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. 10,529,029

PETITION FOR *INTER PARTES* REVIEW
OF U.S. PATENT NO. 10,529,029

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2. Independent Claim 1 19
a. [1.P]: A method for automatically categorizing a repair condition of a property characteristic, comprising: 19
b. [1.1]: receiving, from a user at a remote computing device, a request for a property condition classification, wherein the property classification

request includes identification of a property and at least one property characteristic; 21

c. [1.2]: obtaining, by processing circuitry of a computing system responsive to receiving the request, an aerial image of a geographic region including the property;..... 25

d. [1.3]: extracting, by the processing circuitry, one or more of a plurality of features from the aerial image corresponding to the property characteristic, wherein the extracted features include pixel groupings representing the property characteristic; 26

e. [1.4]: determining, by the processing circuitry from the extracted features, a property characteristic classification for the property characteristic, wherein determining the property characteristic classification includes applying the pixel groupings for the property characteristic to a first machine learning classifier trained to identify property characteristics from a set of pixel groupings;..... 28

f. [1.5]: determining, by the processing circuitry based on the identified property characteristic and the extracted features, a condition classification for the property characteristic, wherein identifying the condition classification includes applying the pixel groupings for the property characteristic to a second machine learning classifier trained to identify property characteristic conditions from a set of pixel groupings; 30

g. [1.6]: determining, by the processing circuitry based in part on the property characteristic classification and the condition classification, a risk estimate of damage to the property due to one or more disasters; and..... 33

h. [1.7]: returning, to the user at the remote computing device via a graphical user interface responsive to receiving the request, a condition assessment of the property characteristic including the condition

classification and the risk estimate of damage to the property due to the one or more disasters. 36

3. Independent Claim 15 39

a. [15.P] 39

b. [15.1] 39

c. [15.2] 39

d. [15.3] 39

e. [15.4]: for each of the at least one property characteristic, ... 39

f. [15.5] 40

g. [15.6] 40

h. [15.7] 40

4. Claim 2 40

5. Claim 3 41

6. Claim 4 42

7. Claim 5 43

8. Claim 6 45

9. Claim 7 46

a. [7.1]: The method of claim 1, wherein identifying the condition classification for the property characteristic comprises: generating, from the pixel groupings, a pixel intensity distribution of the property characteristic; and 46

b. [7.2]: determining, by applying the second machine learning classifier, the condition classification based on the pixel intensity distribution of the property characteristic. 47

10. Claim 16 48

11. Claim 17 49

a. [17.1]: The non-transitory computer readable medium of claim 16, wherein: the at least one

property characteristic comprises two or more property characteristics; and 49

b. [17.2]: the instructions, when executed by the processing circuitry, cause the processing circuitry to, responsive to determining the preferred image type corresponding to a first property characteristic of the at least one property characteristic is a terrestrial image, obtain a terrestrial image of the geographic region including the property..... 50

12. Claim 18 51

13. Claim 19 52

14. Claim 20 54

a. [20.1]: The non-transitory computer readable medium of claim 15, wherein: receiving identification of the property and the at least one property characteristic comprises receiving, via a network from a remote computing device, the identification of the property; and 54

b. [20.2]: the instructions, when executed by the processing circuitry, cause the processing circuitry to provide, via the network to a graphical user interface at the remote computing device in real-time responsive to receiving the at least one property characteristic, the at least one risk estimate. 54

B. Ground 2: Gross renders obvious claims 8 and 11-14. 54

1. Independent Claim 8 54

a. [8.P]..... 55

b. [8.1] 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 55

c. [8.2]..... 55

d. [8.3]..... 55

e. [8.4] 56

f. [8.5] 56

g. [8.6] 56

h. [8.7]: determine, in real-time responsive to receiving the property classification request and using the property characteristic classification and the condition classification, a replacement cost for replacing the property characteristic. 56

2. Claim 11 58

3. Claim 12 59

4. Claim 13 61

5. Claim 14 62

C. Ground 3: The combination of Gross and Furukawa renders obvious claims 9 and 10. 64

1. Claim 9 64

a. [9.1]: The system of claim 8, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to identifying the one or more of the plurality of features: obtain a shape map image including the property; 64

b. [9.2]: overlay the aerial image with the shape map image; and 69

c. [9.3]: determine whether a boundary of the property as identified by the shape map matches a boundary of the property as illustrated in the aerial image. 70

