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. 10,650,285

PETITION FOR *INTER PARTES* REVIEW
OF U.S. PATENT NO. 10,650,285

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1. A POSA would have found it obvious to combine different embodiments of Gross. 15
2. Independent Claim 1 17
a. [1.P]: A method for automatically categorizing a condition of a characteristic of a property, the method comprising: 17
b. [1.1]: obtaining, by processing circuitry, an aerial image of a geographic region including the property; 19
c. [1.2]: extracting, by the processing circuitry, one or more features of a plurality of features from the aerial image, wherein the one or more features are each represented by a set of pixel groupings, and the

one or more features represent the characteristic of the property, ... 20

d. [1.3]: wherein each pixel grouping of the set of pixel groupings comprises at least one of angles, outlines, or substantially homogenous pixel fields; 23

e. [1.4]: 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, wherein the first machine learning classifier is trained to identify at least a portion of the one or more features from the first portion of the set of pixel groupings; and..... 23

f. [1.5]: 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, wherein the second machine learning classifier is trained to identify, from the second portion of the set of pixel groupings, property characteristic conditions of the characteristic having the characteristic classification. 25

3. Independent Claim 9 30

a. [9.P]: A system for automatically categorizing a condition of a property feature of a property, the system comprising: 30

b. [9.1]: a non-transitory computer readable storage region storing a first machine learning analysis model trained to identify one or more property characteristics, and..... 31

c. [9.2]: a second machine learning analysis model trained to identify one or more property conditions; 31

d. [9.3]: processing circuitry; and a non-transitory computer readable medium having instructions

stored thereon; wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to extract a set of image-related features from an aerial image, wherein the set of image-related features represent the property feature; 31

e. [9.4]: apply a first portion of the set of image-related features to the first machine learning analysis model to determine a characteristic classification of the property feature from a plurality of potential characteristic classifications of the property feature; and..... 32

f. [9.5]: apply a second portion of the image-related features to the second machine learning analysis model to determine a condition classification of the property feature from a plurality of potential condition classifications of the property feature, wherein the second machine learning analysis model is trained to identify, from the second portion of the set of image-related features, property characteristic conditions of the property feature having the characteristic classification. 32

4. Independent Claim 16 33

a. [16.P]: A non-transitory computer readable medium having instructions stored thereon, wherein the instructions, when executed by processing circuitry, cause the processing circuitry to: 33

b. [16.1]: obtain aerial and/or terrestrial imagery including a property;..... 33

c. [16.2]: 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, wherein 34

d. [16.3]: each pixel grouping of the set of pixel groupings comprises at least one of angles, outlines, or substantially homogenous pixel fields; and 34

e. [16.4]: determine at least one characteristic and at least one condition of the property, wherein determining comprises, for each feature of the one or more features of the property, ... 34

f. [16.5]: 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, and 35

g. [16.6]: 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. 35

5. Claim 2 35

6. Claim 3 37

7. Claim 4 39

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9. Claim 6 40

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11. Claim 10 42

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14. Claim 13 45

15. Claim 14 46

16. Claim 15 48

17. Claim 17 50

18. Claim 18 50

a. [18.1]: The non-transitory computer readable medium of claim 17, wherein the instructions, when executed by the processing circuitry, cause the

processing circuitry to access one or more known property characteristics, ... 50

b. [18.2]: wherein determining the one or more of the damage risk estimate, the repair estimate, or the replacement estimate comprises applying, to the determining, the one or more known property characteristics. 51

19. Claim 19 52

20. Claim 20 52

21. Claim 21 54

22. Claim 22 55

B. Ground 2: The combination of Gross and Davis renders obvious claim 8. 57

VIII. CONCLUSION 62

PETITIONER'S EXHIBIT LIST

Exhibit No.	Description
1001	U.S. Patent No. 10,650,285 to Okazaki ("'285 patent")
1002	Prosecution History of U.S. Patent No. 10,650,285 ("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	U.S. Patent No. 10,755,357 to Davis et al. ("Davis")
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 1-22 of U.S. Patent No 10,650,285 ("the '285 patent," EX1001), assigned to Patent Owner Aon Re, Inc. ("Aon").

I. INTRODUCTION

The '285 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 extract features from an image (e.g., of property), detect and classify features in the image (e.g., a roof), and classify the 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 '285 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."); *id.*, ¶7 (describing prior art camera system for surveying property). And the '285 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 techniques and the well-known existing machine learning capabilities to detect and classify the property features and conditions. EX1003, ¶¶44-48.

In fact, the primary reference asserted herein—Gross—renders obvious the independent claims and virtually *all* of the limitations recited in the dependent challenged claims. To the extent that Aon may argue arson is not a disaster, Gross in combination with Davis (a patent developed by State Farm) renders obvious the claimed risk estimate *due to one or more disasters* recited in a dependent claim.

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 '285 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 ’285 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. 11,030,491 (IPR2024-00XXX);
- U.S. Patent No. 11,195,058 (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 ’285 patent is available for *inter partes* review and that Petitioner is not barred or estopped from requesting

inter partes review of any ’285 patent claim on the grounds herein.

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

A. Identification of Prior Art

The ’285 patent’s earliest possible priority date is September 23, 2016. Without conceding that this is the correct priority date, all references relied upon herein are 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).

Davis (EX1006) was filed on April 8, 2016 and issued on August 25, 2020. Davis is prior art under at least 35 U.S.C. § 102(a)(2).

Each prior art reference is analogous art in the same field and reasonably pertinent to the problems of the ’285 patent. EX1003, ¶¶49, 54. None of the prior art relied on in this Petition was previously before the Office.

B. Grounds Summary

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

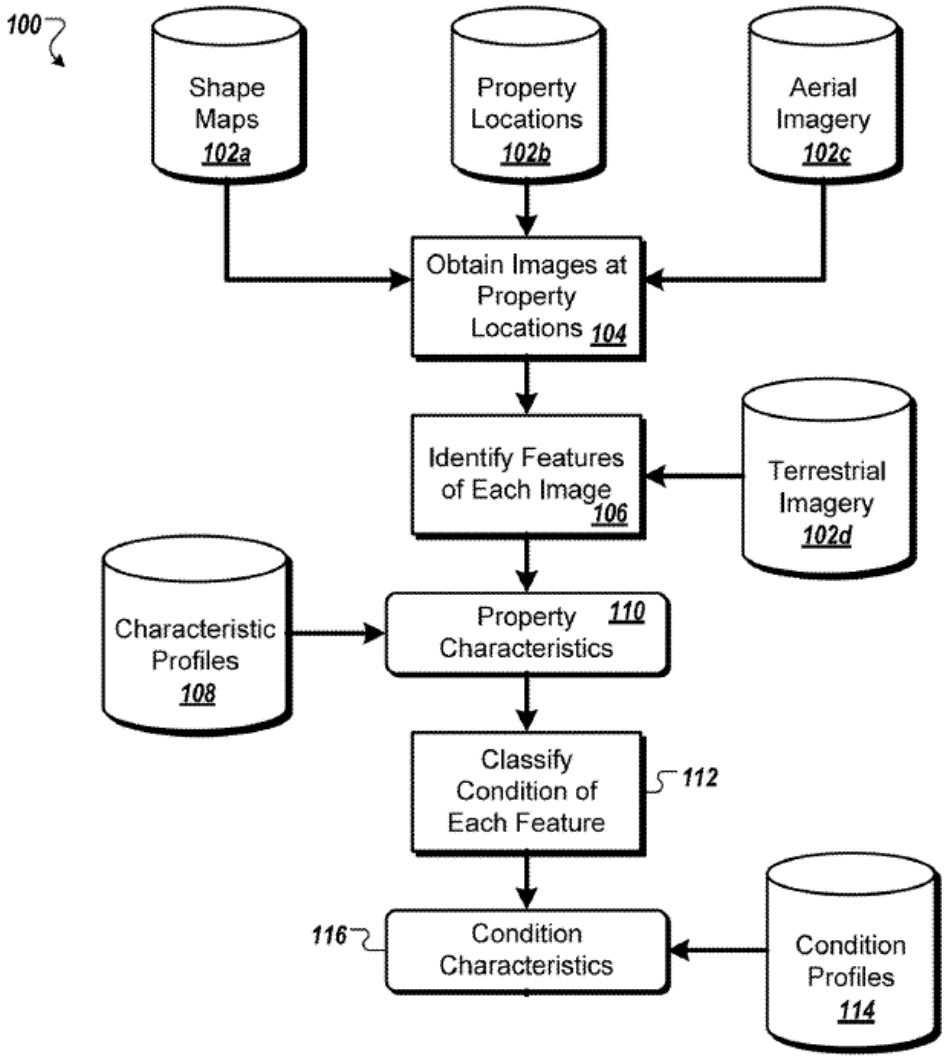
Ground	Basis	Claims	References
1	§103	1-7 and 9-22	Gross
2	§103	8	Gross and Davis

V. THE ’285 PATENT

A. Summary of the ’285 Patent

The ’285 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. *Id.*, 1:36-41, 2:29-37. 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. *Id.*, 2:37-44; *id.*, 12:23-27 (“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 ’285 patent teaches 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. *Id.*, 2:11–20, 29–37 (emphasis added). Figure 1, reproduced below, illustrates an “example system operational flow 100 for matching aerial image features to corresponding property maintenance levels” (*id.*, 6:12-14):



EX1001, FIG. 1 (cropped).

As shown in Figure 1, the system first obtains images at property locations at step 104. At step 106, the system then identifies (or "extracts") "features" of each image, such as "substantially homogenous fields" and "pixel groupings" (groups of pixels). EX1001, 8:22–32. These "features" represent a characteristic of the property, such as a "rooftop" or a "tree." *Id*., 8:26–36; *see also id*., 2:56–66 ("The property characteristic of a structure such as a house, factory, or barn, in

some examples, can include a rooftop, porch, chimney, or skylights. Property characteristics of manmade structures within a property location, in some examples, can include a deck, swimming pool, shed, gazebo, detached garage, tennis court, fence, retaining wall, dock, playground equipment, equipment or vehicles, or greenhouse. Property characteristics of natural features within a property location, in some examples, include trees, ponds, marshes, rivers, lakes, grasses, cliffs, or ocean shore.”).

Then, at step 110, the system determines a “characteristic classification” for the identified property characteristic from the image. *Id*., 8:32–42. For example, this may include determining the “type of rooftop” (e.g., gambrel, gable, hipped, square, flat). *Id.*, 8:32–42, 9:15-35, FIG. 2A; *see also id.*, 2:66-3:6 (“Further, property characteristic classifications can include shapes, materials, size (breadth and/or height, relative or actual), and/or distance of the property characteristic from other features. In some embodiments, the property characteristic classification may include existing versus not existing (e.g., in the event of determining replacement or removal of a manmade feature at a property location such as a fence)”). This classification is done using “characteristic profiles 108,” which include machine learning models trained to classify property characteristics. *Id*., 8:43–9:14.

