization of a particular property feature" using "characteristic profile(s) 360" (step "4"). EX1001, 16:10–19, 26–33. For example, the property characteristic may be a roof and the property characteristic classification may be "hipped rooftop." EX1001, 12:8–10. The "property characteristic profiles" "may be developed through training the machine learning algorithms using aerial images" "of known property characteristics," such as "through a sample data set and learning process." EX1001, 9:6–11, 16:26–39.

The system "classifies the condition of each property characteristic" (e.g., a "good" condition or a "bad" condition) via a "characteristic condition classification engine 324" (step "5"). EX1001, 16:55–17:3. To classify the conditions of property characteristics, characteristic condition classification engine 324 may process the image(s) using "condition profile(s) 362" trained "through a sample data set and learning process" (e.g., "logistic regression" machine learning).

EX1001, 17:8–25, 11:55–12:6. The system returns the characteristic and condition classification to a user of client 306 via a graphical interface (step "6"). EX1001, 14:56–59, 19:19–23. *See* EX1003, ¶¶34-39.

B. Prosecution History

The '058 patent issued from U.S. Application No. 16/868,113 ("the '113 application") without any substantive prior art examination. The '058 patent is a continuation of U.S. Application No. 16/733,888 (now U.S. Patent No. 10,650,285 ("the '285 patent")), which is a continuation-in-part of U.S. Application No. 15/714,376 (now U.S. Patent No. 10,529,029 ("the '029 patent")). EX1002, 96-97. The prosecution history reveals that the claims never underwent meaningful analysis against the prior art that renders them obvious. *See, generally*, *id*.

During prosecution, the '113 application was filed as a continuation with a single claim identical to claim 1 of the '888 application, resulting in a double-patenting rejection over the '285 and '029 patents. *Id.*, 218-221. The applicant responded by cancelling the identical claim and adding twenty new claims. *Id.*, 276-283. The Examiner then allowed the application. *Id.*, 289-297.

Notably, the Examiner conducted no prior art analysis in any 35 U.S.C. §§102, 103 rejections against the twenty new claims. The only prior art discussion appears in the Notice of Allowance's "Reasons for Allowance" section, where the Examiner distinguished three references (Swanson, Downey, and Cuttell) without

having issued a single rejection against the allowed claims of the ’058 patent and without the detailed analysis typically conducted during examination.[2] *Id.*, 294-297. This limited prior art consideration occurred despite the robust prior art landscape that existed at the time of filing. *See* EX1003, ¶¶40-41.

C. Person of Ordinary Skill in the Art

A person of ordinary skill in the art (“POSA”) 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, and significant work experience could substitute for formal education. EX1003, ¶¶42-43.

D. Claim Construction

In an *inter partes* review, claims are “construed using the same claim construction standard that would be used to construe the claim in a civil action under 35 U.S.C. 282(b).” 37 C.F.R. §42.100(b). All claim terms must be given their ordinary and customary meaning as understood by a POSA at the time of the invention, in light of the specification and prosecution history of the patent. *See*

[2] The “Reasons for Allowance” also discusses an *Alice* rejection, but again there were no substantive rejections made of the claims during prosecution of the ’058 patent.

Phillips v. AWH Corp., 415 F.3d 1303, 1312-13 (Fed. Cir. 2005).

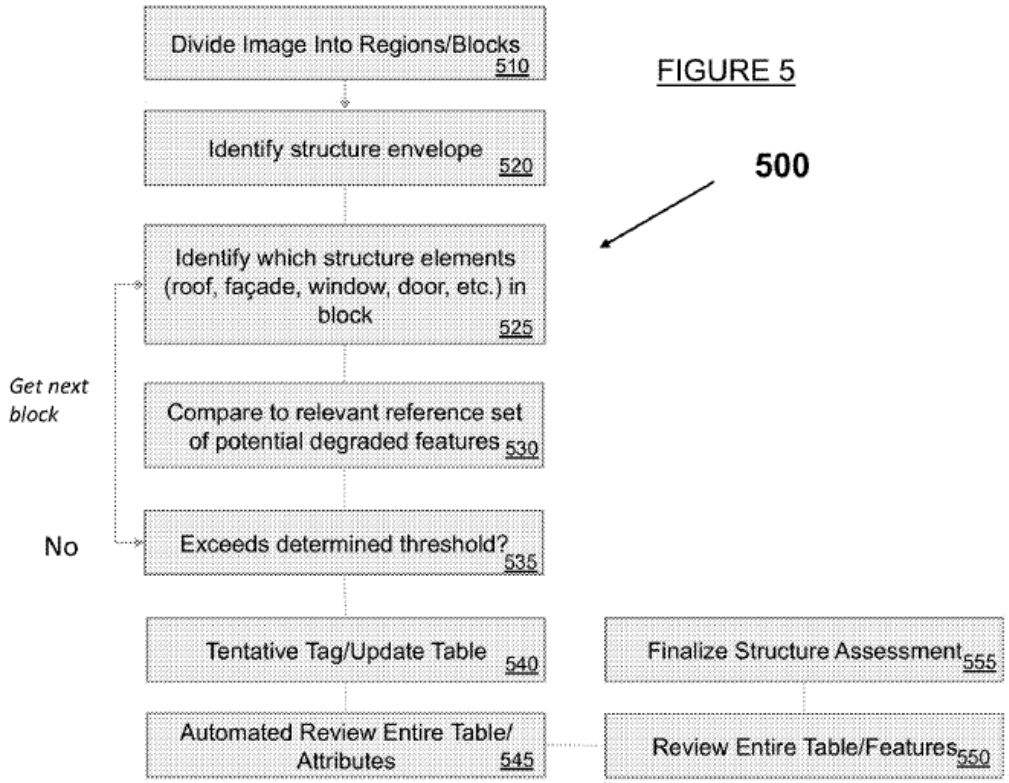
Solely for the purposes of this Petition, Petitioner submits that all claim terms should receive their plain and ordinary meaning in the context of the ’058 patent specification. EX1003, ¶44.

VI. OVERVIEW OF GROSS

Gross discloses “tools, methods, and systems which assess the condition of living structures and other appurtenant real property features.” EX1005, ¶2. Gross teaches that these tools are useful in the area of insurance, among others. EX1005, ¶¶2, 5, 186, 237-238.

Similar to the ’058 patent, Gross’s property assessment computing system involves training a “Classifier Engine” and using it to assess and rate different properties. EX1005, ¶57. To train the classifier engine, Gross’s system first collects reference images of “building elements” (e.g., roof, tree) along with their “types” (e.g., pitched roof, double pitched roof, shingle roof). EX1005, ¶¶57–58. Gross’s system then defines and associates the building elements within each reference image with a corresponding “condition,” such as “new,” “damaged,” “missing,” and more. EX1005, ¶¶60–70. Gross’s system trains the Classifier Engine “using a variety of techniques, including statistical processing, neural networks, etc., which can be used to detect and extract features.” EX1005, ¶¶77–78.