2. Claim 10 71

VIII. CONCLUSION 74

PETITIONER'S EXHIBIT LIST

Exhibit No.	Description
1001	U.S. Patent No. 10,529,029 to Okazaki ("'029 patent")
1002	Prosecution History of U.S. Patent No. 10,529,029 ("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	U.S. Patent No. 6,970,593 to Furukawa ("Furukawa")
1008	Jafri, *et al.*, "A Survey of Face Recognition Techniques," *Journal of Information Processing Systems*, Vol. 5, No. 2, June 2009, pp. 41-68 ("Jafri")
1009	U.S. Patent No. 8,078,436 to Pershing et al. ("Pershing")
1010	U.S. Patent No. 6,885,771 to Takahashi ("Takahashi")
1011	U.S. Publication No. 2009/0265193 to Collins et al. ("Collins")
1012	U.S. Publication No. 2015/0302529 to Jagannathan ("Jagannathan")
1013	U.S. Patent No. 4,941,122 to Weideman ("Weideman")
1014	U.S. Patent No. 8,995,757 to Ciarcia et al. ("Ciarcia")
1015	Redistricting Data Hub, "TIGER Boundary Files," accessible at https://redistrictingdatahub.org/data/about-our-data/tiger-boundary-files/ (last accessed July 10, 2025)
1016	Norman, J., "Origins of Google Earth," History of Information, accessible at https://www.historyofinformation.com/detail.php?entryid=3145 (last accessed July 13, 2025)
1017	Krizhevsky, *et al.*, "ImageNet Classification with Deep Convolutional Neural Networks," Communications of the ACM, Vol. 60, No. 6, May 2017
1018	Lin, *et al.*, "Network In Network," 2013

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

Petitioner Zesty.ai, Inc. ("Petitioner") petitions for *inter partes* review, seeking cancellation of claims 1-20 of U.S. Patent No 10,529,029 ("the '029 patent," EX1001), assigned to Patent Owner Aon Re, Inc. ("Aon").

I. INTRODUCTION

The '029 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, detect and classify features in the image, classify the condition of the feature, determine a risk estimate of damage to the property, and return to a user a condition assessment of the property and the risk estimate. The claimed concepts were known to anyone who ever performed such a risk assessment of a property (e.g., for insurance purposes). In fact, property assessment was performed manually—either by manually reviewing images or by inspecting the property in person—long before the '029 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); *id.*, ¶7 (describing prior art camera system for surveying property). And the '029 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 describe it in any detail. EX1001, 8:11-35. 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 property features and conditions and calculate risk assessment. EX1003, ¶¶45-49.

Indeed, the primary reference asserted herein—Gross—renders obvious virtually all of the limitations recited in the challenged claims. To the extent Aon may argue arson is not a disaster, Gross in combination Davis (a patent developed by State Farm) renders obvious the claimed risk estimate *due to one or more disasters*. And the well-known "shape map" limitations cited in two dependent claims are rendered obvious by the Gross-Davis-Furukawa combination.

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 '029 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 '029 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. 10,650,285 (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 the '029 patent is available for *inter partes* review and Petitioner is not barred or estopped from requesting *inter partes*

review of any ’029 patent claim on the grounds herein.

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

A. Identification of Prior Art

The ’029 patent’s earliest possible priority date is September 23, 2016. Without conceding 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).

Furukawa (EX1007) was filed on November 8, 2001, and issued on November 29, 2005. Furukawa is prior art under at least 35 U.S.C. § 102(a)(1).

Each prior art reference is analogous art in the same field and reasonably pertinent to the problems of the ’029 patent. EX1003, ¶¶50, 56, 58. 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, 15-20	Gross and Davis
2	§103	8, 11-14	Gross
2	§103	9, 10	Gross in view of Furukawa