At step 112, the system determines a “condition classification” of the property characteristic, such as, e.g., a “good” condition or a “bad” condition. *Id*.,

3:17–18, 10:41–49. To do so, "condition profiles 114" (e.g., machine learning models trained to classify conditions of property characteristics) are applied to the extracted image features from step 106. *Id*., 10:52–11:12.

The '285 patent does not purport to have invented any new machine learning or image analysis techniques. Rather, the classification steps 110 and 112 described by the '285 patent merely apply existing machine learning and image analysis techniques. For example, the '285 patent identifies convolutional neural network (CNN) technology as one example, which the '285 patent describes as "a well-established and popular machine-learning methodology." *Id*., 8:42–67, Claim 5. *See* EX1003, ¶¶34-39.

B. Prosecution History

The '285 patent issued from U.S. Application No. 16/733,888 ("the '888 application"), without any substantive prior art examination. The '285 patent is a continuation-in-part of U.S. Application No. 15/714,376 ("the '376 application") that is now U.S. Patent No. 10,529,029. EX1002, 11. The prosecution history reveals that the claims never underwent meaningful analysis against the prior art that renders them obvious. *See, generally*, EX1002.

During prosecution, the '888 application received an objection to claim 5 for including an acronym ("CNN") and a double-patenting rejection over the '029 patent. EX1002, 204-09. In response, the applicant amended the claims to spell out

the acronym and filed a terminal disclaimer. EX1002, 246-47, 254-60. 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 '285 patent and without the detailed analysis typically conducted during examination.[1] EX1002, 271-73. This limited prior art consideration occurred despite the robust prior art landscape that existed at the time of filing. *See* EX1003, ¶40.

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, ¶¶41-42.

D. Claim Construction

In an *inter partes* review, claims are "construed using the same claim

[1] The "Reasons for Allowance" also discusses an *Alice* rejection, but again there were no substantive rejections made of the claims during prosecution of the '285 patent.

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 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 '285 patent specification. *See* EX1003, ¶43.

VI. OVERVIEW OF THE APPLIED REFERENCES

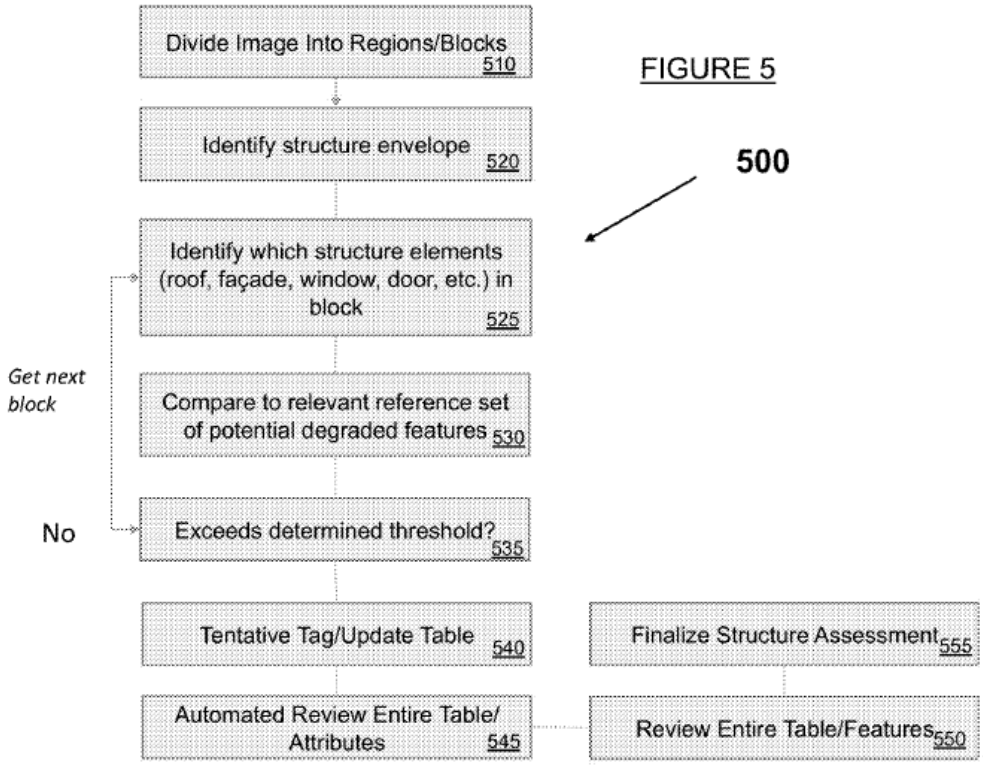
A. Gross

Gross discloses "tools, methods and systems which assess the condition of living structures and other appurtenant real property features." EX1005, ¶2. Like the '285 patent, Gross teaches that these tools are useful in the area of insurance, among others. *Id.*, ¶¶2, 5, 186, 237-238.

Gross's property assessment computing system involves training a "Classifier Engine" and using it to assess and rate different properties. *Id.*, ¶57. To train the classifier engine, Gross's system first collects reference images of "building elements" (e.g., roof, tree, etc.) along with their "types" (e.g., pitched roof, double pitched roof, shingle roof, etc.). *Id.*, ¶¶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. *Id.*, ¶¶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." *Id.*, ¶¶77–78.

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



EX1005, FIG. 2.

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

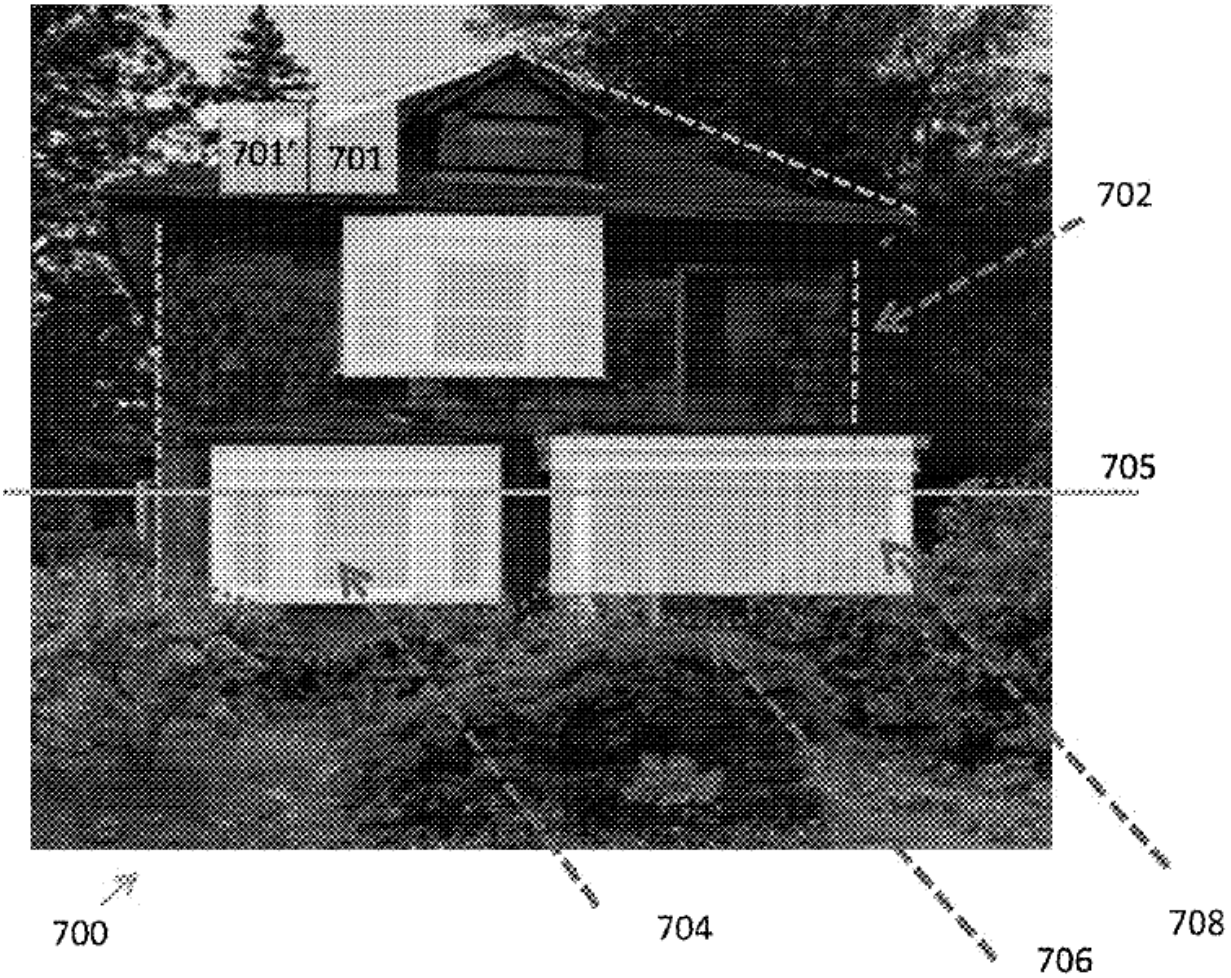


FIGURE 7B

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. *Id*., ¶122, FIG. 7B; EX1003, ¶52. Such "boundaries" (e.g., edges) of other objects in the property (e.g., landscaping, trees, etc.) can also be determined. EX1005, ¶122. The image blocks include "structural elements" (e.g., a roof, tree, etc.), which are determined (alongside a "type" of the structural element (e.g., pitched roof, shingle roof, etc.) at step 525. *Id.*, ¶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. *Id.* As Gross explains, and similar to the '285 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." *Id*.

Again similar to the '285 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. *Id*., ¶¶126–127, 141. The condition classification is then stored into memory at step 540. *Id*., ¶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. *Id*., ¶¶129–133. *See* EX1003, ¶¶49-53.

B. Davis

Davis discloses a computer-implemented method for determining property

features from aerial images and analyzing the property features to determine an estimated risk of damage to the property. EX1006, Abstract. Davis's system "allow[s] an insurance provider to more accurately and efficiently underwrite risk for a home insurance policy" and "reduc[e] the number, frequency and/or cost of … risk mitigation requests." *Id*., 1:64–2:3. A policyholder user (e.g. "the owner of [a] property") may first request "a risk mitigation program." *Id*., 7:53–60. In response, Davis's system, like the '285 patent, obtains and processes an aerial image of the property associated with the request. *Id*. Davis's system then processes the aerial image to "determine one or more features of the property," using techniques such as feature extraction. *Id*., 18:27–34.