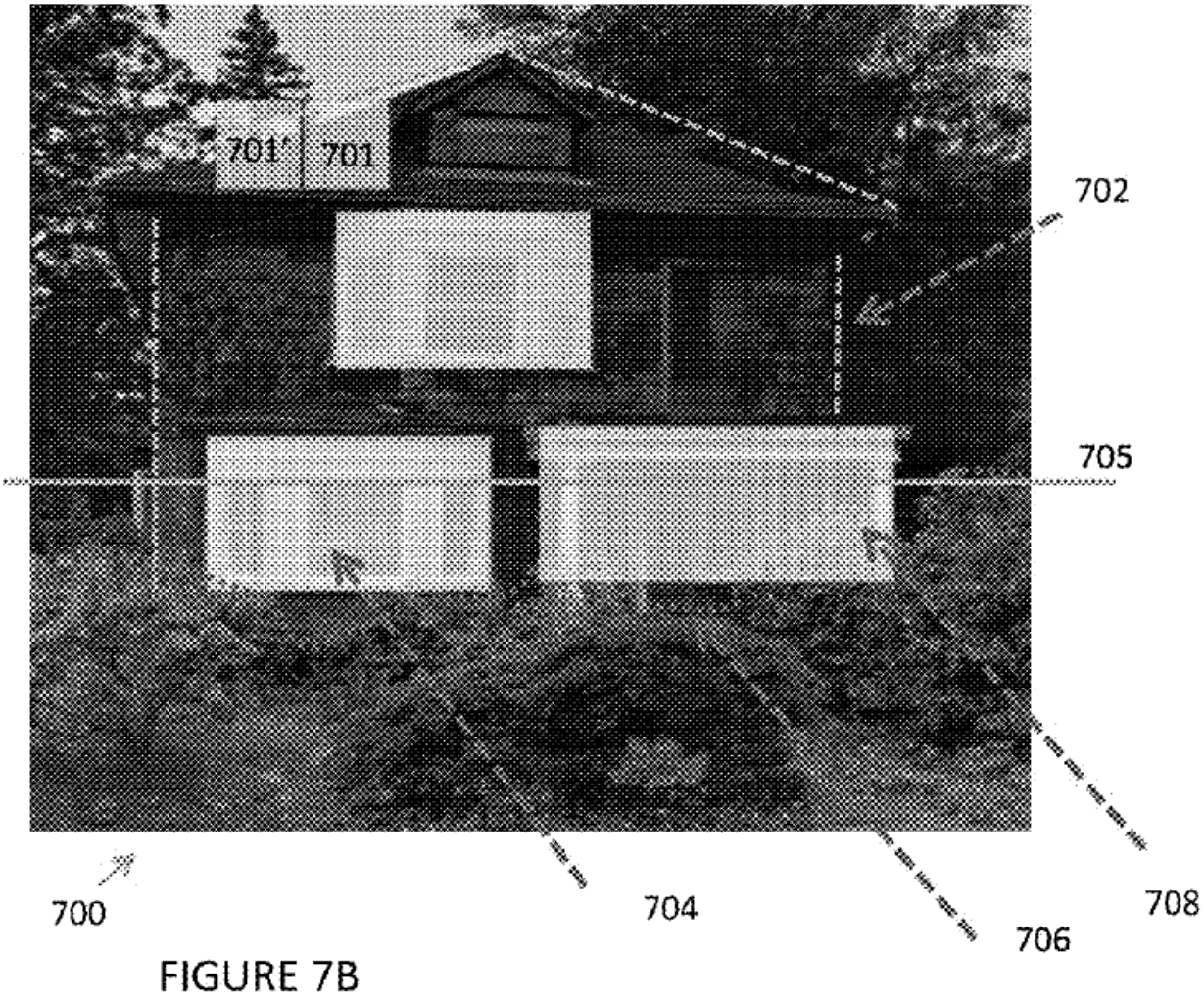
After training the Classifier Engine, Gross's system uses it to assess new images of properties, like the '058 patent. EX1005, ¶¶57, 123. These images of a property to be assessed are first retrieved from a database. EX1005, ¶121. The images may be aerial images captured by "aerial drones, satellite, balloon, and similar technology." EX1005, ¶164. The property images may also be obtained via a camera of a mobile device. EX1005, ¶¶108-109. Gross's Figure 5, reproduced below, illustrates one embodiment of the assessment process.



EX1005, FIG. 5.

Once the image is retrieved, it is divided into distinct regions or "blocks" 701 at step 510. EX1005, ¶121. This is shown, for example, in Figure 7B,

reproduced below.



EX1005, FIG. 7B.

At step 520 of the method of Figure 5, Gross's system identifies a "building envelope 702" (which as seen in Figure 7B is essentially an outline of the building) by detecting edges of structures in the image. EX1005, ¶122, FIG. 7B; EX1003, ¶53. Such "boundaries" (e.g., edges) of other objects in the property (e.g., landscaping, trees) can also be determined. EX1005, ¶122. The image blocks

include "structural elements" (e.g., a roof, tree), which are determined (alongside a "type" of the structural element (e.g., pitched roof, shingle roof)) at step 525. EX1005, ¶123. As one example, "the first block 701 may be coded to denote that an attribute {roof} with type {pitched} and {shingle} is contained" therein. EX1005, ¶123. As Gross explains, and similar to the '058 patent, identifying the structural element and its classification "can be performed in any number of ways by Classifier Engine … including by pattern recognition techniques and statistical image processing using models." EX1005, ¶123.

Again similar to the '058 patent, Gross's system then employs Classifier Engine to determine a "condition" of the determined structural element at steps 530 and 535, such as a "good" condition or a "poor" condition. EX1005, ¶¶126–127, 141. The condition classification is then stored into memory at step 540. EX1005, ¶127. This assessment process is repeated for one or more extracted image blocks for the image and the final assessment data is reviewed and finalized at steps 545, 550, and 555, which, like the '058 patent, includes presenting the types and conditions of the structural elements at an interface. EX1005, ¶¶129–133, FIG. 7E. *See* EX1003, ¶¶50-54.

VII. GROUND 1: GROSS RENDERS OBVIOUS CLAIMS 1-20

Claims 1-20 would have been obvious in view of Gross. EX1003, ¶¶14, 55.

A. A POSA would have found it obvious to combine different embodiments of Gross.

As explained above, Gross discloses training a Classifier Engine 150 and using it to assess and rate properties. EX1005, ¶57, FIG. 2. Gross describes specific details on how its Classifier Engine 150 is trained with reference images and uses conventional image processing techniques to extract attributes of a property and classify conditions of the attributes. *See* EX1005, ¶¶77-93; EX1003, ¶56. Gross further describes that, after it has been trained, Classifier Engine 150 may be used to identify attributes (and their types and conditions) contained in an image of a property to be assessed. *See* EX1005, ¶¶120-129, FIG. 5; EX1003, ¶57. Gross describes that "the identification of such attributes (and their types) can be performed in any number of ways by Classifier Engine 150." EX1005, ¶123. For example, Classifier Engine 150 may be trained to assess whether the following exemplary structure attributes, attribute types, and conditions/impairments are contained in an image: roof {new, missing/damage tile, shingle metal, holes/cracks, unevenness, brightness (moss mold)}; façade (new, missing, shingles/siding, breaks, holes, discontinuities, discoloration, warping, paint bubbles/blistering/peeling—aging, weathering, water damage}; and other exemplary attributes/types/conditions. EX1005, ¶¶60-70; EX1003, ¶58.

A POSA reading Gross would have understood that the image processing and attribute classification techniques used to train Classifier Engine 150 were

intended to also be utilized in its building attribute/condition assessment process. EX1003, ¶59. Indeed, that is the whole point of Gross—to use its trained classifier to determine building attributes and condition assessments. EX1003, ¶59. Both processes involve analyzing property images to identify attributes (such as roof elements, window elements, etc.), their types (e.g. for a roof – shingle, metal, tile), and conditions (e.g., for a roof – missing/damaged tile, holes/cracks). EX1003, ¶59. A POSA would have recognized that Classifier Engine 150 would employ the same, or very similar techniques as those used during training to process images to identify and classify attributes contained therein. EX1003, ¶59; *see also* EX1005, ¶245 (Gross describing that "conventional steps that would be included … have been omitted"). Such implementation would merely amount to combining (as intended) Gross's disclosure of the image processing elements used to train the Classifier Engine with its disclosure of image processing used in its building attribute/condition assessment process, according to known methods to yield predictable results with a reasonable expectation of success. EX1003, ¶¶59-60. *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 417 (2007).

B. Independent Claim 1

1. [1.P]: A system for automatically assessing features of a property location comprising a structure, the system comprising:

To the extent limiting, Gross discloses the preamble. EX1003, ¶61.

Gross discloses "training [a] Classifier Engine … and using it to assess and rate" properties. EX1005, ¶57. "[A]n identification is performed" by Classifier Engine "to determine structural elements presented in a first block" of an image, "including such attributes as roof elements, window elements, façade elements, etc." EX1005, ¶123. These attributes are *features of a property location comprising a structure*, as claimed, because they are physical parts of a structure, such as a house or building. EX1003, ¶¶62-63.

Gross also discloses that Classifier Engine identifies conditions associated with a particular attribute (i.e., feature of a property location). EX1005, ¶60. For example, the Classifier Engine may automatically assess the condition of a roof (feature of a property location) as "new," "missing/damage tile," and/or "holes/cracks." EX1005, ¶61. In some instances, "severity weightings (i.e., a scaling factor of any convenient range (1-10, or the like) for the identified condition" may also be assigned by Classifier Engine. EX1005, ¶70; *see also* EX1005, ¶126 (Gross's description that a "condition score is computed [by Classifier Engine] for the detected attribute."). Gross further discloses that "with sufficient training an automated classifier could participate in the process, if not perform the entire process of classifying structural features," i.e., *automatically*. EX1005, ¶145; *also id.*, ¶¶174, 176. Thus, Gross discloses *automatically assessing features of a property location comprising a structure*. EX1003, ¶64.

2. [1.1]: a non-volatile computer readable medium storing

Gross teaches element [1.1]. EX1003, ¶65. Gross describes the details "required to effectuate the functionality disclosed … are not material to the present invention, and may be implemented in any number of ways know to those skilled in the art. Such code, routines, etc. may be stored in any number of forms of machine readable media" (i.e., *a non-volatile computer readable medium*). EX1005 ¶247. For the reasons set forth in elements [1.2] and [1.3], Gross teaches the claimed property characteristic profiles and property condition profiles, which are "stored in a database" (i.e., stored on a non-volatile computer readable medium). EX1005, ¶77; EX1003, ¶65.