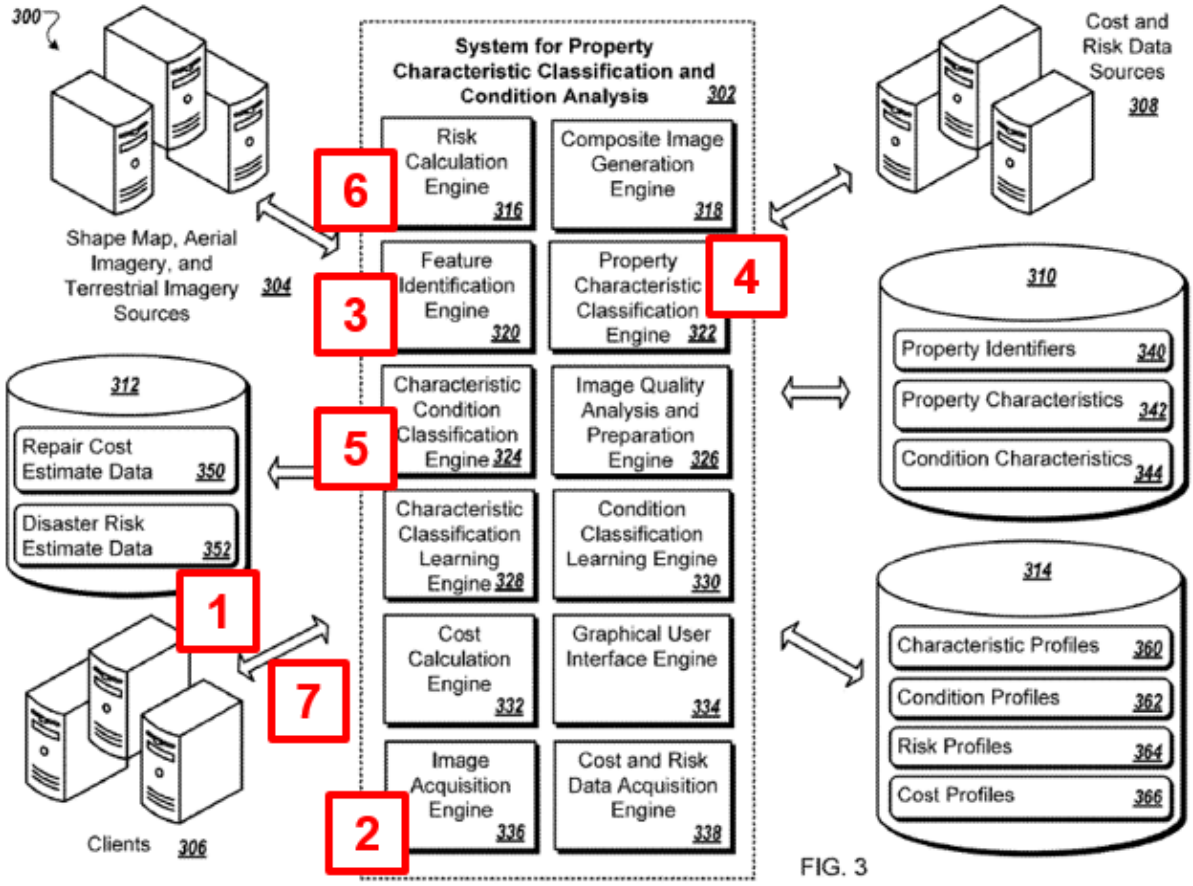
V. THE ’029 PATENT

A. Summary of the ’029 Patent

The ’029 patent discloses techniques for analyzing aerial imagery to evaluate property characteristics, condition classifications, and risk estimates of damage to a property. 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 (describing exemplary types of disasters, such as fire).

The ’029 patent discusses applying “machine learning analysis” to “analyze aerial imagery and automatically extract characteristics of individual properties,

providing *fast and efficient automated classification* of building styles and repair conditions," in order to perform risk evaluations. *Id.*, 2:6–15, 24–28.[1] Figure 3 (annotated below) illustrates an exemplary embodiment of the '029 patent's alleged invention.



EX1001, FIG. 3 (annotated).

The system operates in a series of steps, corresponding to numeric annotations in Figure 3 above. First, the system receives a request by "a user of a

[1] Emphasis added throughout, unless otherwise noted.

particular client computing system 306" to classify a property. EX1001, 13:21–24. The request "may include at least one property identifier 340" "as well as one or more property characteristics 342" (e.g., a "rooftop type") (step "1"). *Id*., 13:24–36, 8:3–5. The system then obtains "imagery of the property from the imagery source computing system(s) 304 using an image acquisition engine 336" (step "2"). *Id*., 14:24–26.

Upon obtaining the image(s), the system "extracts features from the property image(s) related to the identified property characteristics 342" via a "feature identification engine 320." *Id*., 15:27–29. "Features" (or "image-related features") can include, for example, angles, outlines, substantially homogenous fields (step "3"). *Id*., 7:64–8:1.

The system "classifies the property characteristic" via "a property characteristic classification engine 322," for example, into "a grouping, type, or other characterization of a particular property feature" (step "4"). *Id*., 15:34–43. For example, the property characteristic may be a roof and the property characteristic classification may be "hipped rooftop." *Id*., 11:32–34. Property characteristic classification engine 322 may use "one or more machine learning techniques" to classify the property characteristic. *Id*., 15:37–40.

The system "classifies the condition of each property characteristic" via a "characteristic condition classification engine 324" (step "5"). *Id*., 16:12–27. To

classify the conditions of property characteristics, characteristic condition classification engine 324 may process the image(s) through a "machine learning classifier." *Id*., 16:32–39; 10:28–42. The system "estimate[s] risk of damage based upon one or more types of disaster" based on the property characteristic classification and the condition classification via a "risk calculation engine 316" (step "6"). *Id*., 16:50–57. The system returns the risk estimate data to a user of client 306 via a graphical interface (step "7"). *Id*., 18:19–31. *See* EX1003, ¶¶34-39.

B. Prosecution History

The '029 patent issued from U.S. Application No. 15/714,376 ("the '376 application") without any substantive prior art examination. The claims never underwent meaningful analysis against the prior art that renders them obvious despite the robust prior art landscape that existed at the time of filing. *See, generally*, EX1002. Instead, the claims of the '376 application received a single substantive rejection—a § 101 rejection for being directed to an abstract idea. EX1002, 90-97.

The only prior art discussion appears in the "Reasons for Allowance," where the Examiner distinguished three references without having issued a single rejection against the allowed claims and without the detailed analysis typically conducted during examination. EX1002, 1048-1050. The Office did not consider the prior art applied herein, which teaches all claim limitations. *See* EX1003, ¶¶40-

41.

C. Person of Ordinary Skill in the Art

A person of ordinary skill in the art ("POSA") would have had a bachelor's degree in Computer or Electrical Engineering or equivalent discipline, and approximately two years' experience in image processing and machine learning. Additional education could substitute for professional experience, and significant work experience could substitute for formal education. EX1003, ¶¶42-43.