Davis's system also performs "object detection/identification," for example, to "identify a particular tree" of a property or "a type of roof" on a house on a property from the aerial image. *Id*., 18:36–39, 48–52; 9:24–29. Subsequently, Davis's system employs "other image analysis techniques" (e.g., image classification) to determine classifications of the detected object, such as "a size of at least a portion of the tree[,] a species of the tree, an orientation of a portion of the tree with respect to the structure or object, etc." or "a type of roof on a structure." *Id*., 18:27–39; 9:22–29. Based on these determinations, Davis's system then, similar to the '285 patent, analyzes a risk of damage to a structure on the property (e.g., a house). *Id*., 19:6–16. *See* EX1003, ¶¶54-55.

VII. GROUNDS OF UNPATENTABILITY

A. Ground 1: Claims 1–7 and 9-22 would have been obvious in view of Gross.

Claims 1-7 and 9-22 would have been obvious over Gross. EX1003, ¶¶14, 56.

1. 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, ¶¶57-58. 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, ¶59. 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, ¶¶57-59.

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, ¶60. Indeed, that is the whole point of Gross—to use its trained classifier to determine building attributes and condition assessments. 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). *Id.* 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. *Id.*; *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, ¶¶60-61; *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 417 (2007).

2. Independent Claim 1

a. [1.P]: A method for automatically categorizing a condition of a characteristic of a property, the method comprising:

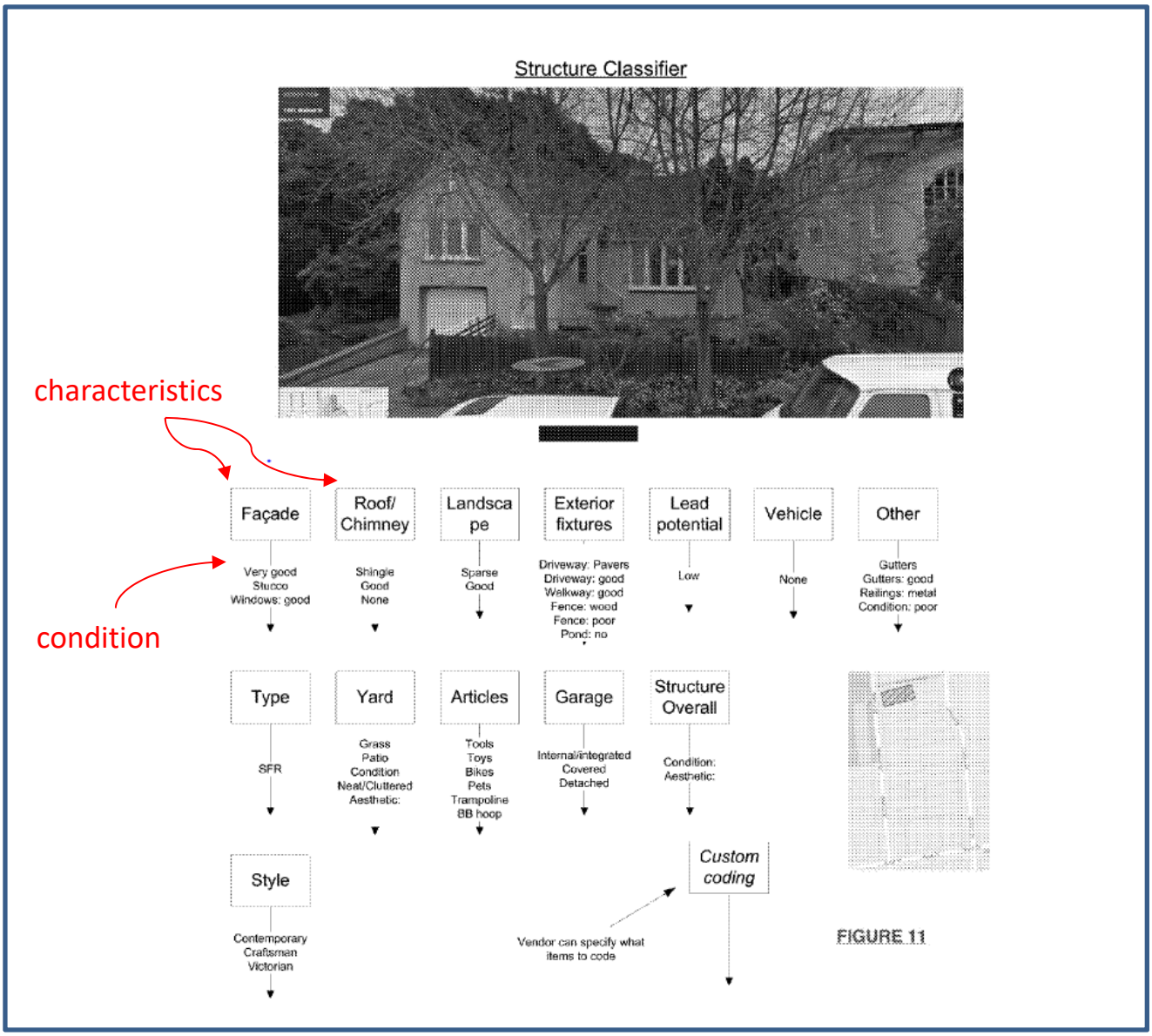
To the extent limiting, Gross discloses the preamble. EX1003, ¶62.

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 *characteristics of a property*, as claimed, because they are physical parts of a structure, such as a house or building. EX1003, ¶¶63-65.

Gross discloses a "condition score is computed [by Classifier Engine] for the detected attribute" (i.e., *a condition of a characteristic of the property*). EX1005, ¶126. For example, the Classifier Engine may automatically categorize the condition of a roof (characteristic of a property) as "new," "missing/damage tile," and/or "holes/cracks." EX1005, ¶61. In some instances, "severity weightings … for the identified condition" may also be assigned by Classifier Engine. EX1005, ¶70. 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." EX1005, ¶145; *also id.*, ¶¶174, 176. Thus, Gross discloses *a*

method for automatically categorizing a condition of a characteristic of a property. EX1003, ¶66.

Gross's Figure 11 "identifies examples of structural features, parameters, conditions … for a particular building structure," which illustrates the results of the Classifier Engine categorizing conditions of a characteristic of a property, as claimed. EX1005, ¶21; EX1003, ¶67.



EX1005, FIG. 11 (annotated).

b. [1.1]: obtaining, by processing circuitry, an aerial image of a geographic region including the property;

Gross teaches element [1.1]. EX1003, ¶68. In particular, Gross 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. "[A]erial

drones, satellite, balloon and similar technology can be used … to easily capture structure image data." EX1005, ¶164. These images captured by the aerial drones, satellite, and balloon are thus *aerial images of a geographic region that includes the property*. EX1003, ¶68. The building image data is stored in a structure image database. EX1005, ¶165.

Gross further describes "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." EX1003, ¶69. Accordingly Gross teaches *obtaining by processing circuitry* the aerial image. *Id.*

c. [1.2]: extracting, by the processing circuitry, one or more features of a plurality of features from the aerial image, wherein the one or more features are each represented by a set of pixel groupings, and the one or more features represent the characteristic of the property,

Gross teaches element [1.2]. EX1003, ¶70. Element [1.2] includes three parts: (i) extracting, by the processing circuitry, one or more features of a plurality of features from the aerial imagine; (ii) the one or more features are each represented by a set of pixel groupings; and (iii) the one or more features represent the characteristic of the property. Gross teaches all three parts.

First, 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 [1.1]) 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, etc." EX1005, ¶¶120, 123. A POSA would have understood or found obvious this identification is performed *by processing circuitry* that *extracts features from the aerial image*. EX1003, ¶¶71-72. In fact, Gross specifically discloses that its Classifier Engine is trained by extracting smaller distinct (image) features from reference images and further notes that "[f]eature extraction algorithms are well-known in the art." EX1005, ¶¶77, 79; EX1003, ¶72.

Second, Gross explicitly teaches that the *one or more features are represented by a set of pixel groupings*. EX1003, ¶73. Gross discloses that "[u]sing conventional image processing, each attribute" (i.e., property characteristic) "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, ¶¶73-74. 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 "*A Survey of Face Recognition Techniques* by Jafri," which is incorporated by reference. EX1005, ¶79. 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.* EX1008, 43, 51, FIG. 19 (illustrating pixel groupings around nose, eye, lips); EX1003, ¶75; *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)).

Third, Gross discloses the attributes (i.e., characteristics of the property) "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, the extracted feature(s) *represent the characteristic of the property*. EX1003, ¶76. Exemplary characteristics of the property that may be represented by the image features include roof elements, window elements and façade elements. *See* EX1005, ¶¶60-68, 123; EX1003, ¶76.

d. [1.3]: wherein each pixel grouping of the set of pixel groupings comprises at least one of angles, outlines, or substantially homogenous pixel fields;

Gross teaches element [1.3]. EX1003, ¶77. As discussed above, 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, sizes, proportions, curves, textures, or other mathematically derivable feature from the image." EX1005, ¶78. Additionally, Gross—through the incorporated Jafri material—discloses extracting features and computing geometric relationships (e.g., "distances, areas and angles") to represent pixel groupings of facial features. EX1003, ¶77; 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, ¶77. Thus, Gross teaches *each pixel grouping comprises at least one of angles* ("angles" or "other mathematically derivable feature"); *outlines* (shapes, curves, building envelope), *or substantially homogenous pixel fields*. EX1003, ¶77.

e. [1.4]: 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, wherein the first machine learning classifier is trained to

identify at least a portion of the one or more features from the first portion of the set of pixel groupings; and

Gross teaches element [1.4]. EX1003, ¶78. Gross discloses that, after it has been trained, Classifier Engine 150 (the claimed *first machine learning classifier*) performs identification of attributes (e.g., roof elements) presented in an image. EX1005, ¶123. The specific types of the attributes (i.e., *characteristic classification(s)*) are also captured "(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. 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. 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." EX1005, ¶¶120, 123; EX1003, ¶¶79-80. For the reasons provided for element [1.1], a POSA would have understood or found obvious that processing circuitry executes the process performed by Classifier Engine. EX1003, ¶81; *see also* EX1005, ¶161 (describing that the critical steps in the process can be implemented into executable software routines and modules). Thus, Gross teaches that the processing circuitry, *applies a first portion of the set of pixel groupings* (e.g., the pixel groupings contained in the image block 701 that represents the attribute (e.g., roof)) *to*

determine a characteristic classification (e.g., shingle) *of the characteristic* (e.g., roof type) *from a plurality of potential classifications of the characteristic* (e.g., metal, tile, shingle, slate). EX1003, ¶81.