3. [1.2]: a set of property characteristic profiles, each property characteristic profile of the set of property characteristic profiles being developed through training one or more machine learning algorithms using first property images to identify one or more characteristics of at least one property feature of one or more property features, and

Gross teaches, or renders obvious, element [1.2]. EX1003, ¶66.

First, for the reasons that follow, a POSA would have understood or found obvious that Gross's Classifier Engine comprises *one or more machine learning algorithms* that is trained *using first property images to identify one or more characteristics of at least one property feature of one or more property features*. EX1003, ¶¶67-69. In particular, Gross discloses its Classifier Engine is trained with reference images (i.e., first property images) and analyzes objects in the

images, using neural networks, to detect and extract image features that can be readily detected. EX1005, ¶77. Gross 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 "*A Survey of Face Recognition Techniques* by Jafri," which is incorporated by reference. EX1005, ¶79. Gross—through the incorporated Jafri material—describes using "a hybrid neural network solution" to analyze image patterns. EX1008, 49; *see also Cook Biotech Inc. v. Acell, Inc.*, 460 F.3d 1365, 1376 (Fed. Cir. 2006) (incorporation by reference "provides a method for integrating material from various documents into a host document … by citing such material in a manner that makes clear that the material is effectively part of the host document as if it were explicitly contained therein." (quoting *Advanced Display Sys., Inc. v. Kent State Univ.*, 212 F.3d 1272, 1282 (Fed. Cir. 2000)). A POSA would have understood that neural networks comprise *one or more machine learning algorithms.* EX1003, ¶69.

Classifier Engine 150 (the claimed *one or more machine learning algorithms*) is trained with reference images and analyzes attributes (i.e., *characteristics of at least one property feature*) and reduces the attributes into distinct features that can be readily detected. EX1005, ¶77. Gross teaches property characteristic profiles by explaining that the "attribute-condition-feature dataset" is stored in the form of models, template, or other suitable form in a database."

EX1005, ¶77. These models/templates are *property characteristic profiles* because, like the ’058 patent, these models/templates associate features with property characteristics. EX1003, ¶70. Specifically, the model/templates (*property characteristic profile*) associate an attribute (*characteristic of at least one property feature*, such as a “tile” roof) with distinct image features that can be readily detected. EX1005, ¶77; EX1003, ¶70. Gross describes exemplary types of attributes (i.e., *characteristics of a property feature*) that can be tagged (and then analyzed by Classifier Engine to reduce into detectable image features and stored in characteristic profiles) include roof {tile, shingle, metal} and façade {shingles, siding). EX1005, ¶¶57, 60-69, 77; EX1003, ¶70. The training “results in extraction and optimization of specific features most appropriate for a particular element.” EX10056, ¶78. Thus, the *property characteristic profiles* (models/templates) are *developed through training* Classifier Engine. EX1003, ¶70.

Thus, Gross teaches , or renders obvious, Classifier Engine (i.e., *one or more machine learning algorithms*) is trained to *identify one or more characteristics of at least one property feature* (e.g., characteristics of a roof, such as “pitched, double pitched, hipped, flat, metal, tile, shingle, slate, parapet, dormer, mansard”). EX1005, ¶57; EX1003, ¶71.

4. [1.3]: a set of property condition profiles, each property condition profile of the set of property condition profiles being developed through training one or more machine learning algorithms using second property images to identify

one or more conditions of at least one property characteristic of one or more property characteristics corresponding to a given feature or features of the one or more property features; and

Gross teaches, or renders obvious, element [1.3]. EX1003, ¶72. As described in element [1.2], Classifier Engine (the claimed *one or more machine learning algorithms*) uses conventional image processing to characterize attributes "and related condition qualifier[s]" and develops "attribute-condition-feature dataset[s]" that are "stored in the form of models, template, or other suitable form." EX1005, ¶¶77, 78. These models/templates (which include conditions) are *property condition profiles developed through training* Classifier Engine EX1003, ¶72.

Additionally, for the reasons set forth in element [1.2], Gross teaches that its Classifier Engine includes *one or machine learning algorithms*. EX1003, ¶73; EX1005, ¶77. Gross describes Classifier Engine is trained with reference images (i.e., *second property images* for reasons explained below)) to identify "conditions/impairments … associated with a particular building attribute" (i.e., *condition of at least one property characteristic corresponding to a given feature*). EX1005, ¶60; EX1003, ¶73. Gross describes examples of property features (e.g., roof), property characteristics corresponding to the feature (e.g. for a roof, pitched, tile, shingle), and related conditions (e.g., missing/damaged tile, holes/cracks). EX1005, ¶¶57, 60-69. The examples provided are just a partial list and other individual structure attributes or elements (property characteristic)/condition

pairings can be identified by Classifier Engine. EX1005, ¶70.

Gross further teaches, or renders obvious, that the machine learning algorithms are trained with *second property images*. EX1003, ¶74. In particular, Gross describes training its Classifier Engine with "a reference set" of images that includes "sufficient exemplars representing different building elements" (*first property images* as described above) and "image exemplars of the building elements or attributes in various physical conditions or impairment" (*second property images*). EX1005, ¶¶58, 60; EX1003, ¶74.Gross discloses multiple conditions for property characteristics that Classifier Engine (*one or more machine learning algorithms*) is trained to recognize (e.g., a roof that is new, has missing/damaged tile(s), has holes/cracks"). *See* EX1005, ¶¶60-69. In light of these teachings in Gross, a POSA would have understood, or found obvious, Gross's Classifier Engine is trained *using second property images* to identify conditions of a property characteristic. EX1003, ¶74.

5. [1.4]: processing circuitry configured to

Gross teaches element [1.4]. EX1003, ¶75. Gross discloses "the critical steps identified in this process can be implemented into executable software routines and modules using any number of ways by skilled artisans." EX1005, ¶161. A POSA would have understood or found obvious that "these "executable software routines" are executed via *processing circuitry*, which is *configured to* execute the

software routines (i.e., the process steps recited in elements [1.5]-[1.11]). EX1003, ¶75.

6. [1.5]: receive, from a user at a remote computing device via a network, a request comprising identification of a property location,

Gross renders obvious element [1.5]. EX1003, ¶76.

Gross describes a building attribute/condition assessment process that, as described in element [1.11] below, causes presentation of, for review by a user, an interactive web page (i.e., a graphical user interface) with a report of the results of its assessment. EX1005, ¶¶120, 130, FIGS. 5, 7E; EX1003, ¶77. In particular, the output that is presented to the user includes "additional classifying details about the building structure" to "allow[] the user to quickly see the assessment of the property as performed by Building Classifier Engine 150." EX1005, ¶103, FIG. 7E. In a preferred embodiment, building structures in "a target city or other convenient population unit" are assessed. EX1005, ¶¶161-162.

Gross does not explicitly disclose how its assessment process of Figure 5 is initiated. *See* EX1005, ¶¶120-121 (stating Figure 5 depicts a building attribute/condition assessment process; beginning the process with retrieving an image). However, a POSA would have understood, or found obvious, that receiving *a request from a user* is one of "a finite number of identified, predictable solutions" that could have been used to initiate Gross's assessment process.

EX1003, ¶78; *see KSR*, 550 U.S. at 402-03 (illustrating that the use of a finite number of identified, predictable solutions is likely the product of ordinary skill and common sense). A POSA would have been motivated to allow the user to request performance of the attribute/condition assessment process when needed for a particular property in order to reduce processing costs associated with unnecessary mass batch processing of property images and to allow the user to request the assessment they want performed. EX1003, ¶78.

Gross further describes that users engage with system 110 employing computing devices 112, such as smartphones, tablets, laptops, and desktops (i.e., *remote computing devices*) through interface logic 120 (i.e., *via a network*). EX1005, ¶43, FIG. 1 (illustrating Gross's system 110 connecting through interface logic 120 with external (remote) data sources 113, 114 and user's computing devices 112). In a preferred embodiment, system 110 is part of a website which can be accessed through a conventional browser. EX1005, ¶43. Gross discloses an interactive user interface, which in a preferred embodiment is implemented as part of an interactive web page. EX1005, ¶98. The interactive user interface has "a number of query selection boxes," including query box 360 to specify a location for a property search. EX1005, ¶¶98-99. EX1003, ¶79.