D. Claim Construction

In an *inter partes* review, claims are "construed using the same claim construction standard that would be used to construe the claim in a civil action under 35 U.S.C. 282(b)." 37 C.F.R. §42.100(b). All claim terms must be given their ordinary and customary meaning as understood by a POSA at the time of the invention, in light of the specification and prosecution history of the patent. *See Phillips v. AWH Corp.*, 415 F.3d 1303, 1312-13 (Fed. Cir. 2005).

Solely for the purposes of this Petition, Petitioner submits all claim terms should receive their plain and ordinary meaning in the context of the '029 patent specification. EX1003, ¶44.

VI. OVERVIEW OF THE APPLIED REFERENCES

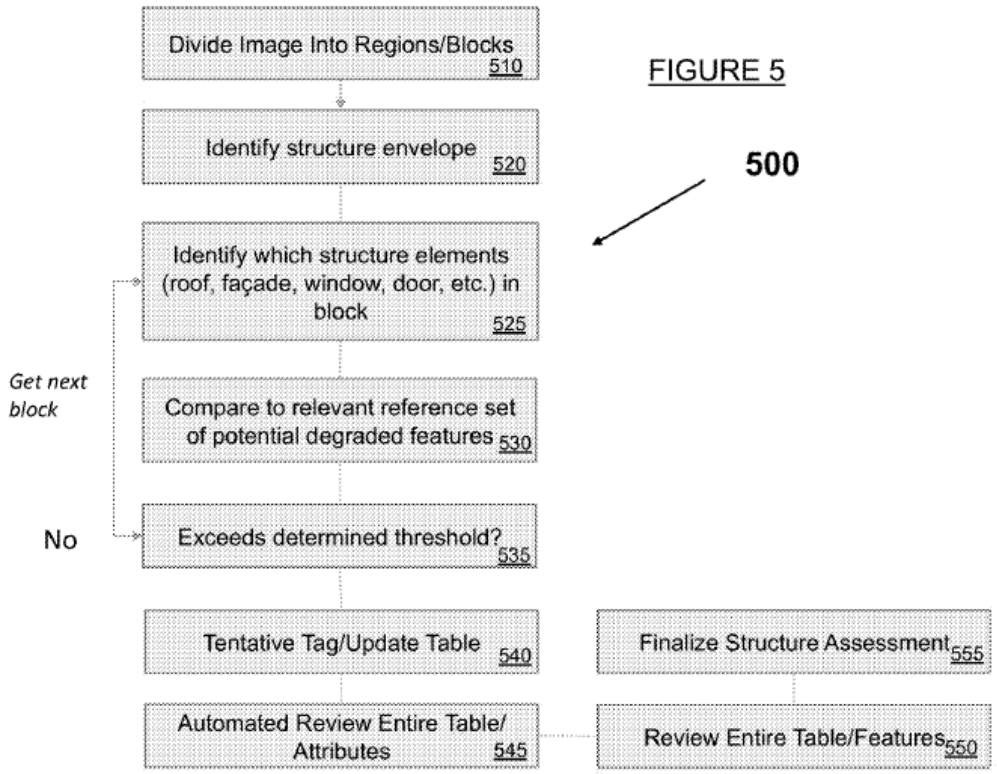
A. Gross

Gross discloses "tools, methods and systems which assess the condition of living structures and other appurtenant real property features." EX1005, ¶2. Like

the ’029 patent, Gross teaches 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 Classifier Engine, Gross’s system collects reference images of “building elements” (e.g., roof) along with their “types” (e.g., pitched). *Id*., ¶¶57–58. Gross’s system then defines and associates the building elements within each reference image with a corresponding “condition,” such as “damaged.” *Id*., ¶¶60–70. Classifier Engine is trained “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. Gross’s Figure 5 illustrates one embodiment of the assessment process.



EX1005, FIG. 5.