Gross's Classifier Engine 150 is *a machine learning classifier trained to identify at least a portion of the one or more features from the first portion of the set of pixel groupings*. EX1003, ¶82. In particular, Gross discloses its Classifier Engine is trained with reference images and that objects in the image are analyzed using neural networks to detect and extract features. EX1005, ¶77. Classifier Engine analyzes images to extract smaller distinct features that can be readily detected. EX1005, ¶77. Gross—through the incorporated Jafri material—describes using "a hybrid neural network solution" (i.e., a form of classifier) to analyze image patterns. EX1008, 49. Gross describes that the training results in extraction of specific features *characterized* by a "***distinct set of pixels***, shapes … or otherwise mathematically derivable feature" (i.e., pixel groupings). EX1005, ¶78; EX1003, ¶83. Thus, Classifier Engine 150 is *a machine learning classifier that is trained to identify a portion of the one or more features from the first portion of pixel groupings* (features characterized by the pixel groupings). EX1003, ¶83; EX1005, ¶¶77, 123.

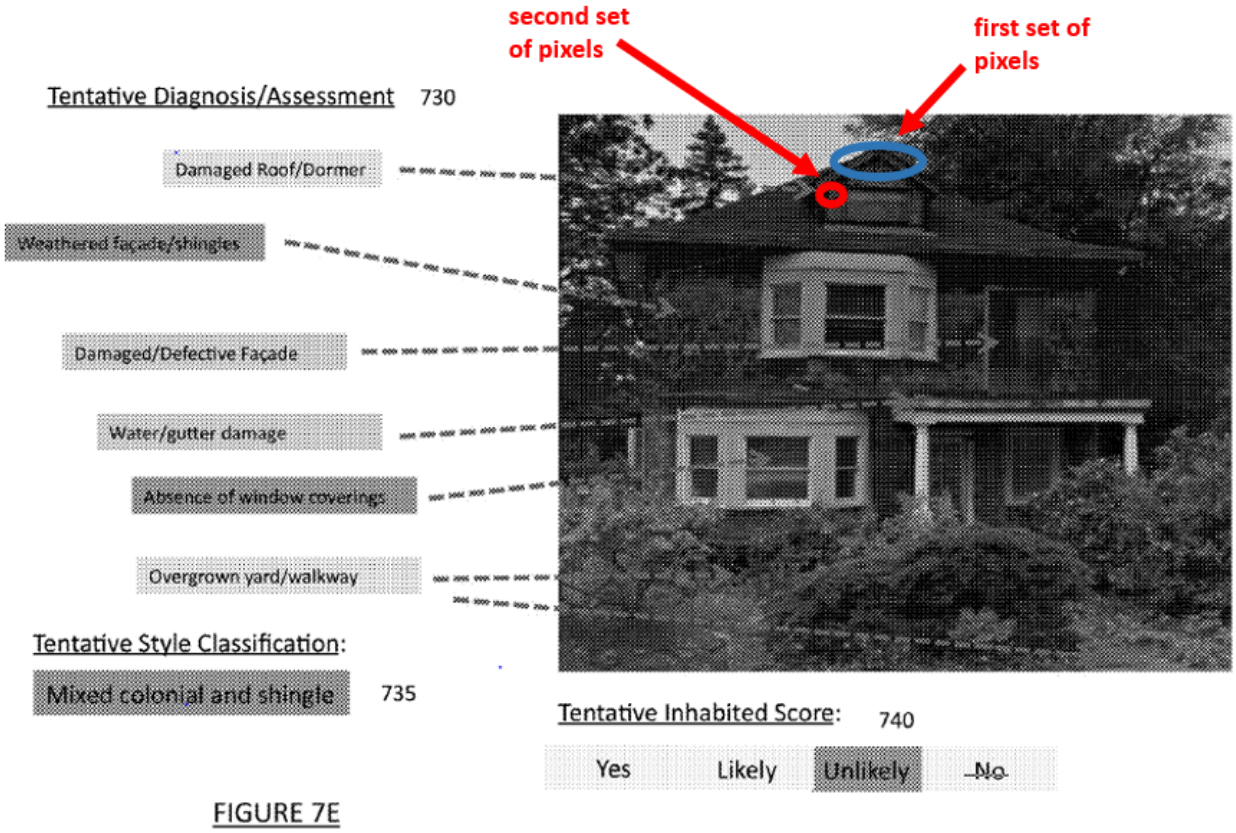
f. [1.5]: applying, by the processing circuitry, a second portion of the set of pixel groupings to a second machine learning classifier to determine a condition classification of the characteristic from a plurality of

> **potential condition classifications of the characteristic, wherein the second machine learning classifier is trained to identify, from the second portion of the set of pixel groupings, property characteristic conditions of the characteristic having the characteristic classification.**

Gross teaches, or at least renders obvious, element [1.5]. EX1003, ¶84. Gross discloses identifying and classifying "conditions/impairments … associated with a particular building attribute" (i.e., *determines a condition classification of the characteristic*). EX1005, ¶60. Gross describes examples of structure attributes (characteristics) and related conditions (condition classifications), 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; EX1003, ¶84.

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. To do this, Classifier Engine (i.e., *second machine learning classifier* for reasons explained below) "employs image processing" and each related condition qualifier "may be characterized by a distinct set of pixels, shapes, sizes, proportions, curves, textures, or otherwise mathematically derivable feature from the image" (i.e., *applies pixel grouping to determine the condition classification*). EX1005, ¶¶78, 120; EX1003, ¶85. A

POSA would have found obvious the pixel groupings that characterizes the condition qualifier is *a second portion of the pixel groupings* as compared to the first portion used to classify the characteristic. EX1003, ¶86. For example, a first portion of the pixel groupings may be the pixels that identify the characteristic is a roof and the second portion of the pixel groupings may identify a damaged condition of the roof that was first identified by the first portion of pixels in limitation [1.4]. EX1003, ¶86. Figure 7E of Gross (depicted below) has been annotated to illustrate a first portion of pixels (identified with the blue circle) that Classifier Engine may apply to identify the characteristic is a roof and a second portion of pixels (identified with a red circle) that may be applied by Classifier Engine to identify a damaged section of the roof. EX1003, ¶86.



EX1005, FIG. 7E (annotated).

Thus, Gross teaches *applying, by the processing circuitry, a second portion of the set of pixel groupings to determine a condition classification* (e.g., missing tile) *of the characteristic* (e.g., roof) *from a plurality of potential condition classifications* (e.g., new, missing/damage tile, holes/cracks) *of the characteristic*. EX1003, ¶87.

Additionally, for the reasons provided for element [1.4], Gross teaches that its Classifier Engine is *a machine learning classifier*. EX1003, ¶88; EX1005, ¶77. And although Gross does not explicitly disclose that its condition qualifiers are classified via a different machine learning classifier than was used to identify

attributes, Gross explicitly discloses that "it may be useful to employ multiple classifiers … to identify the attributes and classify the structure." EX1005, ¶80; EX1003, ¶88. Gross further discloses examples of using a classifier to identify conditions, such as "damaged/exposed roof elements" and "broken—façade," EX1005 ¶¶85, 91, which correspond to the attributes (*characteristic of the property*) discussed above for Element [1.4], such as a "roof" or "façade." Gross also 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***." EX1005, claim 26 (emphasis added).

In light of these teachings, a POSA would have understood that Gross teaches, or renders obvious, the use of *a second machine learning classifier*, as claimed, to classify the property characteristic conditions because customized classifiers are more accurate or more appropriate for different vendors. EX1003, ¶89. A POSA would have been motivated to employ a second machine learning classifier to identify property characteristic conditions because Gross explicitly suggests that different classifiers can be used and that classifiers can be customized for different purposes. EX1003, ¶90; EX1005, ¶80, claim 26. Moreover, a POSA 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 improve the accuracy of their classifications, such as in this case the identification of property characteristic conditions. EX1003, ¶90. *See* EX1005, ¶¶80, 81; *see also id.*, ¶84 (identifying "types of attributes and conditions that can be used to train the classifier"). A POSA would have readily implemented the predictable variation of implementing Gross's Classifier Engine as two machine learning classifiers—a first classifier trained to identify features that represent property characteristics and a second classifier trained to identify conditions of those characteristics. EX1003, ¶90; *see KSR*, 550 U.S. at 416 ("If a person of ordinary skill can implement a predictable variation, § 103 likely bars its patentability."). Therefore, Gross teaches, or at least renders obvious, *a second machine learning classifier trained to identify* (using image processing techniques), *from the second portion of the set of pixel groupings, property characteristic conditions* (e.g., missing tile) *of the characteristic* (e.g., roof) *having the characteristic classification* (e.g., "tile roof"). EX1003, ¶90; EX1005, ¶¶60, 61, 123, 126.

3. Independent Claim 9

a. [9.P]: A system for automatically categorizing a condition of a property feature of a property, the system comprising:

To the extent limiting, Gross discloses the preamble of claim 9 for the reasons provided for element [1.P]. EX1003, ¶91. Gross further describes that its

property assessment computing system may be "an online collection of computing machines and accompanying software modules suitable and configured particularly for performing the operations described." EX1005, ¶42.

b. [9.1]: a non-transitory computer readable storage region storing a first machine learning analysis model trained to identify one or more property characteristics, and

Gross teaches element [9.1] for the reasons provided for element [1.4]. EX1003, ¶92. Gross's Classifier Engine, which is trained and uses neural networks and a "hybrid neural network solution" to analyze images, is a *machine learning analysis model*. EX1003, ¶92; EX1005, ¶¶77, 79; EX1008, 49. Gross further discloses that its "applications," which would include its Classifier Engine, "can be embodied in tangible, machine readable form for causing a computing system to execute appropriate operations in accordance" with the teachings. EX1005, ¶56.

c. [9.2]: a second machine learning analysis model trained to identify one or more property conditions;

Gross teaches, or renders obvious, element [9.2] for the reasons provided for element [1.5] and [9.1]. EX1003, ¶93.

d. [9.3]: processing circuitry; and a non-transitory computer readable medium having instructions stored thereon; wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to extract a set of image-related features from an aerial image, wherein the set of image-related features represent the property feature;

Gross teaches element [9.3] for the reasons provided for element [1.1] and

[1.2]. EX1003, ¶94. The *image-related features* of this element correspond to the "features represented by a set of pixel groupings" in [1.2] and *property feature* corresponds to *the characteristic of the property* in [1.2]. EX1003, ¶94. Gross further discloses that its "applications can be embodied in tangible, machine readable form for causing a computing system to execute appropriate operations in accordance" with the teachings. EX1005, ¶56.

e. [9.4]: apply a first portion of the set of image-related features to the first machine learning analysis model to determine a characteristic classification of the property feature from a plurality of potential characteristic classifications of the property feature; and

Gross teaches element [9.4] for the reasons provided for element [1.4] and [9.1]. EX1003, ¶95.

f. [9.5]: apply a second portion of the image-related features to the second machine learning analysis model to determine a condition classification of the property feature from a plurality of potential condition classifications of the property feature, wherein the second machine learning analysis model is trained to identify, from the second portion of the set of image-related features, property characteristic conditions of the property feature having the characteristic classification.