Although Gross describes its interactive web user interface 350 is used to search for real estate/building stock that meet certain criteria of interest (EX1005,

¶95), a POSA would have found obvious that a similar interactive interface could be used to allow a user to submit the request for performance of the attribute/condition assessment process because interactive user interfaces were a well-known way in which to receive information from a user. EX1003, ¶80. A POSA would have been further motivated to modify this interactive user interface described in Gross to initiate the assessment for a specific *identification of a property*. Such a modification would allow the user to request Gross's property assessment be performed for a target property of interest, and this would reduce processing costs otherwise associated with processing properties for an entire city or regional area. EX1003, ¶81.

Thus, Gross renders obvious *receiving a request* (through a modified interactive user interface) *comprising identification of a property location.* EX1003, ¶82.

7. [1.6]: access aerial imagery of the property location,

Gross teaches element [1.6]. EX1003, ¶83.

Gross describes "aerial drones, satellite, balloon, and similar technology can be used … to easily capture structure image data" and can "facilitate building out a comprehensive image database." EX1005, ¶164. These images captured by the aerial drones, satellite, and balloon are thus *aerial images of the property location*. EX1003, ¶84. The building image data is stored in a structure image database.

EX1005, ¶165.

Gross further describes "a data acquisition process" used by a classifier (e.g., Classifier Engine 150) and that "the purpose "of this specialized computing module is to acquire appropriate image data for structures within a target area," such as a city. EX1005, ¶161. Classifier Engine retrieves an image 700 from a database to begin the building attribute/condition assessment process. EX1005, ¶¶120-21. Image data for the building structure is retrieved (accessed) for the target address. EX1005, ¶164. Gross teaches obtaining the aerial image in response to a user request (as described in limitation [1.5]) because its data acquisition process *obtains the aerial image* of the property from the database so that Classifier Engine can perform the assessment process and provide to the user the requested assessment. EX1003, ¶85.

8. [1.7]: classify a condition of one or more features of the property location, wherein classifying comprises, for each feature of the one or more features,

Gross teaches element [1.7]. EX1003, ¶86. Gross discloses classifying "conditions/impairments … associated with a particular building attribute." EX1005, ¶60. The building attributes are *features of the property location*. EX1003, ¶86. Gross describes examples of building/structure attributes (features) and related conditions, including: roof (new, missing/damage tile, holes/cracks); façade (new, missing, holes); and support (leaning/damaged columns). EX1005,

¶¶60-69. The examples provided are just a partial list and other individual structure attribute/condition pairings can be identified by Classifier Engine. EX1005, ¶70.

For the reasons provided for elements [1.8]-[1.10], Gross teaches *wherein classifying comprises, for each feature of the one or more features*, the limitations set forth in [1.8]-[1.10] are performed (for one or more features (e.g., a single feature) as required by the claim). EX1003, ¶87.

9. [1.8]: identifying the respective feature from at least one image obtained from the aerial imagery,

Gross teaches element [1.8]. EX1003, ¶88. Gross discloses objects can be analyzed in image patterns, using a variety of techniques that can be used to detect and extract features of attributes. EX1005, ¶77. After aerial imagery is accessed as discussed in element [1.6], "an identification is performed to determine structural elements presented in a first block 701 [of the image], including such attributes as roof elements, window elements, façade elements, etc." (i.e., *identifying the respective feature*) presented in the *at least one image*. EX1005, ¶¶121, 123; EX1003, ¶88.

10. [1.9]: applying one or more property characteristic profiles of the set of property characteristic profiles to at least a portion of each image of the at least one image to determine a plurality of characteristics of the respective feature, wherein a first characteristic of the plurality of characteristics comprises a type of material of the feature or a shape of the feature, and

Gross teaches element [1.9]. EX1003, ¶89. Gross discloses that, after it has

been trained, Classifier Engine 150 performs identification of attributes (e.g., roof elements) (i.e., *the property feature*) presented in an image. EX1005, ¶123. The specific types of the attributes (i.e., *characteristics of the feature*) are also determined "(i.e., façade (shingle, siding, brick), … roof {pitched, double pitched, hipped, flat, metal, tile, shingle, slate, parapet, dormer, mansard, fascia, brackets, eaves, pent, pediment, etc.})." EX1005, ¶57. To do this, Classifier Engine "employs image processing" and the "identification of such attributes (and their types) can be performed in any number of ways by Classifier Engine 150 after it has been trained, including by … statistical image processing using models, templates, etc."—i.e., Classifier Engine *applies* the models/templates (which are *property characteristic profiles* for the reasons set forth in element [1.2]) to the image *to determine a plurality of characteristics of the feature*. EX1005, ¶¶120, 123; EX1003, ¶90. For example, a first block of the image "may be coded [by Classifier Engine] to denote that an attribute {roof} with type {pitched} and {shingle} is contained" in the image. EX1005, ¶123. Thus, Gross teaches *a first characteristic comprises* a *type of material* (e.g., shingle) and additionally teaches determining a characteristic that comprise *a shape of the feature* (e.g., pitched). EX1005, ¶123; EX1003, ¶¶89-90.

11. [1.10]: applying one or more property condition profiles of the set of property condition profiles to at least a portion of

each image of the at least one image to classify a condition of the respective property feature, and

Gross teaches element [1.10]. EX1003, ¶91. After the Classifier Engine is trained, it can identify indicators in attributes "of an irregularity, defect, damage, or the like" and compute a condition score for the detected attribute. EX1005, ¶¶123, 126. Classifier Engine assesses "the condition of the attribute against a reference set of conditions to determine an appropriate rating." EX1005, ¶126. To do this, Classifier Engine "employs image processing" and the identification can be performed in any number of ways "including by … statistical image processing using models, templates, etc."—i.e., Classifier Engine *applies* the reference conditions stored as models/templates (which are *property condition profiles* for the reasons set forth in element [1.3]) to the image *to classify a condition of the respective property feature*. EX1005, ¶¶120, 126; EX1003, ¶92. Gross describes examples of conditions of a property feature include: roof (new, missing/damage tile, holes/cracks); façade (new, missing, holes); and support (leaning/damaged columns). EX1005, ¶¶60-69. The examples provided are just a partial list and other individual condition pairings can be identified by Classifier Engine. EX1005, ¶70.

12. [1.11]: responsive to receiving the request, cause presentation of, for review by the user at the remote computing device, a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature.

Gross teaches, or renders obvious, element [1.11]. EX1003, ¶93. As

described in limitation [1.5], Gross discloses its user interface is preferably an interactive web page, which is *a graphical user interface*. EX1005, ¶98; EX1003, ¶93. Gross describes that a report of the results is presented to the user (*at the remote computing device*) in response to receiving the request. EX1005, ¶96. The user can be provided with "classifying details about the building structure such as highlighted, tagged or annotated version of the building structure identified in FIG. 7E … to quickly see the assessment of the property as performed by Building Classifier Engine 150" (i.e., *information regarding the plurality of characteristics and the condition of each feature*) EX1005, ¶103; EX1003, ¶93. Figure 7E (depicted below) presents an embodiment of this visual assessment report and illustrates exemplary *plurality of characteristics* (e.g., a "dormer" roof, "shingle" façade) and *condition of property features* (e.g., "damaged" roof; "damaged/defective façade).

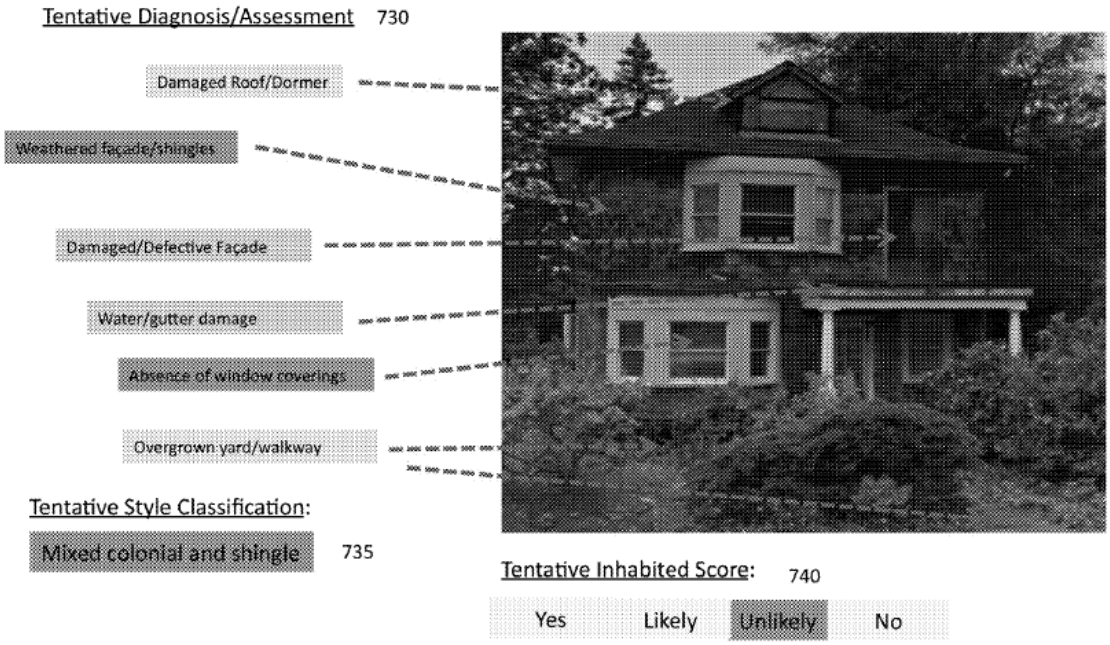


FIGURE 7E

EX1005, FIG. 7E.