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

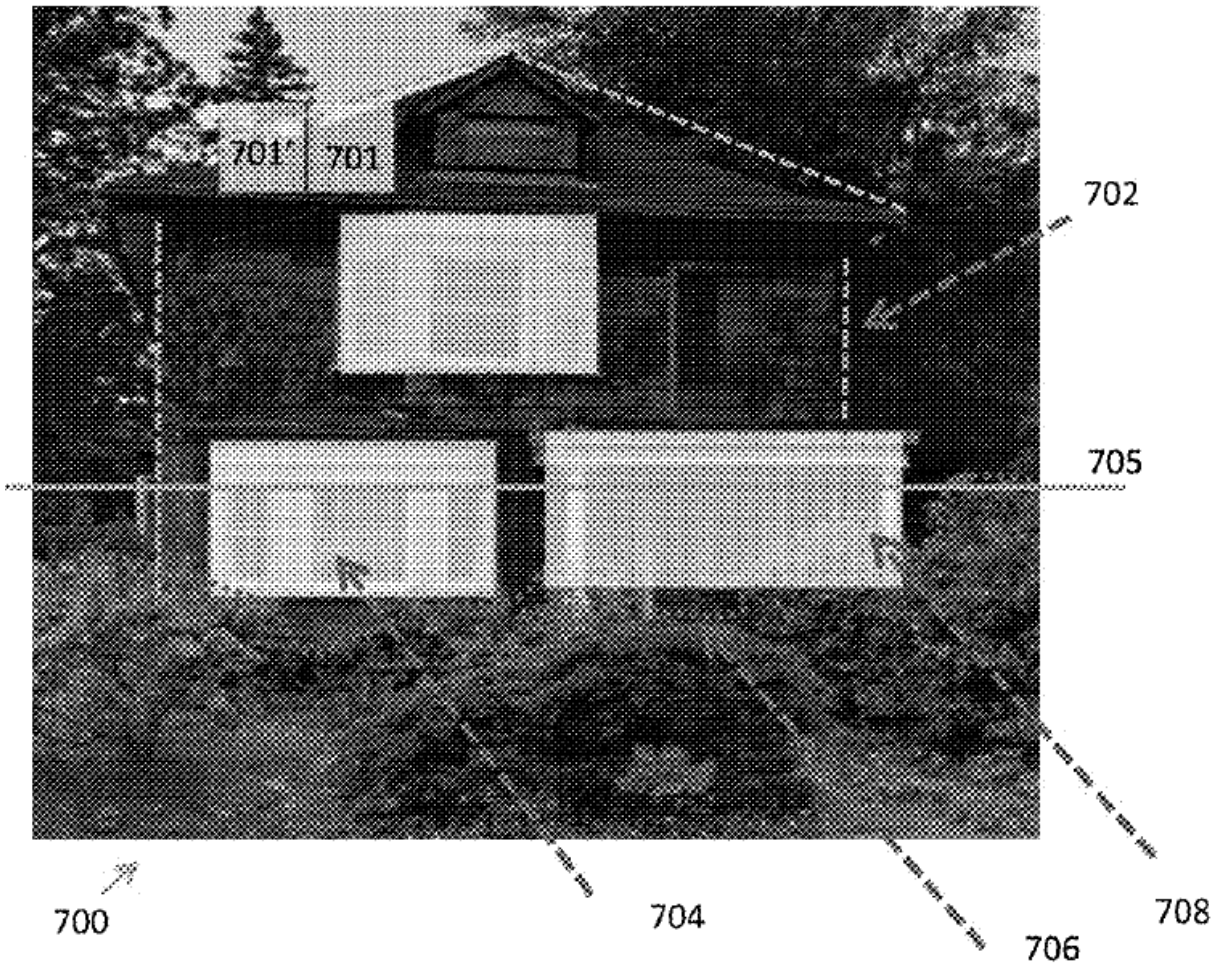


FIGURE 7B

EX1005, FIG. 7B.

Gross's system identifies a "building envelope 702" (which is essentially an outline of the building) by detecting edges of structures in the image. EX1005, ¶122, FIG. 7B; EX1003, ¶53. Such "boundaries" of other objects in the property can also be determined. EX1005, ¶122. The image blocks include "structural elements" (e.g., a roof), which are determined (alongside a "type" of the structural element) (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 '029 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*.

Gross's system then employs Classifier Engine to determine a "condition" of the determined structural element (steps 530 and 535), such as a "good" or "poor" condition. *Id*., ¶¶126–127, 141. The condition classification is stored into memory (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. *Id*., ¶¶129–133.

Like the '029 patent, these condition determinations can then be used for assessing risk. *Id*., ¶238. For example, a "property insurer" may be interested in knowing if a building has any potential hazards. EX1005, ¶238. Based on an evaluation of the property, the system can assess risk, such as whether a property has "a higher risk of arson" and notify a property insurer accordingly. *Id*. *See* EX1003, ¶¶50-55.

B. Davis

Davis discloses a method for determining property features from aerial images and analyzing 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 may request "a risk mitigation program." *Id*., 7:53–60. In response, Davis's system obtains an aerial image of the property associated with the request. *Id*. Davis's system 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" from the aerial image. *Id*., 18:36–39, 48–52; 9:24–29. Davis's system employs "other image analysis techniques" to determine classifications of the detected object, such as a size or species of a tree or a type of roof on a structure. *Id*., 18:27–39; 9:22–29. Based on these determinations, Davis's system, similar to the '029 patent, analyzes a risk of damage to a structure on the property. *Id*., 19:6–16. Davis's system then generates "a risk output … based on the risk of damage" and transmits "[i]nformation indicative of the generated risk output" to an insurance provider employee and/or to the policyholder. *Id*., 20:40–42, 20:59–64. *See* EX1003, ¶¶56-57.

C. Furukawa

Furukawa describes techniques for processing image data and correcting errors using map data that, for example, contain "information of external shape of buildings." EX1007, Abstract. Furukawa's system "extracts shape information of a building from images" or "obtains the same from … existing map data." EX1007, 6:43–46, 32:65–33:7. Furukawa's system compares the extracted "building external shape information …with the map data" to determine whether the map data and image data match. EX1007, 35:17–31, 21:66–22:22. If the map data and image data do not match, Furukawa's system modifies the map data to obtain an alternate image. *See, e.g.*, EX1007, 35:50–57, 30:56–31:53. *See* EX1003, ¶58.