Gross teaches, or renders obvious, element [9.5] for the reasons provided for element [1.5] and [9.2]. EX1003, ¶96.

4. Independent Claim 16

a. [16.P]: A non-transitory computer readable medium having instructions stored thereon, wherein the instructions, when executed by processing circuitry, cause the processing circuitry to:

To the extent limiting, Gross discloses the preamble of claim 16. EX1003, ¶97. In particular, Gross teaches that its "applications can be embodied in tangible, machine readable form for causing a computing system to execute appropriate operations in accordance" with the teachings. EX1005, ¶56.

b. [16.1]: obtain aerial and/or terrestrial imagery including a property;

For the reasons provided for element [1.1], Gross teaches instructions that cause the processing circuitry to obtain aerial imagery including a property. EX1003, ¶98.

Although not required by the claim, Gross also teaches obtaining *terrestrial images*. EX1003, ¶99. Gross discloses images may be obtained directly from a user's camera and the "user's image data of the property can easily be broken down and analyzed for attributes, features, etc. by Classifier Engine [] in a similar manner as discussed above, even if it takes more time." EX1005, ¶¶108-109; *see also* FIG. 7A (illustrating an image taken from the perspective of a ground location (a "terrestrial image")). These user-captured images are "terrestrial imagery" because they are images of the property taken from a location on the ground. EX1003, ¶¶99-100. Thus, Gross further teaches *instructions that cause the*

processing circuitry to obtain terrestrial imagery including a property. EX1003, ¶100.

c. [16.2]: 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, wherein

Gross teaches element [16.2] for the reasons provided for element [1.2] and [16.1]. EX1003, ¶101. As described in element [1.2], Gross discloses an image is obtained and "an identification is performed to determine structural elements presented." EX1005, ¶¶120, 123. The image may be an "aerial image" as discussed in element [1.2] or the "terrestrial image" obtained from a user camera as described in element [16.1]. After the image (aerial or terrestrial) is obtained, the *extract a plurality of pixel groupings* is performed for the reasons described in element [1.2]. EX1003, ¶101.

d. [16.3]: each pixel grouping of the set of pixel groupings comprises at least one of angles, outlines, or substantially homogenous pixel fields; and

Gross teaches element [16.3] for the reasons provided for element [1.3]. EX1003, ¶102.

e. [16.4]: determine at least one characteristic and at least one condition of the property, wherein determining comprises, for each feature of the one or more features of the property,

Gross teaches element [16.4] for the reasons provided for element [1.4] and

[1.5]. EX1003, ¶103.

f. [16.5]: 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, and

Gross teaches element [16.5] for the reasons provided for element [1.4]. EX1003, ¶104.

g. [16.6]: 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.

Gross teaches, or renders obvious, element [16.6] for the reasons provided for element [1.5]. EX1003, ¶105.

5. Claim 2

Claim 2 depends from claim 1 and further recites, "*comparing, by the processing circuitry, the condition classification to a historic condition classification to identify a change in condition of the characteristic of the property.*"

Gross teaches this claim. EX1003, ¶¶106-109. For instance, 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 classification*) "in database 142"

during the feature coding process. EX1005, ¶133; *see also id*., ¶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). EX1003, ¶107.

Gross also explains that "the coding process," which 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, etc." EX1005, ¶¶146, 134. Given the recorded "structure assessment data," a POSA would have understood or found obvious that to identify these "structural improvements" (e.g., that a new roof was added) a comparison is made between assessment data of current, updated images of a property (e.g., a roof in "good" condition) and prior, stored historic assessment data of the same property (e.g., a roof in "damaged" condition). EX1003, ¶108; EX1005, ¶¶133, 146. These comparisons would indicate the *change in condition* of the property structure and whether it was a positive change (i.e., an "improvement") or otherwise. EX1003, ¶108.

Thus, Gross teaches *comparing, by the processing circuitry, the condition classification* (e.g., "good" condition roof) *to a historic condition classification* (e.g., "damaged" roof) *to identify a change in condition of the characteristic of the property* (e.g., "new" roof). EX1003, ¶109.

6. Claim 3

Claim 3 depends from claim 1 and further recites, "*preparing, by the processing circuitry for presentation to a user, a graphical report comprising condition information regarding the condition classification.*"

Gross teaches this claim. EX1003, ¶¶110-114. Specifically, Gross discloses that a "visual assessment report 730 can be generated [] which preferably identifies at least those attributes identified by the system as having some measure of damage, impairment, aging, weathering, etc." EX1005, ¶130. 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., *condition information regarding the condition classification*) EX1005, ¶103; EX1003, ¶111. Figure 7E (depicted below) presents an embodiment of this visual assessment report.

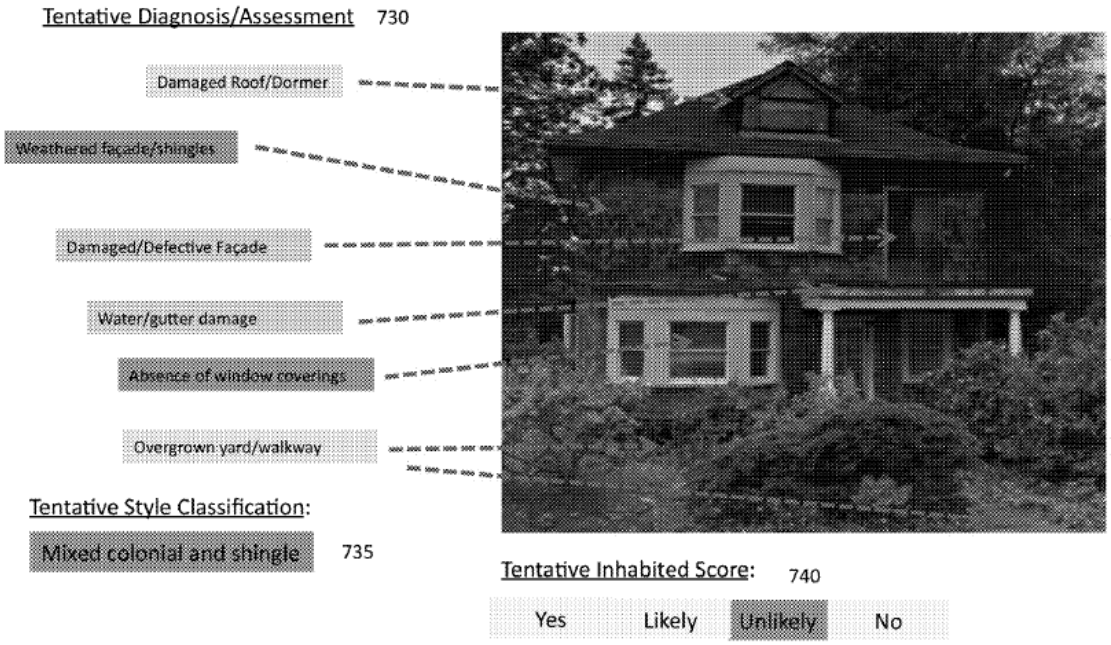


FIGURE 7E

EX1005, FIG. 7E.

Gross further discloses that "[t]his data is presented in a list and visual form for a human reviewer." EX1005, ¶130. And Gross describes its system 110 engages with users employing computing devices 112 and, in a preferred embodiment, system 110 is part of a website which can be accessed through a conventional browser. EX1005, ¶43. The '285 patent does not provide any details about what is required of a "graphical report." In light of Gross's disclosure of a website interface, a POSA would have understood or found obvious that a "visual assessment report" is a *graphical report* that is *for presentation to a user* because it provides assessment report data in graphical form (i.e., in a graphical user interface, such as a website). EX1003, ¶112.

Gross also discloses that "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. These "executable software routines" are executed via *processing circuitry*. EX1003, ¶113.

Thus Gross teaches *preparing, by the processing circuitry for presentation to a user, a graphical report* (e.g., visual assessment report 730) *comprising condition information regarding the condition classification* (e.g., "damaged" roof). EX1003, ¶114.

7. Claim 4

Claim 4 depends from claim 3 and further recites, "*wherein the preparing comprises preparing the graphical report as an interactive user interface*."

Gross teaches this claim. EX1003, ¶¶115-116. Gross discloses that the assessment data in its "visual assessment report" is prepared as an "interactive user interface." Specifically, "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 (emphasis added).

8. Claim 5

Claim 5 depends from claim 1 and further recites, "*wherein at least one of the first machine learning classifier or the second machine learning classifier*

comprises a convolutional neural network (CNN) model."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶117-118. Gross discloses that its feature extraction can be accomplished "using a variety of techniques, including … neural networks, etc." EX1005, ¶77. 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 "*A Survey of Face Recognition Techniques*, by Jafri," which is 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 the disclosed "neural networks" included a *convolutional neural network (CNN) model*, which, regardless, was a well-known neural network model for image processing. EX1003, ¶118.

9. Claim 6

Claim 6 depends from claim 1 and further recites, "*wherein the plurality of potential condition classifications comprises a numeric scale of condition classifications ranging between a needs replacement condition and a like new condition*."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶119-120. For

instance, 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," i.e., *like new condition*. EX1005, ¶135. Gross discloses that this condition scale can also be a numeric scale, such as 1–10 (*see*, *e.g.*, *id*., ¶70, disclosing "severity weightings (i.e., a scaling factor of any convenient range (1-10, or the like) for the identified condition)," and *id.*, ¶179, disclosing "types of conditions are associated with a particular feature across a spectrum of classified values–i.e., what constitutes a poor condition shingle (level 1) an excellent condition shingle (level 10) and so on"). A POSA would have understood or found obvious that the level 10 "top" condition would be a "like new" condition for the property characteristic and that a level 1 "poor" condition would be a "needs replacement" condition for the property characteristic. EX1003, ¶120.