Gross further discloses that "[t]his data is presented in a list and visual form for a human reviewer." EX1005, ¶130. This "visual assessment report" is *a presentation of, for review by a user, a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature*. EX1003, ¶94. Although in the example shown in Figure 7E, the visual assessment report may not depict a plurality of characteristics for a feature, this is just an example of a report. Gross teaches a plurality of characteristics may be assessed for a feature for reasons set forth in [1.9] (e.g., for a roof, "dormer" and "shingle"). And Gross describes "the user can be provided with additional classifying details about the building structure …

identified in Fig. 7E" to allow the user "to quickly see the assessment of the property" (EX1005, ¶103)—i.e., Gross teaches or renders obvious that its report can include the *plurality of characteristics* identified in its assessment process. EX1003, ¶94*; see also* EX1005, ¶140, FIG. 11 (illustrating examples of a plurality of characteristics that can be identified, assessed, and stored for a particular structure).

As described in element [1.5], Gross teaches, or renders obvious, a request *comprising identification of a property location* through its interactive user interface (such as an interactive web page). EX1005, ¶43; EX1003, ¶95. It would have been obvious *to cause presentation* of the graphical user interface *responsive to receiving the request* (e.g., a request to perform an assessment for the identified property location) so that a human reviewer could "accept or modify the initial classification" performed by Classifier Engine prior to it being recorded. EX1003, ¶95; EX1005 ¶¶132-33.

C. Independent Claim 13

1. [13.P]: A method for automatically assessing features of a property location comprising a structure, the method comprising:

To the extent limiting, Gross teaches element [13.P] for the reasons provided for element [1.P]. EX1003, ¶96.

2. [13.1]: receiving, from a user at a remote computing device via a network, a request comprising identification of a property location;

Gross teaches, or renders obvious, element [13.1] for the reasons provided for element [1.5]. EX1003, ¶97.

3. [13.2]: accessing, by processing circuitry, aerial imagery of the property location;

Gross teaches element [13.2] for the reasons provided for element [1.4] and [1.6]. EX1003, ¶98.

4. [13.3]: classifying, by the processing circuitry, a condition of one or more features of the property location, wherein classifying comprises, for each feature of the one or more features, identifying the respective feature from at least one image obtained from the aerial imagery,

Gross teaches element [13.3] for the reasons provided for element [1.4], [1.8], and [1.7]. EX1003, ¶99.

5. [13.4]: applying one or more property characteristic profiles of a set of property characteristic profiles to at least a portion of each image of the at least one image to determine a plurality of characteristics of the respective feature,

Gross teaches element [13.4] for the reasons provided for element [1.9]. EX1003, ¶100.

6. [13.5]: wherein each property characteristic profile of the set of property characteristic profiles is developed through training one or more machine learning algorithms using first property images to identify one or more characteristics of at least one property feature of one or more property features, and a first characteristic of the plurality of characteristics

comprises a type of material of the feature or a shape of the feature, and

Gross teaches element [13.5] for the reasons provided for element [1.2] and [1.9]. EX1003, ¶101.

7. [13.6]: applying one or more property condition profiles of a set of property condition profiles to at least a portion of each image of the at least one image to classify a condition of the respective property feature,

Gross teaches element [13.6] for the reasons provided for element [1.10]. EX1003, ¶102.

8. [13.7]: wherein each property condition profile of the set of property condition profiles is developed through training one or more machine learning algorithms using second property images to identify one or more conditions of at least one property characteristic of one or more property characteristics corresponding to a given feature or features of the one or more property features; and

Gross teaches, or renders obvious, element [13.7] for the reasons provided for element [1.3]. EX1003, ¶103.

9. [13.8]: responsive to receiving the request, causing presentation of, for review by the user at the remote computing device, a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature.

Gross teaches, or renders obvious, element [13.8] for the reasons provided for element [1.11]. EX1003, ¶104.

D. Claim 2

Claim 2 depends from claim 1 and further recites, "*wherein identifying the*

respective feature from the at least one image comprises extracting, from the at least one image, one or more pixel groupings representing the respective feature."

Gross teaches this claim. EX1003, ¶¶105-106. Gross discloses objects can be analyzed in image patterns, using a variety of techniques that can be used to detect and *extract* features of attributes. EX1005, ¶77. An image (e.g., an aerial image as discussed in element [1.6]) is obtained and "an identification is performed to determine structural elements presented in a first block 701, including such attributes as roof elements, window elements, façade elements." EX1005, ¶¶120, 123. Gross further discloses that its Classifier Engine is trained by extracting smaller distinct (image) features from reference images and notes that "[f]eature extraction algorithms are well-known in the art." EX1003, ¶106; EX1005, ¶¶77, 79.

Gross also explicitly teaches *one or more pixel groupings representing the respective feature*. EX1003, ¶107. Gross discloses that "[u]sing conventional image processing, each attribute" (i.e., *feature*) "may be … characterized by a distinct set of pixels, shapes, proportions, curves, textures, or otherwise mathematically derivable feature from the image." EX1005, ¶78. These are all examples of *pixel groupings* that represent one or more features because each exemplary type of characterization is an underlying group of pixels in the image (e.g., an extracted feature characterized by a "shape" is a pixel group that

represents the shape). EX1003, ¶107. 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, which is incorporated by reference. EX1005, ¶79. Gross, through the incorporated Jafri material, discloses *pixel groupings representing features* through Jafri's description of a recognition system that detects "prominent facial landmarks (i.e., the eyes, nose, and mouth)" to identify those *features.* EX1008, 43, 51, FIG. 19 (illustrating pixel groupings around nose, eye, lips); EX1003, ¶107.

Gross discloses the attributes (i.e., *features*) "are analyzed in the images to break them down and reduce them into (or extract) smaller distinct features that can be more readily detected." EX1005, ¶76. Thus, Gross teaches *extracting, from the at least one image, one or more pixel groupings representing the respective feature* (of the property location). EX1003, ¶¶108-109. Exemplary features of a property location that that may be extracted from the image include roof elements, window elements and façade elements. *See* EX1005, ¶¶60-68, 123; EX1003, ¶109.

E. Claim 3

Claim 3 depends from claim 2 and further recites, "*wherein each pixel grouping of the one or more pixel groupings comprises angles, outlines, and/or substantially homogenous pixel fields*."

For the reasons provided in claim 2, Gross discloses the claimed pixel

groupings through its description that each attribute in the image may be "characterized by a distinct set of pixels, shapes, proportions, curves, textures, or other mathematically derivable feature from the image" (which are examples of *pixel groupings* because each exemplary type of characterization is an underlying group of pixels in the image). EX1005, ¶78; EX1003, ¶¶110-111. Additionally, Gross—through the incorporated Jafri material—expressly discloses extracting features and computing geometric relationships (e.g., "distances, areas and angles") to represent pixel groupings of facial features. EX1003, ¶111; EX1008, 43; *see also* EX1005, ¶79 (noting that Jafri's feature extraction algorithms are suitable or can easily be adapted for use in Gross's embodiments). Gross further discloses identification of a building envelope (i.e., *outline of the building*). EX1005, ¶122; EX1003, ¶111. Thus, Gross teaches this claim. EX1003, ¶111.

F. Claim 4

Claim 4 depends from claim 1 and further recites, "*wherein the aerial imagery comprises at least one aerial image of a geographic region including the property*."

For the reasons discussed in element [1.6], Gross teaches aerial imagery of the property location through its description that "aerial drones, satellite, balloon, and similar technology can be used … to easily capture structure image data." EX1005, ¶164. The structure image data can be captured from a variety of

perspectives and at different times and these images are stored in a structure image database. EX1005, ¶¶164-65. Gross further discloses a data acquisition process used by a classifier to acquire appropriate image data within a target area. EX1005, ¶161. Gross discloses that when proceeding to a subsequent address in the target area being processed, "an image view of a street under consideration" (i.e., *aerial image of a geographic region including the property*) can be accessed. EX1005, ¶167. Thus, Gross teaches this claim. EX1003, ¶¶112-113.