VII. GROUNDS OF UNPATENTABILITY

A. Ground 1: The combination of Gross and Davis renders obvious claims 1-7 and 15-20.

Claims 1-7 and 15-20 would have been obvious over Gross and Davis. EX1003, ¶¶14, 59.

1. Motivation to Combine

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

As explained above, Gross discloses training a Classifier Engine and using it to assess and rate properties. EX1005, ¶57, FIG. 2. Gross describes specific details on how its Classifier Engine 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. Gross describes that, after it has been trained, Classifier Engine 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. Gross describes "the identification of such attributes (and their types) can be performed in any number of ways by Classifier Engine." EX1005, ¶123. For example, Classifier Engine 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}; façade (shingles/siding, weathering}; and other exemplary attributes/types/conditions. EX1005, ¶¶60-70; EX1003, ¶¶60-62.

A POSA reading Gross would have understood the image processing and attribute classification techniques used to train Classifier Engine were intended to also be utilized in its building attribute/condition assessment process. 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), their types (e.g., shingle), and conditions (e.g., missing/damaged tile). A POSA would have recognized Classifier Engine would employ the same, or very similar, techniques as those used during training to process images to identify and classify attributes contained therein. EX1005, ¶245 (Gross describing "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 know methods to yield predictable results with a reasonable expectation of success. EX1003, ¶¶63-64; *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 417 (2007).

b. A POSA would have found it obvious to combine Gross and Davis.

With respect to the claimed *risk estimate of damage to the property due to one or more disasters*, Gross discloses its system and processes may be used for insurance risk assessments. EX1005, ¶238. "[C]orrelations may be developed between property condition ratings" and "type of claim, severity, etc." EX1005, ¶238. These risk assessments can be risk estimates due to one or more potential disasters, such as due to "arson" or other potential hazards (e.g., trees that are too close." *Id.*; EX1003, ¶65. Gross describes a prior art risk assessment used to assess a risk of damage to a house as a result of physical disasters, such as wind and earthquakes (EX1005, ¶6), but does not explicitly discuss use of its property assessment system to perform risk assessments due to such natural disasters.

To the extent Aon may argue "arson" is not a disaster, as recited in the claims, or otherwise argues Gross does not teach a risk assessment of damage to property due specifically to disasters, Davis teaches this. Like Gross, Davis also

describes analyzing digital images and features of a property to determine risk of damage to a property structure. EX1006, 2:7-16. Davis describes analyzing features contained in an aerial image of a property "to determine whether particular homes are at high risk of fire damage, for example." EX1006, 11:18-24. Davis also discloses determining risk of damage based on a hurricane forecast. EX1006, 4:9-18. 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. Thus, Davis more explicitly discloses determining risk assessment of damage to the property based on disasters (fires, hurricanes). EX1003, ¶¶66-67.

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. 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. EX1006, 10:23–25; *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 and machine learning to analyze features of properties to determine insurance risk. EX1003, ¶¶68-70.