10. Claim 7

Claim 7 depends from claim 1 and further recites, "*determining, by the processing circuitry based in part on the characteristic classification and the condition classification, a cost for repair or replacement of the characteristic of the property*."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶121-122. For instance, Gross discloses generating "an overall estimate [that] identif[ies] a cost to

restore the building structure to a nominal target state," which is calculated by "correlating each of the impairments to repair or improvement figures, and summing over all the attribute conditions." EX1005, ¶134. These "improvement figures" teach, or at least render obvious, *a cost for repair or replacement of the characteristic of the property* (e.g., attribute, such as a roof) because it is common sense that one way to improve the attribute is to replace the attribute. EX1003, ¶122; *see KSR*, 550 U.S. 398 at 421 (factfinders may consider common sense in obviousness inquiry). Gross teaches its determination of the replacement cost uses: *the condition classification* ("summing over all the attribute *conditions*"); and *the characteristic classification* because repair and improvement figures depend on the classification (e.g., a tile roof replacement has a different cost than a slate roof). EX1003, ¶122; EX1005, ¶134.

11. Claim 10

Claim 10 depends from claim 9 and further recites, "*wherein each image-related feature of the set of image-related features comprises at least one of angles, outlines, or substantially homogenous pixel fields*."

Gross teaches this claim for at least the reasons provided for element [1.3]. EX1003, ¶¶123-124.

12. Claim 11

Claim 11 depends from claim 9 and further recites, "*wherein the*

instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to extracting the set of image-related features, assess orthogonality of the aerial image."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶125-128. Gross teaches *assess[ing] orthogonality of the aerial image*. EX1003, ¶126. Orthogonality of an image refers to the degree to which a camera's optical axis is perpendicular to the imaged surface (e.g., its degree of alignment with the true vertical axis of the captured image). *Id.* Gross describes how various tools can be used for assessing buildings via satellite aerial inspections of roof, such as the techniques set forth in U.S. Patent No. 8,078,436 to Pershing et al., which is incorporated by reference. EX1005, ¶6. Gross—through the incorporated Pershing material—describes a system that assesses orthogonal characteristics of an aerial image, such as when "the vertical axis of a particular aerial image sometimes will not substantially match the actual vertical axis of its scene," and then "adjust[s] the scale and/or relative angle of the aerial image to correct for such errors." EX1009, 8:59–9:1; EX1003, ¶¶126-127.

Gross also teaches assessing orthogonality prior to training Classifier Engine: "customized image processing operations (rotations, noise clean up, etc.) may also be performed" as part of an image pre-processing or "normaliz[ation]" process. EX1005, ¶76. A POSA would have found obvious that these "customized

image processing operations"—in view of the disclosure of Pershing—would have included correcting orthogonality, because normalizing the orthogonality of reference images would improve the accuracy of Classifier Engine and reduce errors that occur, for example, when "the vertical axis of a particular aerial image [does] not substantially match the actual vertical axis of its scene." EX1003, ¶128; EX1009, 8:59–9:1. Such implementation would merely amount to combining Gross's disclosure of pre-processing techniques prior to training Classifier Engine with its disclosure of orthogonality assessment according to known methods to yield predictable results. EX1003, ¶128; *KSR*, 550 U.S. at 417. Additionally, since Gross's pre-processing process occurs "prior to training" (and using) Classifier Engine, the orthogonality assessment would also occur *prior to extracting the set of image-related features*. EX1005, ¶76.

13. Claim 12

Claim 12 depends from claim 11 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, responsive to assessing that the orthogonality of the aerial image does not correspond to a true orthophoto form, cause correction of the aerial image to the true orthophoto form*."

Gross teaches, or renders obvious, this claim for at least the reasons provided for Claim 11. EX1003, ¶¶129-131. Gross teaches *caus*[ing] *correction of*

the aerial image to the true orthophoto form. EX1003, ¶130. As described above, orthogonality of an image refers to the degree to which a camera's optical axis is perpendicular to the imaged surface, (e.g., its degree of alignment with the true vertical axis of the captured image). *Id.* The '285 patent does not provide a definition, or describe, "true orthophoto form." A POSA would understand an image in *true orthophoto form* is one where the camera's optical axis is geometrically corrected to perfectly (or near-perfectly) align with the true vertical axis of the captured image. *Id.*; *see also*, *e.g.*, EX1001, 20:57–62 (describing "generat[ing] a true orthophoto form" of an image "if the aerial imagery is not orthogonal").

As described above, Gross—through the incorporated Pershing material—describes a system that assesses orthogonal characteristics of an aerial image, such as when "the vertical axis of a particular aerial image sometimes will not substantially match the actual vertical axis of its scene," and "adjust[s] the scale and/or relative angle of the aerial image to correct for such errors." EX1009, 8:59–9:1. In light of these teachings, a POSA would have understood or found obvious that correcting the orthogonality of an aerial image would produce a true orthophoto form of the original image. EX1003, ¶131.

14. Claim 13

Claim 13 depends from claim 9 and further recites, "*wherein the*

instructions, when executed by the processing circuitry, cause the processing circuitry to obtain, via a network from a remote computing system, the aerial image of the geographic area."

Gross teaches, or renders obvious, this claim for at least the reasons provided for element [1.1]. EX1003, ¶¶132-135. Additionally, Gross teaches *obtain*[ing], the images *via a network from a remote computing system.* For instance, Gross discloses that "image data [] is obtained from a third party vendor" (i.e., *remote computing system*) and that "the software modules described [] can be implemented from the present teachings using [] large scale computing systems, including servers connected to a network (such as the Internet)." EX1005, ¶¶164, 56. In view of these teachings that Gross is implemented using large scale computing systems and servers connected to a network, it would have been obvious that obtaining image data from a third party vendor (the *remote computing system*) would involve obtaining the image data *via a network* (e.g., the Internet). EX1003, ¶¶134-135; EX1005, ¶56.

15. Claim 14

Claim 14 depends from claim 13 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to obtaining the aerial image, determine, based at least in part on the property feature, a preferred image type corresponding to the property*

feature."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶136-139. Gross discloses "a data acquisition process 1600 [] to acquire appropriate image data for structures within a target area." EX1005, ¶161. This "data acquisition process" involves retrieving "image data" corresponding to a specific property. *Id*., ¶164. Gross discloses that when retrieving this "image data," "it is expected that aerial drones, satellite, balloon and similar technology can be used in certain areas to easily capture structure image data from a variety of perspectives, and at different times," and that "this will also facilitate building out a comprehensive image database." *Id*. Gross explains further how obtaining images "at different angles, elevations and profiles" helps "increase building coverage and feature currency/accuracy." *Id*., ¶148; EX1003, ¶137.

In light of these teachings, a POSA would have understood or found obvious that this "comprehensive image database" (containing different types of images) would allow the classifier to use certain, preferred types of images for certain property classification tasks with the goal of increased classification "accuracy." EX1003, ¶138. For example, an image that would "increase building coverage" of the roof of a property and therefore increase the "accuracy" of the roof condition classification would be a top-down image of the property that exposes a higher amount of rooftop surface area (e.g., as opposed to an image of the property at

street elevation). EX1005, ¶148. A POSA could have readily implemented the predictable variation of determining the preferred type of image (that would provide increased "accuracy") based on the specific property feature being classified. EX1003, ¶138; *KSR*, 550 U.S. at 417. Additionally, since such a determination influences which image type to obtain—and consequently the actual image—the determination would also occur *prior to obtaining the aerial image*. EX1003, ¶138.

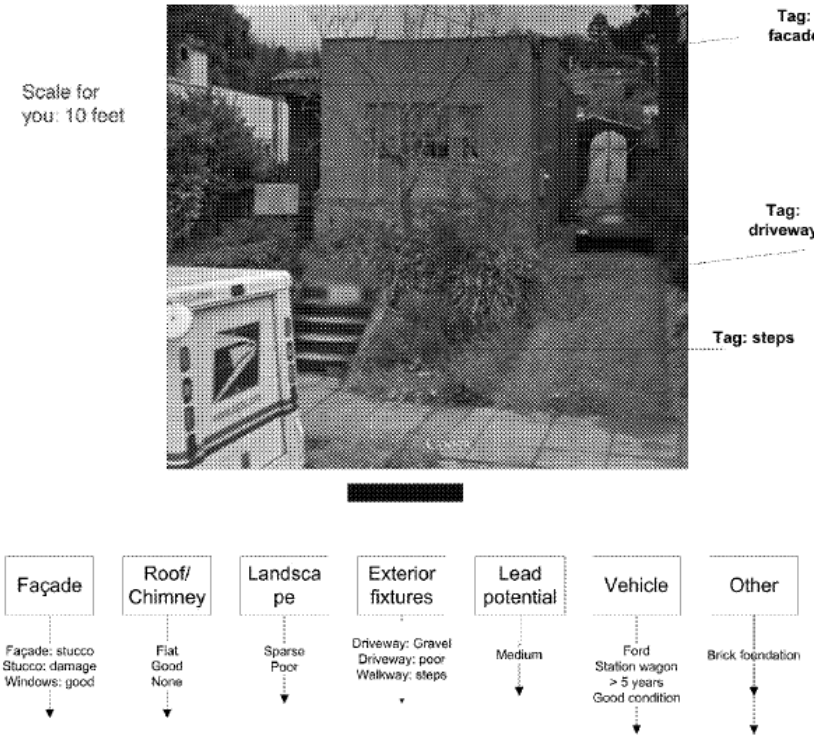
Thus, Gross teaches *instructions* (e.g., instructions on "the computing system") that *cause the processing circuitry to, prior to obtaining the aerial image of the geographic region, determine, based at least in part on the property feature* (e.g., roof), *a preferred image type corresponding to the property feature* (e.g., a top-down image, an image that "increase[s] feature currency/accuracy," etc.). EX1003, ¶139.

16. Claim 15

Claim 15 depends from claim 9 and further recites, "*wherein the plurality of potential characteristic classifications comprises at least one of a plurality of potential sizes, a plurality of potential shapes, or a plurality of potential materials of the property feature*."

Gross teaches this claim. EX1003, ¶¶140-142. For instance, Figure 12 of Gross depicts examples of "structural features, parameters, conditions, etc. that can

be identified, assessed, tagged, coded and stored," such as roof shapes. EX1005, ¶¶21, 146.



EX1005, FIG. 12.

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. The examples of "specific types" corresponding to each attribute include *a plurality of potential shapes* (e.g., pitched, hipped, flat) and *a plurality of potential materials* (e.g., metal, tile, shingle). EX1003, ¶142.