G. Claim 5

Claim 5 depends from claim 1 and further recites, "*wherein the one or more characteristics of a first feature of the one or more property features comprises a shape characteristic and a material characteristic*."

Gross teaches this claim. EX1003, ¶¶114-115. As described in element [1.2], Gross teaches training one or more machine learning algorithms *to identify one or more characteristics of at least one property feature of one or more property features*. EX1003, ¶115. Gross also discloses additional attributes, "such as façade, eaves, windows, balcony, porch, arch, piers, columns, lattices, false timbering, ornamental, etc. along with specific types (i.e., façade (shingle, siding, brick, stone, horizontal boards, vertical boards, etc.) roof {pitched, double pitched, hipped, flat, metal, tile, shingle, slate, parapet, dormer, mansard, fascia, brackets, eaves, pent, pediment, etc.} and so on)." EX1005, ¶57. Thus, these characteristics include

shape characteristics and material characteristics—e.g., characteristics of a roof (*first feature of the one or more property features*) can be identified as flat (*a shape characteristic*) and metal (*a material characteristic*). EX1005, ¶57; EX1003, ¶116.

H. Claim 6

Claim 6 depends from claim 1 and further recites, "*wherein the information regarding a first feature of the at least one property feature comprises identification of at least one of a shape or a material of the first feature*."

Gross teaches this claim. EX1003, ¶¶117-118. For the reasons discussed in element [1.11], Gross teaches presentation of *information regarding the plurality of characteristics and the condition of each feature of the at least one property feature*. EX1003, ¶118. In the example depicted in Figure 7E (described above), the façade information is shown as "shingle" (i.e., *a material of the first feature*). EX1005, FIG. 7E. And, as explained in [1.11], Gross teaches the information in its report can include additional classifying details about the property features identified in its assessment process. EX1003, ¶119; EX1005, ¶103. The additional classifying details include more examples of identification of shapes and materials of property features (e.g., a roof that is "double pitched" (shape) and "tile" (material). EX1005, ¶57; EX1003, ¶119.

I. Claim 7

Claim 7 depends from claim 1 and further recites, "*wherein the information*

regarding a first feature of the at least one property feature comprises a condition classification indicating at least one of: a good condition, an acceptable condition, a needs repair condition, or a needs replacement condition."

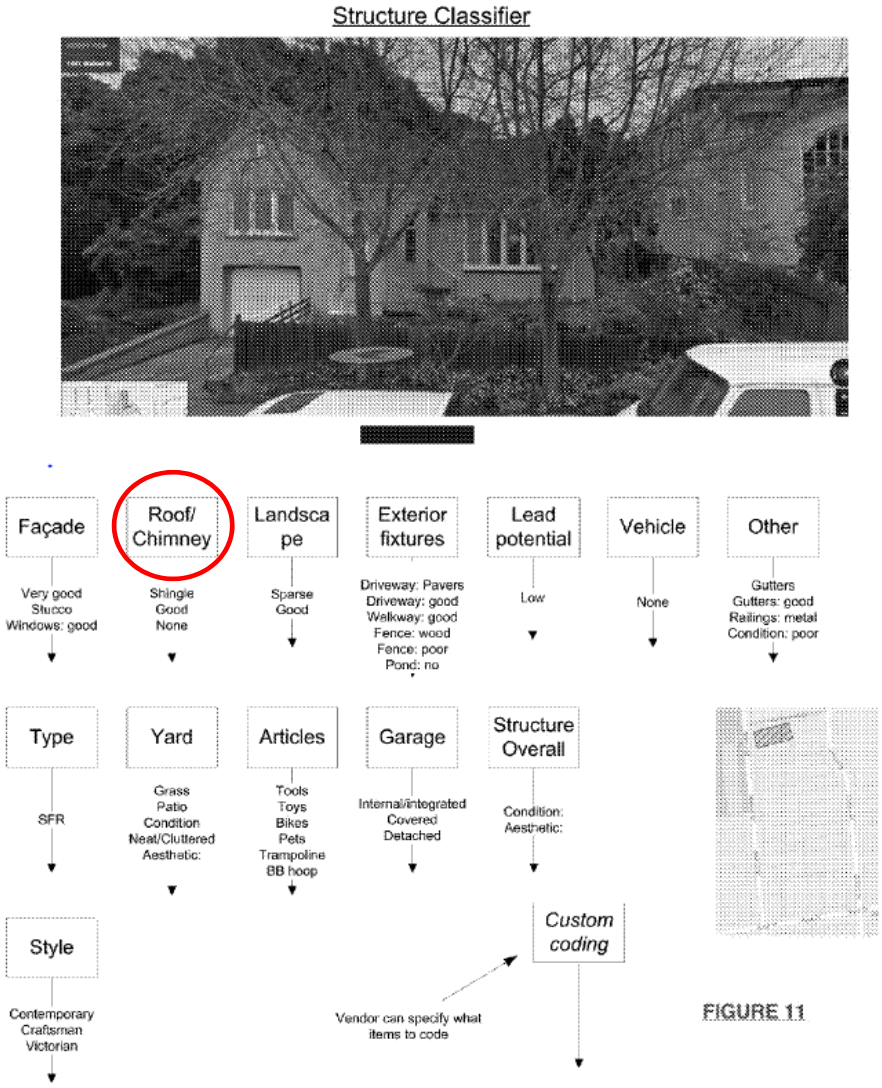
Gross teaches this claim. EX1003, ¶¶120-121. Gross discloses that "[t]he attributes of reference property 830 [] can be classified as corresponding to a positive or high end of a condition scale, i.e. being in top condition and lacking any noticeable weathering or aging … and examples of each building attribute can be captured and analyzed … to help characterize elements having opposite valued ratings." EX1005, ¶135. For example, Figure 11 provides examples of condition classifications *indicating a good condition* (e.g., roof is classified as "good"). EX1005, FIG. 11; EX1003, ¶121. And Gross discloses many other examples of condition classifications *indicating a needs repair condition* or *a needs replacement condition* (e.g., a roof with a "missing/damage tile" (needs repair); a window that has holes (needs replacement). EX1005, ¶¶61-67; EX1003, ¶122.

J. Claim 8

Claim 8 depends from claim 1 and further recites, "*wherein the at least one property feature comprises a rooftop and a chimney*."

Gross teaches this claim. EX1003, ¶¶123-124. Gross describes that the attributes (*property features*) identified and assessed by its Classifier Engine include "roof elements" (*a rooftop*). EX1005, ¶¶57, 61,123. Other structural

features that can be classified include chimneys. EX1005, ¶148. In fact, Figure 11 of Gross (reproduced below) depicts the classification of a chimney.



EX1005, FIG. 11 (annotated).

K. Claim 9

Claim 9 depends from claim 1 and further recites, "*wherein at least one profile of the one or more property condition profiles includes a convolutional neural network (CNN)*."

Gross teaches this claim. EX1003, ¶¶125-126. The ’058 patent describes using machine learning analysis that includes deep learning analysis such as CNN to classify the condition of property characteristics 110 as condition characteristics 116 using condition profiles. EX1001, 10:66-17; EX1003, ¶127; *see also* EX1001, 12:10-23 (describing generating condition profiles 114), FIG. 1 (illustrating condition profiles 114 being applied as input to determine condition characteristics 116). Similarly, for the reasons described in element [1.3], Gross teaches property condition profiles developed through training one or more machine learning algorithms. And, similar to the ’058 patent, Gross’s Classifier Engine applies the condition profiles to classify a condition of the property feature for the reasons described in element [1.10].

Gross’s Classifier Engine analyzes images to identify attributes (and related condition qualifiers) “using a variety of techniques, including … neural networks, etc.” EX1005, ¶¶77-78; EX1003, ¶128. Gross further discloses that these “neural networks” can be “convolutional neural network models” Specifically, Gross describes that suitable examples of well-known feature extraction algorithms that can be adapted for use in its embodiments are set forth in Jafri (incorporated by reference). EX1005, ¶79. Gross—through the incorporated Jafri material—expressly describes using “a hybrid neural network solution which combines [] a convolutional neural network.” EX1008, 49. Thus, a POSA would have understood

or found obvious that, similar to the ’058 patent, Gross teaches its condition profiles may be part of the disclosed “*convolutional neural network (CNN) model*,” which, regardless, was a well-known neural network model for image processing. EX1003, ¶128.

L. Claim 10

Claim 10 depends from claim 1 and further recites, “*wherein the processing circuitry is further configured to compare a current condition classification of the property characteristic to a historic condition classification of the property characteristic*.”