2. Independent Claim 1

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

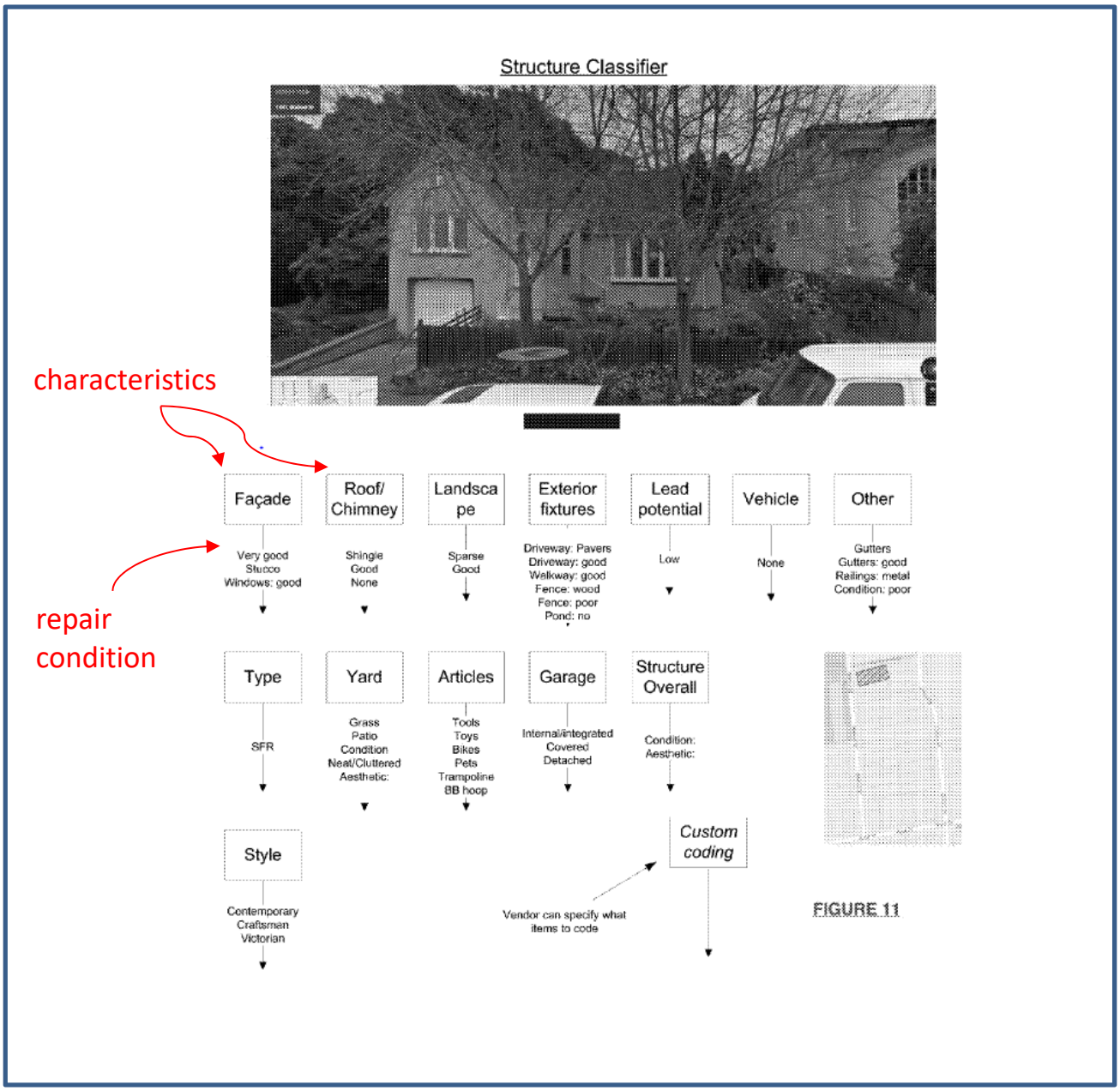
To the extent limiting, Gross discloses the preamble. EX1003, ¶71.

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." EX1005, ¶123. These attributes are *property characteristics*, as claimed, because they are physical parts of a structure, such as a house or building. EX1003, ¶¶72-74.

Gross discloses Classifier Engine identifies repair conditions associated with a particular attribute (i.e., *a repair condition of a property characteristic*). EX1005, ¶60. For example, Classifier Engine may automatically categorize the condition of

a roof (*property characteristic*) as "new." EX1005, ¶61. In some instances, "severity weightings (i.e., a scaling factor of any convenient range (1-10, or the like) for the identified condition" may also be assigned by Classifier Engine. EX1005, ¶70; *also id.*, ¶126 (Gross's description that a "condition score is computed [by Classifier Engine] for the detected attribute."). These condition categorization and condition scores/severity are *a repair condition* and they are associated with an attribute, i.e., *a property characteristic*. Gross further discloses "with sufficient training an automated classifier could participate in the process, if not perform the entire process of classifying structural features," i.e., *automatically*. EX1005, ¶145; *also id.*, ¶¶174, 176. Thus, Gross discloses element [1.P]. EX1003, ¶¶75-76.

Gross's Figure 11 "identifies examples of structural features, parameters, conditions … for a particular building structure," which illustrates the results of Classifier Engine categorizing repair conditions of property characteristic, as claimed. EX1005, ¶21; EX1003, ¶77.



EX1005, FIG. 11 (annotated).

b. [1.1]: receiving, from a user at a remote computing device, a request for a property condition classification, wherein the property classification request includes identification of a property and at least one property characteristic;

Gross renders obvious element [1.1]. EX1003, ¶78.

Gross describes *a property condition classification* process that, as described in element [1.7], returns to a user (via a graphical user interface) a condition assessment of a property characteristic. EX1005, ¶¶120, 130, FIGs. 5, 7E; EX1003, ¶79. The output includes "additional classifying details about the building structure" to "allow[] the user to quickly see the assessment of the property as performed by Building Classifier Engine 150." EX1005, ¶103, FIG. 7E. In a preferred embodiment, building structures in "a target city or other convenient population unit" are assessed. EX1005, ¶¶161-162.

Gross does not explicitly disclose how Figure 5's assessment process is initiated. *See* EX1005, ¶¶120-121 (stating Figure 5 depicts a building attribute/condition assessment process; beginning the process with retrieving an image). However, a POSA would have understood, or found obvious, that a *request from a user* is one of "a finite number of identified, predictable solutions" that could have been used to initiate Gross's assessment process. *KSR*, 550 U.S. at 402-03 (use of a finite number of identified, predictable solutions is likely the product of ordinary skill and common sense). A POSA would have been motivated to allow the user to request performance of the attribute/condition assessment process when needed for a particular property in order to reduce processing costs associated with unnecessary mass batch processing of property images. EX1003, ¶80.