17. Claim 17

Claim 17 depends from claim 16 and further recites, "*using the at least one characteristic and the at least one condition to determine one or more of a risk estimate, a repair estimate, or a replacement estimate*."

Gross teaches, or renders obvious, this claim for at least the reasons provided for claim 7. As explained, Gross discloses using the property attribute and the attribute condition to determine a cost for repair or replacement. EX1003, ¶¶143-144; *see also* EX1005, ¶134.

18. Claim 18

a. [18.1]: The non-transitory computer readable medium of claim 17, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to access one or more known property characteristics,

Gross teaches, or renders obvious, this element for at least the reasons provided for claims 7 and 17. EX1003, ¶145. Additionally, Gross discloses generating "a score [] identifying a likelihood of current occupancy of the structure," which "may be associated or mapped to other content labels, such as 'confirmed vacant' or 'confirmed occupied,' etc." EX1005, ¶118. Gross also describes "where this information is already known with certainty by reference to public records it can be included" in a record generated by the Classifier Engine. *Id*., ¶¶118, 115. It would have been obvious that obtaining occupancy information from "public records" would require accessing, at least in part, the "public records"

for the occupancy information. EX1003, ¶145. Here, the property occupancy information is the *known property characteristic*.

b. [18.2]: wherein determining the one or more of the damage risk estimate, the repair estimate, or the replacement estimate comprises applying, to the determining, the one or more known property characteristics.

Gross teaches, or renders obvious, this element for at least the reasons provided for claims 7 and 17 and element [18.1]. EX1003, ¶146. Additionally, Gross describes its property assessment system can be used for "[i]nsurance … risk assessments" (i.e., *a damage risk estimate*). EX1005, ¶238. Gross discloses determining "policy premiums, risk assessments, etc., based on an evaluation of an upkeep/maintenance evidenced for a particular property," and developing correlations for "occupancy estimates." EX1005, ¶238. For example, Gross discloses that "a property insurer is likely to be interested in knowing if a building is vacant and thus more likely to be vandalized or have a higher risk of arson, etc." *Id*. As described above, property occupancy is an example of a "known property characteristic" that can be accessed by Gross's system. *Id*., ¶¶118, 115. A POSA would have understood or found obvious that developing a risk estimate correlation value from property occupancy would involve *applying* a *known property characteristic* (e.g., applying occupancy information accessed from "public records" to a mathematical model) when determining a risk estimate.

EX1003, ¶146.

Further, a POSA would have understood or found obvious that in addition to the applying the "property occupancy" characteristic disclosed by Gross, the insurance risk assessment taught by Gross would have also been based, at least in part, on applying other property characteristic classification because it is common sense the risk varies depending on the classification (e.g., a metal roof would have less insurance risk of damage from a fire than a slate roof). EX1003, ¶146; *see KSR*, 550 U.S. 398 at 421 (factfinders may consider common sense in obviousness inquiry).

19. Claim 19

Claim 19 depends from claim 16 and further recites, "*wherein the one or more characteristics of a first feature of the one or more features comprises a shape characteristic and a material characteristic*."

Gross teaches this claim for at least the reasons provided for claim 15. As explained, the Classifier Engine in Gross is trained to identify and assess "structural features, parameters, conditions, etc." such as roof shape and material. EX1005, ¶21; EX1003, ¶¶147-148; *see also* EX1005, ¶57, FIG. 12.

20. Claim 20

Claim 20 depends from claim 16 and further recites, "*wherein extracting the plurality of pixel groupings from the aerial and/or terrestrial imagery comprises*

extracting a first set of pixel groupings from an aerial image and a second set of pixel groupings from a terrestrial image."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶149-152. For at least the reasons provided for elements [1.1] and [1.2], Gross discloses *extracting a first set of pixel groupings from an aerial image*. EX1003, ¶150. As explained, pixel groupings that represent image features can be extracted from aerial property images captured via "aerial drones, satellite, balloon and similar technology." EX1003, ¶150; EX1005, ¶164. Gross also teaches *extracting a second set of pixel groupings from a terrestrial image* for at least the reasons provided for elements [16.1] and [16.2]. EX1003, ¶150. For instance, Gross describes how terrestrial images may be obtained directly from a user's camera and "be broken down and analyzed for attributes, features, etc. by Classifier Engine [] in a similar manner as discussed above, even if it takes more time." EX1005, ¶¶108, 109.

Gross further teaches, or at least renders obvious, using both types of images in identifying and classifying property features. Gross explains that obtaining images "at different angles, elevations and profiles" (e.g., aerial images and terrestrial images) helps "increase building coverage and feature currency/accuracy." *Id*., ¶148; *see also id*., ¶164 (describing how "image data from a variety of perspectives [] will also facilitate building out a comprehensive image database."). For example, an aerial image would "increase building coverage" of a

roof of a property (e.g., as opposed to a terrestrial image that exposes a lower amount of rooftop surface area) and a terrestrial image would "increase building coverage" of a window of a property (e.g., as opposed to an aerial image containing fewer pixels corresponding to the window). EX1003, ¶151.

Accordingly, in light of Gross's teachings that multiple property characteristics are assessed (e.g., roofs, windows) and images at different angles/elevations/profiles increase building coverage and feature accuracy, a POSA would have understood or found obvious to extract *a first set of pixel groupings* from an *aerial image* (e.g., a group of pixels corresponding to a rooftop) and to extract *a second set of pixel groupings* from an *terrestrial image* (e.g., a group of pixels corresponding to a window), because higher "accuracy" of the respective property characteristic condition classifications would be obtained as a result. EX1003, ¶152.

21. Claim 21

Claim 21 depends from claim 16 and further recites, "*wherein a first feature of the one or more features comprises a rooftop of a house, and a second feature of the one or more features comprises a structure adjacent to the house*."

Gross teaches this claim. EX1003, ¶¶153-155. Gross discloses *a first feature of the one or more features* (of the property) *comprises a rooftop of a house.* EX1003, ¶154. For instance, Gross discloses that during the building

attribute/condition assessment process, "an image 700 is retrieved from database 144 [] and is divided into distinct regions or blocks 701." EX1005, ¶121. A "building envelope" is then identified to determine which blocks should be classified. *Id.*, ¶122. These blocks can include a rooftop of a house. *See id.*, ¶123 ("an identification is performed to determine structural elements presented in a first block 701, including such attributes as roof elements").

Further, Gross discloses *a second feature of the one or more features comprises a structure adjacent to the house*. In addition to a "building envelope," Gross discloses that "[o]ther boundaries for other objects such as landscaping 706, trees 70, etc., can also be determined and logged." *Id.*, ¶122. The image blocks corresponding to these boundaries would include *a structure adjacent to the house* (e.g., natural structures such as landscaping and trees, or ancillary structures). *Id.*, ¶122, ¶¶67–70 (describing additional natural and man-made structures adjacent to a house that may be included as features), ¶238 (identifying "trees that are too close or overgrown [and] dilapidated ancillary structures adjacent to a structure"). EX1003, ¶155.

22. Claim 22

Claim 22 depends from claim 16 and further recites, "*wherein the aerial and/or terrestrial imagery comprises a three-dimensional (3D) aerial image*."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶156-161. As an

initial matter, the ’285 patent does not provide much detail as to what a *three-dimensional (3D) aerial image* refers to. The ’285 patent merely describes that “[t]hree-dimensional images, in comparison [to two-dimensional images], can be used to determine location coordinates, street name, construction type, occupancy type, year built, building height, soft stories, number of stories, roof condition, roof shape, roof covering, roof anchors, roof equipment, cladding, and pounding.” EX1001, 7:25–30. EX1003, ¶157.

Based on this description, Gross teaches, or at least renders obvious, this element. EX1003, ¶158. As explained, Gross discloses obtaining aerial images via “aerial drones, satellite, balloon and similar technology.” EX1005, ¶164. From such images, Gross discloses that “[r]elative sizes and areas of objects in the image data can also be collected [] such as a size of a roof area, amount of landscaping, height/size of trees, hedges, a size of a driveway, size of window openings, sidewalks, etc.” EX1005, ¶143. Gross also discloses that “[a]n amount of height displacement from street level can also be measured if desired.” *Id*. Gross yet further discloses capturing a “street address” or “[t]he number of distinct visible stories” of a property from such images. *Id*., ¶140.

In addition, to the extent the claimed *three-dimensional aerial image* refers to a three-dimensional (3D) model of a property, Gross renders obvious this element. For instance, various aerial inspection methods are set forth in U.S. Patent

No. 8,078,436 to Pershing et al., which is incorporated by reference in Gross's disclosure. EX1005, ¶6. As noted in Gross, Pershing describes aerial inspections of roofs. *Id*. And Pershing describes building a 3D model as part of its roof assessment process. EX1009, 6:14-17, 6:56-67, 7:12-18. EX1003, ¶159.

Gross—through the incorporated Pershing material—describes a system that obtains a 3D model of a building, e.g., via "photographs taken from two or more view points to 'triangulate' points of interest on the object in three-dimensional ('3D') space [] to build a 3D model of the structure." EX1009, 6:56–67. As described above, Gross explains that obtaining images "at different angles, elevations and profiles" (e.g., aerial images and terrestrial images) helps "increase building coverage and feature currency/accuracy." EX1005, ¶148. In light of these teachings, a POSA would have found obvious to use a 3D model as the input aerial image for Gross's system, because a 3D model would provide "different angles" and "increase building coverage" as compared to a two dimensional image with one viewing angle. EX1003, ¶¶159-161; EX1005, ¶148. Such implementation would merely amount to combining Gross's disclosure of the feature extraction elements with its disclosure of obtaining 3D models for a property according to known methods to yield predictable results. EX1003, ¶161; *KSR*, 550 U.S. at 417.

B. Ground 2: The combination of Gross and Davis renders obvious claim 8.

1. Claim 8

Claim 8 depends from claim 1 and further recites, "*determining, by the processing circuitry based in part on the characteristic classification and the condition classification, a risk estimate of damage to the characteristic of the property due to one or more disasters*."

The combination of Gross and Davis renders obvious this claim. EX1003, ¶¶14, 162-170. The '285 patent describes a "risk estimate" as "corresponding to a risk of damage." EX1001, 12:19-23. Similarly, Gross describes its property assessment system can be used for "[i]nsurance … risk assessments" (i.e., *a risk estimate of damage to the property*). EX1005, ¶238. For example, a "missing/damage tile" or "holes/cracks" roof condition evidences poor upkeep and maintenance. EX1005, ¶¶60-70, 238. Gross further discloses that "correlations may be developed between property condition ratings" (i.e., the *condition classifications* described above in element [1.5]) and insurance metrics such as "number of claims filed, type of claim, severity, etc." EX1005, ¶238. In other words, Gross teaches, or renders obvious, risk assessments based on the condition classification (evaluation of upkeep and correlation between property condition rating and insurance claims/severity). *Id.*; EX1003, ¶164.