Gross teaches this claim. EX1003, ¶¶129-130. Gross discloses using “long term evaluations over defined time periods … to identify changes in a property condition.” EX1005, ¶134. Gross accomplishes this by storing the “final structure assessment data” (i.e., historic condition classifications) “in database 142” during the feature coding (e.g., condition assessment) process. EX1005, ¶133; *see also* EX1005, ¶141 (describing how “the presence of [a building] feature, type and condition is coded and collected and stored in digital form,” including “the presence, type and condition of facades, roofs, awnings,” and more).

Gross also explains “the coding process” that obtains the property assessments for the “long term evaluations” described above “may be targeted primarily or solely for identifying structural improvements, such as the presence of

a new fence, new roof, new paint job." EX1005, ¶¶146, 134. Given the recorded "structure assessment data," a POSA would have understood or found obvious that the way one would identify these "structural improvements" (e.g., that a new roof was added) would be through a comparison between assessment data of current, updated images of a property and prior, stored historic assessment data of the same property. EX1003, ¶131; EX1005, ¶146. These comparisons would indicate the *change in condition* of the property structure and whether it was a positive change (i.e., improvement) or otherwise. EX1003, ¶131.

Thus, Gross teaches *the processing circuitry is further configured to compare a current condition classification of the property characteristic* (e.g., "good" condition roof) *to a historic condition classification of the property characteristic* (e.g., "damaged" roof). EX1003, ¶132; EX1005, ¶¶134, 146, 61.

M. Claim 11

Claim 11 depends from claim 1 and further recites, "*wherein at least one profile of the one or more property condition profiles includes a deep learning algorithm for identifying the respective feature within a given image*."

Gross teaches this claim. EX1003, ¶¶133-134. For the reasons described in Claim 9, Gross teaches its condition profiles may be part of a neural network, such as a CNN. EX1003, ¶134. And, as recognized in the '058 patent, CNN is an example of a *deep learning analysis algorithm*. EX1001, 11:11-13; EX1003, ¶134.

Gross further describes its deep learning algorithm may *identify the respective features within a given image* through its description of using the neural network to detect and extract features of property attributes. EX1005, ¶77; EX1003, ¶134.

N. Claim 12

Claim 12 depends from claim 1 and further recites, "*wherein applying the one or more property characteristic profiles of the set of property characteristic profiles to at least the portion of each image of the at least one image to determine the plurality of characteristics of the respective feature comprises approximating a size of the respective feature*."

Gross teaches this claim. EX1003, ¶¶135-136. Gross discloses that—as part of its assessment process (i.e., *applying the one or more property characteristic profiles of the set of property characteristic profiles to at least the portion of each image of the at least one image to determine the plurality of characteristics*)—"[r]elative sizes and areas of objects in the image data" can be identified, such as "a size of a roof area" and "size of window openings." EX1005, ¶143. Thus, Gross teaches *approximating a size of the respective feature* (e.g., size of a roof). EX1003, ¶136.

O. Claim 14

Claim 14 depends from claim 13 and further recites, "*wherein a given feature of the one or more features of the property location comprises a natural*

feature."

Gross teaches this claim. EX1003, ¶¶137-138. Gross describes that "the presence, type and condition of ... landscaping" (i.e., *natural feature*) can be collected and assessed as part of its classification process. EX1005, ¶141. For example, the landscaping features and related condition pairs that may be identified and classified includes trees and shrubs. EX1005, ¶68. ¶.

P. Claim 15

Claim 15 depends from claim 13 and further recites, "*wherein causing presentation of the graphical user interface comprises causing presentation of an interactive user interface*."

Gross teaches this claim. EX1003, ¶¶139-140. As described in elements [1.5] and [1.11], Gross teaches that is user interface is preferably an *interactive* web page (*graphical user interface*). Gross further discloses that its "visual assessment report 730 [] is presented in a list and visual form for a human reviewer, and within an interface may have *interactive* tags so that the tagged elements/conditions may be further reviewed, modified, etc. by the human operator." EX1005, ¶130. Thus, Gross teaches *causing presentation of an interactive user interface*. EX1003, ¶140.

Q. Claim 16

Claim 16 depends from claim 13 and further recites, "*wherein accessing the*

aerial imagery comprises accessing the aerial imagery via a second network from non-volatile storage media."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶141-142. Gross discloses its "code, routines, etc. may be stored in any number of forms of machine readable media." EX1005, ¶247. And as described in element [1.6], Gross discloses that Classifier Engine retrieves an aerial image from a database to begin the building attribute/condition assessment process. EX1005, ¶¶120-121. A POSA would understand or find obvious that images stored on a database are stored on *a non-volatile storage media* because, unlike volatile media (like RAM), non-volatile media provides for data persistence. EX1003, ¶142. Gross further describes that (aerial) building images may be retrieved from an outside data source through "any known provider of information" and "may be accessed through an API in appropriate instances." EX1005, ¶42; *see also* EX1005, ¶164. A POSA would have understood or found obvious that the APIs may be implemented on a second network to provide enhanced performance for sending image data. EX1003, ¶142. Based on Gross's description, a POSA would have understood or found obvious that the *aerial imagery* may be *access[ed] via a second network*, such as through a dedicated API on a separate network or connection to a cloud network. EX1003, ¶142.

R. Claim 17

Claim 17 depends from claim 13 and further recites, "*wherein a first property condition profile of the set of property condition profiles includes a color histogram machine learning analysis model*."

Gross renders this claim obvious. EX1003, ¶¶143-144. Gross describes that Classifier Engine (*machine learning analysis model*) may color code an image block so that "abrupt changes within the block" can "be used as an indicator of an irregularity, defect, damage, or the like." EX1005, ¶123. Gross further describes assessing conditions of attributes against a reference set of conditions (*property condition profiles*) and that "dark or irregular color" may cause an element to score poorly. EX1005, ¶126. Thus, Gross teaches *property condition profiles includes a color histogram machine learning analysis model* because its Classifier Engine (*machine learning analysis model*) uses color in its image assessment process and in the reference set of conditions. EX1003, ¶144.

Gross does not explicitly disclose the use of histograms in its property condition profiles. However, Gross—through the incorporated Jafri material—describes using histograms to match features in images. EX1008, 49. And histograms were a well-known technique used to analyze and process images. EX1003, ¶145.

In light of Gross's teachings of using color in its condition profiles to

identify conditions of property features, a POSA would have been motivated to include a *color histogram* in property condition profiles used by Classifier Engine (*machine learning analysis model*) because histograms were a well-known technique used in image processing to identify similarities between images (as taught by the incorporated Jafri material). EX1003, ¶146. Gross explicitly provides motivation to combine Jafri's techniques into its assessment process through its description that "examples of [feature extraction algorithms] that are suitable and/or can be easily adapted for use in the present embodiments is set out in literature such as [Jafri]." EX1005, ¶79; EX1003, ¶146. A POSA would have recognized a histogram would aid in Gross's assessment process to identify whether colors in the property image being processed are indicative of a defective/damaged condition. EX1003, ¶146. A POSA could have readily implemented the predictable variation of including color histograms in the property condition profiles used during its assessment process. EX1003, ¶146; *see KSR*, 550 U.S. at 417.

Thus, Gross renders obvious *a first property condition profile of the set of property condition profiles includes a color histogram machine learning analysis model*. EX1003, ¶147.

S. Claim 18

Claim 18 depends from claim 13 and further recites, "*wherein the set of*

property characteristic profiles are part of a neural network."

Gross teaches this claim. EX1003, ¶¶148-149.

The '058 patent describes that the "machine learning classifier used in the machine learning analysis … includes a convolutional neural network … to classify the property features as property characteristics" using property characteristic profiles that are "developed through training the machine learning algorithms." EX1001 8:47–52, 9:6–11. Similarly, for the reasons provided for elements [1.2], [1.9], and [13.5], Gross teaches property characteristic profiles developed through training one or more machine learning algorithms. EX1003, ¶150. And similar to the '058 patent and for the reasons provided for elements [1.9] and [13.4], Gross teaches that its Classifier Engine (which includes *one or more machine learning algorithms*) applies the *property characteristic profiles* to determine characteristics of a property feature. EX1003, ¶150. Gross further descries that Classifier Engine analyzes images to identify attributes "using a variety of techniques, including … neural networks, etc." EX1005, ¶¶77-78; EX1003, ¶150. Thus, Gross teaches that *the characteristic profiles* applied by Classifier Engine *are part of a neural network*. EX1003, ¶150.

T. Claim 19

Claim 19 depends from claim 1 and further recites, "*wherein: the property location comprises multiple structures; and classifying the condition of the one or*

more features of the property location comprises classifying the condition of one or more features of each structure of the multiple structures."