Although Gross does not explicitly disclose basing its risk assessment on the characteristic classification, Davis describes that risk assessment may be based on characteristic classifications through its description that "risk analysis unit 34"

"may analyze the feature(s) to determine a risk of damage to at least a portion of the property" and the rules may, for example, depend "on the type of roof construction." EX1006, 10:19-38. In light of Davis's teachings, a POSA would have understood or found obvious that in addition to the condition classifications (e.g., an old roof), the insurance risk assessment taught by Gross would have also been based, at least in part, on the property characteristic classification because it is common sense the risk varies depending on the classification (e.g., a metal roof would have less risk of damage for certain types of disasters than a slate roof). EX1003, ¶165; *see KSR*, 550 U.S. 398 at 421 (factfinders may consider common sense in obviousness inquiry).

Gross also teaches these risk assessments can be risk estimates *due to one or more potential disasters*, such as due to "arson" (i.e., *a disaster*) or "[o]ther potential hazards (trees that are too close or overgrown, dilapidated ancillary structures adjacent to a structure, [and] undesirable and dangerous fixtures." EX1005, ¶238; *see also, e.g., id*., ¶63 (listing "water damage" as an example condition assessment). "Other potential hazards … can be identified by insurers and used to adjust premiums on a structure by structure basis." EX1005, ¶238. Gross further describes prior art systems that assess "a risk of damage to a house as a result of physical disturbance such as wind, earthquakes, etc." EX1005, ¶6; EX1003, ¶166.

To the extent Aon argues that Gross does not teach risk assessments based on "disasters," Davis does. EX1003, ¶167. Davis teaches "analyzing, by one or more processors, the one or more features of the property to determine a risk of damage to a structure or object located on the property." EX1006, 2:7–14. For example, features of property contained in aerial images may be analyzed "to determine whether particular homes are at high risk of fire damage." EX1006, 11:18-25. To determine risk, Davis describes a risk analysis unit 34 that "utilize[s] certain types of a priori knowledge to determine risk," which "may be incorporated as rules stored in data storage 40." EX1006, 10:22-24. Risk analysis unit 34 "may generate different kinds of risk information based upon the analyzed feature(s) and other information" (i.e., *characteristic classification* and *condition classification*) and "may estimate a likelihood that damage will occur to some portion of the property." EX1006, 11:30-34. Davis teaches its risk assessment may be based on whether the property contains trees of a species (i.e., tree species of a particular *characteristic classification*) more likely to catch fire (i.e., a *disaster*) or whether property contains dead or dying trees (i.e., *condition classification*). *See* EX1006, 11:25-36; EX1003, ¶168. Davis also discloses other types of information may be used to *determine risk estimate of damage to the property*, such as damage based on a hurricane forecast (i.e., another type of *disaster*). EX1006, 4:9-18. Thus, Davis more explicitly discloses determining risk assessment of damage to property

based on disasters (fires, hurricanes). EX1003, ¶168.

A POSA would have been motivated to modify Gross's teachings of a classification system used to rate the condition of a property for insurance risk purposes with Davis's specific teachings of determining the risk of property damage due to disasters because the combined Gross-Davis system would provide more information to the insurer useful to determine the risk of property damage. EX1003, ¶169. The modification would have been a predictable variation of Gross, because Gross explicitly contemplates developing "correlations," and Davis's specific risk correlation techniques—implemented through "rules stored in [a] data storage"—represent straightforward applications of known data correlation and rule-based processing methods that a POSA would routinely use to establish the correlations contemplated by Gross. EX1003, ¶169; EX1006, 10:23–25; *see KSR*, 550 U.S. at 417 ("If a person of ordinary skill can implement a predictable variation, §103 likely bars its patentability."). And a POSA would have readily been able to implement Davis's techniques in Gross because both systems similarly use image analysis to analyze features of properties to determine insurance risk. EX1003, ¶169.

The Gross-Davis combination would, therefore, teach *determining by the processing circuitry* (e.g., Gross's Classifier Engine 150) *based in part on the characteristic classification* (e.g., "tile" roof) *and the condition classification* (e.g.,

"new"), a risk estimate of damage to the property due to one or more disasters (e.g., risk of damage to property due to fire). EX1003, ¶170.

VIII. CONCLUSION

The challenged claims are unpatentable and IPR is warranted.

Respectfully submitted,

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/XX/

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Claims Appendix – U.S. Patent No. 10,650,285

Claim 1

Element	
[1.P]	A method for automatically categorizing a condition of a property, the method comprising:
[1.1]	obtaining, by processing circuitry, an aerial image of a geographic region including the property;
[1.2]	extracting, by the processing circuitry, one or more features of a plurality of features from the aerial image, wherein the one or more features are each represented by a set of pixel groupings, and the one or more features represent the characteristic of the property,
[1.3]	wherein each pixel grouping of the set of pixel groupings comprises at least one of angles, outlines, or substantially homogenous pixel fields;
[1.4]	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, wherein the first machine learning classifier is trained to identify at least a portion of the one or more features from the first portion of the set of pixel groupings; and
[1.5]	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, wherein the second machine learning classifier is trained to identify, from the second portion of the set of pixel groupings, property characteristic conditions of the characteristic having the characteristic classification.

Claim 2

Element	
[2]	The method of claim 1, further comprising comparing, by the processing circuitry, the condition classification to a historic condition classification to identify a change in condition of the characteristic of the property.

Claim 3

Element	
[3]	The method of claim 1, further comprising preparing, by the processing circuitry for presentation to a user, a graphical report comprising condition information regarding the condition classification.

Claim 4

Element	
[4]	The method of claim 3, wherein the preparing comprises preparing the graphical report as an interactive user interface.

Claim 5

Element	
[5]	The method of claim 1, wherein at least one of the first machine learning classifier or the second machine learning classifier comprises a convolutional neural network (CNN) model.

Claim 6

Element	
[6]	The method of claim 1, wherein the plurality of potential condition classifications comprises a numeric scale of condition classifications ranging between a needs replacement condition and a like new condition.

Claim 7

Element	
[7]	The method of claim 1, further comprising determining, by the processing circuitry based in part on the characteristic classification and the condition classification, a cost for repair or replacement of the characteristic of the property.

Claim 8

Element	
[8]	The method of claim 1, further comprising determining, by the processing circuitry based in part on the characteristic classification and the condition classification, a risk estimate of damage to the characteristic of the property due to one or more disasters.

Claim 9

Element	
[9.P]	A system for automatically categorizing a condition of a property feature of a property, the system comprising:
[9.1]	a non-transitory computer readable storage region storing a first machine learning analysis model trained to identify one or more property characteristics, and
[9.2]	a second machine learning analysis model trained to identify one or more property conditions;
[9.3]	processing circuitry; and a non-transitory computer readable medium having instructions stored thereon ; wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to extract a set of image-related features from an aerial image, wherein the set of image-related features represent the property feature;
[9.4]	apply a first portion of the set of image-related features to the first machine learning analysis model to determine a characteristic classification of the property feature from a plurality of potential characteristic classifications of the property feature; and
[9.5]	apply a second portion of the image-related features to the second machine learning analysis model to determine a condition classification of the property feature from a plurality of potential condition classifications of the property feature, wherein the second machine learning analysis model is trained to identify, from the second portion of the set of image-related features, property characteristic conditions of the property feature having the characteristic classification.

Claim 10

Element	
[10]	The system of claim 9, wherein each image-related feature of the set of image-related features comprises at least one of angles, outlines, or substantially homogenous pixel fields.

Claim 11

Element	
[11]	The system of claim 9, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to extracting the set of image-related features, assess orthogonality of the aerial image.

Claim 12

Element	
[12]	The system of claim 11, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, responsive to assessing that the orthogonality of the aerial image does not correspond to a true orthophoto form, cause correction of the aerial image to the true orthophoto form.

Claim 13

Element	
[13]	The system of claim 9, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to obtain, via a network from a remote computing system, the aerial image of the geographic area.

Claim 14

Element	
[14]	The system of claim 13, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to obtaining the aerial image, determine, based at least in part on the property feature, a preferred image type corresponding to the property feature.

Claim 15

Element	
[15]	The system of claim 9, wherein the plurality of potential characteristic classifications comprises at least one of a plurality of potential sizes, a plurality of potential shapes, or a plurality of potential materials of the property feature.

Claim 16

Element	
[16.P]	A non-transitory computer readable medium having instructions stored thereon, wherein the instructions, when executed by processing circuitry, cause the processing circuitry to:
[16.1]	obtain aerial and/or terrestrial imagery including a property;
[16.2]	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, wherein
[16.3]	each pixel grouping of the set of pixel groupings comprises at least one of angles, outlines, or substantially homogenous pixel fields; and
[16.4]	determine at least one characteristic and at least one condition of the property, wherein determining comprises, for each feature of the one or more features of the property,
[16.5]	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, and

[16.6]	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.

Claim 17

Element	
[17]	The non-transitory computer readable medium of claim 16, further comprising using the at least one characteristic and the at least one condition to determine one or more of a risk estimate, a repair estimate, or a replacement estimate.

Claim 18

Element	
[18.1]	The non-transitory computer readable medium of claim 17, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to access one or more known property characteristics,
[18.2]	wherein determining the one or more of the damage risk estimate, the repair estimate, or the replacement estimate comprises applying, to the determining, the one or more known property characteristics.

Claim 19

Element	
[19]	The non-transitory computer readable medium of claim 16, wherein the one or more characteristics of a first feature of the one or more features comprises a shape characteristic and a material characteristic.

Claim 20

Element	
[20]	The non-transitory computer readable medium of claim 16, wherein extracting the plurality of pixel groupings from the aerial and/or terrestrial imagery comprises extracting a first set of pixel groupings from an aerial image and a second set of pixel groupings from a terrestrial image.

Claim 21

Element	
[21]	The non-transitory computer readable medium of claim 16, wherein a first feature of the one or more features comprises a rooftop of a house, and a second feature of the one or more features comprises a structure adjacent to the house.

Claim 22

Element	
[22]	The non-transitory computer readable medium of claim 16, wherein the aerial and/or terrestrial imagery comprises a three-dimensional (3D) aerial 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 12,011 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. 10,650,285** and associated Exhibits 1001-1006 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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Patent Owner's Correspondence Address of Record for U.S. Patent No. 10,650,285

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