Gross teaches this claim. EX1003, ¶¶151-152. Gross discloses structural element fields for a property structure (which were classified by Classifier Engine as part of its assessment process) include "an identification of each structural element presented in the property" (i.e., *multiple structures*) and "a condition of such element." EX1005, ¶¶115-16. Gross discloses the "same information" (classification/assessment information) is made for appurtenant elements presented in the property, including, for example, ancillary buildings and garages." EX1005, ¶116. Thus, Gross teaches *classifying the condition of one or more features of each structure of the multiple structures* (e.g., the building and appurtenant elements. EX1003, ¶152.

U. Claim 20

Claim 20 depends from claim 13 and further recites, "*further comprising, prior to classifying the condition, adjusting color of the at least one image*."

Gross renders obvious this claim. EX1003, ¶¶153-154. Gross teaches that Classifier Engine may analyze color in images to assess property conditions through its description that "dark or irregular color [of a group of pixels representing a roof] may cause a roof element to score poorly" during condition determination. EX1005, ¶126; EX1003, ¶154. Gross further describes that

"customized image processing operations" may be applied to images. EX1005, ¶76. A POSA would have understood or found obvious that adjusting color of the image is one of "a finite number of identified, predictable" image adjustment operations that could be used and that many (if not most) image operations (e.g., adjusting contrast, brightness, hue, saturation, color balance, exposure, and sharpness) adjust the color of an image in some fashion. EX1003, ¶155; *see KSR*, 550 U.S. at 402-03 (use of a finite number of identified, predictable solutions is likely the product of ordinary skill and common sense). A POSA could have readily implemented well-known color adjustment techniques and would have been motivated to do so to adjust color of the image before applying property characteristic profiles and condition profiles to provide better accuracy in the assessment process. EX1003, ¶155.

VIII. CONCLUSION

The challenged claims are unpatentable and IPR is warranted.

Respectfully submitted,

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Claims Appendix – U.S. Patent No. 11,195,058

Claim 1

Element	
[1.P]	A system for automatically assessing features of a property location comprising a structure, the system comprising:
[1.1]	a non-volatile computer readable medium storing
[1.2]	a set of property characteristic profiles, each property characteristic profile of the set of property characteristic profiles being developed through training one or more machine learning algorithms using first property images to identify one or more characteristics of at least one property feature of one or more property features, and
[1.3]	a set of property condition profiles, each property condition profile of the set of property condition profiles being developed through training one or more machine learning algorithms using second property images to identify one or more conditions of at least one property characteristic of one or more property characteristics corresponding to a given feature or features of the one or more property features; and
[1.4]	processing circuitry configured to
[1.5]	receive, from a user at a remote computing device via a network, a request comprising identification of a property location,
[1.6]	access aerial imagery of the property location,
[1.7]	classify a condition of one or more features of the property location, wherein classifying comprises, for each feature of the one or more features,
[1.8]	identifying the respective feature from at least one image obtained from the aerial imagery,
[1.9]	applying one or more property characteristic profiles of the set of property characteristic profiles to at least a portion of each image of the at least one image to determine a plurality of characteristics of the respective feature, wherein a first characteristic of the plurality of characteristics comprises a type of material of the feature or a shape of the feature, and

[1.10]	applying one or more property condition profiles of the set of property condition profiles to at least a portion of each image of the at least one image to classify a condition of the respective property feature, and
[1.11]	responsive to receiving the request, cause presentation of, for review by the user at the remote computing device, a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature.

Claim 2

Element	
[2]	The system of claim 1, wherein identifying the respective feature from the at least one image comprises extracting, from the at least one image, one or more pixel groupings representing the respective feature.

Claim 3

Element	
[3]	The system of claim 2, wherein each pixel grouping of the one or more pixel groupings comprises angles, outlines, and/or substantially homogenous pixel fields.

Claim 4

Element	
[4]	The system of claim 1, wherein the aerial imagery comprises at least one aerial image of a geographic region including the property.

Claim 5

Element	
[5]	The system of claim 1, wherein the one or more characteristics of a first feature of the one or more property features comprises a shape characteristic and a material characteristic.

Claim 6

Element	
[6]	The system of claim 1, wherein the information regarding a first feature of the at least one property feature comprises identification of at least one of a shape or a material of the first feature.

Claim 7

Element	
[7]	The system of claim 1, wherein the information regarding a first feature of the at least one property feature comprises a condition classification indicating at least one of: a good condition, an acceptable condition, a needs repair condition, or a needs replacement condition.

Claim 8

Element	
[8]	The system of claim 1, wherein the at least one property feature comprises a rooftop and a chimney.

Claim 9

Element	
[9]	The system of claim 1, wherein at least one profile of the one or more property condition profiles includes a convolutional neural network (CNN).

Claim 10

Element	
[10]	The system of claim 1, wherein the processing circuitry is further configured to compare a current condition classification of the property characteristic to a historic condition classification of the property characteristic.

Claim 11

Element	
[11]	The system of claim 1, wherein at least one profile of the one or more property condition profiles includes a deep learning algorithm for identifying the respective feature within a given image.

Claim 12

Element	
[12]	The system of claim 1, wherein applying the one or more property characteristic profiles of the set of property characteristic profiles to at least the portion of each image of the at least one image to determine the plurality of characteristics of the respective feature comprises approximating a size of the respective feature.

Claim 13

Element	
[13.P]	A method for automatically assessing features of a property location comprising a structure, the method comprising:
[13.1]	receiving, from a user at a remote computing device via a network, a request comprising identification of a property location;
[13.2]	accessing, by processing circuitry, aerial imagery of the property location;
[13.3]	classifying, by the processing circuitry, a condition of one or more features of the property location, wherein classifying comprises, for each feature of the one or more features, identifying the respective feature from at least one image obtained from the aerial imagery,
[13.4]	applying one or more property characteristic profiles of a set of property characteristic profiles to at least a portion of each image of the at least one image to determine a plurality of characteristics of the respective feature,
[13.5]	wherein each property characteristic profile of the set of property characteristic profiles is developed through training one or more machine learning algorithms using first property images to identify one or more characteristics of at least one property feature of one or

	more property features, and a first characteristic of the plurality of characteristics comprises a type of material of the feature or a shape of the feature, and
[13.6]	applying one or more property condition profiles of a set of property condition profiles to at least a portion of each image of the at least one image to classify a condition of the respective property feature,
[13.7]	wherein each property condition profile of the set of property condition profiles is developed through training one or more machine learning algorithms using second property images to identify one or more conditions of at least one property characteristic of one or more property characteristics corresponding to a given feature or features of the one or more property features; and
[13.8]	responsive to receiving the request, causing presentation of, for review by the user at the remote computing device, a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature.

Claim 14

Element	
[14]	The method of claim 13, wherein a given feature of the one or more features of the property location comprises a natural feature.

Claim 15

Element	
[15]	The method of claim 13, wherein causing presentation of the graphical user interface comprises causing presentation of an interactive user interface.

Claim 16

Element	
[16]	The method of claim 13, wherein accessing the aerial imagery comprises accessing the aerial imagery via a second network from non-volatile storage media.

Claim 17

Element	
[17]	The method of claim 13, wherein a first property condition profile of the set of property condition profiles includes a color histogram machine learning analysis model.

Claim 18

Element	
[18]	The method of claim 13, wherein the set of property characteristic profiles are part of a neural network.

Claim 19

Element	
[19]	The method of claim 13, wherein: the property location comprises multiple structures; and classifying the condition of the one or more features of the property location comprises classifying the condition of one or more features of each structure of the multiple structures.

Claim 20

Element	
[20]	The method of claim 13, further comprising, prior to classifying the condition, adjusting color of the at least one image.

CERTIFICATE OF WORD COUNT (37 C.F.R. § 42.24(d))

1. This Petition for *Inter Partes* Review complies with the type-volume limitation of 14,000 words, comprising 9,939 words, excluding the parts exempted by 37 C.F.R. § 42.24(a)(1).

2. This Petition for *Inter Partes* Review complies with the general format requirements of 37 C.F.R. § 42.6(a) and has been prepared using Microsoft® Word 2016 in 14-point Times New Roman font.

Respectfully submitted,

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CERTIFICATE OF SERVICE (37 C.F.R. §§ 42.6(e)), 42.105(a))

I certify that the above-captioned **PETITION FOR *INTER PARTES* REVIEW OF U.S. PATENT NO. 11,195,058** and associated Exhibits 1001-1005 and 1008-1023 were served in their entireties upon the Patent Owner on August 1, 2025, via FedEx® Express at the following addresses:

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Manchester, NH 03101
UNITED STATES
Patent Owner's Correspondence Address of Record for U.S. Patent No. 11,195,058

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