Gross further describes its system 110 engages with users employing computing devices 112, such as smartphones, tablets, laptops, and desktops (i.e., *remote computing devices*) through interface logic 120. EX1005, ¶43, FIG. 1 (illustrating Gross's system 110 connecting through interface logic 120 with external (remote) data sources 113, 114 and user's computing devices 112). In a preferred embodiment, system 110 is part of a website that can be accessed through a conventional browser. EX1005, ¶43. Gross discloses an interactive user interface, which in a preferred embodiment is implemented as part of an interactive web page. EX1005, ¶98. The interactive user interface has "a number of query selection boxes," including query box 360 to specify a location for a property search and query box 366 to specify additional property structural elements (such as specific attribute styles for facades). EX1005, ¶¶98-99, 102.

Although Gross describes its interactive web user interface 350 is used to search for real estate/building stock that meet certain criteria of interest (EX1005, ¶95), a POSA would have found obvious that a similar interactive interface could be used to allow a user to submit the request for performance of the attribute/condition assessment process (i.e., *a property condition classification*) described above, because interactive user interfaces were a well-known way in which to receive information from a user. A POSA would have been further motivated to modify this interactive user interface described in Gross to initiate the

assessment for a specific *identification of a property*. Such a modification would allow the user to request Gross's property assessment be performed for a target property of interest, and this would reduce processing costs otherwise associated with processing properties for an entire city or regional area. EX1003, ¶¶81-83.

In light of Gross's teachings that its interface includes query boxes for property characteristics (e.g., façade types) (EX1005, ¶107), a POSA would have been motivated to allow a user to identify in its assessment request *at least one property characteristic*, allowing a user to request an assessment only for specific characteristics of interest (e.g., a roof company may only wish to perform the assessment for a roof). This modification would reduce processing costs by only performing the assessment for relevant property characteristics. The described modifications to Gross's interactive web interface would have been a predictable variation of a web interface and readily implemented by a POSA. EX1003, ¶84

Thus, Gross renders obvious *receiving a request* (through a modified interactive user interface) *for a property condition classification* (output of Classifier Engine's assessment of the condition(s) of property attribute(s)). *The request includes identification of a property and at least one property characteristic* (allowing the user to perform a targeted assessment), thereby reducing processing costs. EX1003, ¶85.

c. [1.2]: obtaining, by processing circuitry of a computing system responsive to receiving the request, an aerial image of a geographic region including the property;

Gross teaches element [1.2]. EX1003, ¶86.

Gross describes "aerial drones, satellite, balloon and similar technology can be used … to easily capture structure image data" and can "facilitate building out a comprehensive image database." EX1005, ¶164. These images are thus *aerial images of a geographic region that includes the property*. EX1003, ¶87. The building image data is stored in a structure image database. EX1005, ¶165.

Gross's "data acquisition process" is used by a classifier (e.g., Classifier Engine) "to acquire" (i.e., *obtain[]*) "appropriate image data for structures within a target area," such as a city. EX1005, ¶161. Classifier Engine retrieves an image 700 from a database to begin the building attribute/condition assessment process. EX1005, ¶¶120-21. Gross obtains the aerial image *responsive to receiving the request* in limitation [1.1], because the data acquisition process described in Gross *obtains the aerial image* of the property from the database so Classifier Engine can perform the assessment process and provide to the user the requested property condition classification. EX1003, ¶88.

Gross 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. These "executable software routines" are

executed via "processing circuitry." Accordingly Gross discloses *obtaining by processing circuitry* the aerial image. EX1003, ¶89.

d. [1.3]: extracting, by the processing circuitry, one or more of a plurality of features from the aerial image corresponding to the property characteristic, wherein the extracted features include pixel groupings representing the property characteristic;

Gross teaches element [1.3]. EX1003, ¶90. Gross discloses objects can be analyzed in image patterns, using a variety of techniques to detect and *extract* features of attributes. EX1005, ¶77. An image (e.g., an aerial image) is obtained and "an identification is performed to determine structural elements presented in a first block 701, including such attributes as roof elements, window elements, façade elements." EX1005, ¶¶120, 123. A POSA would have understood or found obvious this identification is performed *by processing circuitry* that *extracts one or more of a plurality of features from the aerial image*. Gross specifically discloses Classifier Engine is trained by extracting smaller distinct (image) features from reference images and notes such image "[f]eature extraction algorithms are well-known in the art." EX1003, ¶¶91-92; EX1005, ¶¶77, 79.

Gross discloses exemplary attributes identified by its Classifier Engine include roof elements, window elements and façade elements. EX1005, ¶123. As explained above, these elements represent *property characteristics*. The image feature(s) extracted by Classifier Engine correspond to "the property

characteristic" identified in limitation [1.1]. EX1003, ¶93.

Gross additionally teaches *the extracted features include pixel groupings representing the property characteristic*. *Id.* Gross discloses "[u]sing conventional image processing, each attribute" (i.e., property characteristic) "may be … characterized by a distinct set of pixels, shapes, sizes, proportions, curves, textures, or other mathematically derivable feature from the image." EX1005, ¶78. These are all examples of *pixel groupings representing the property characteristic* 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). Gross notes feature extraction algorithms are well-known in the art, and identifies a suitable example to be used in its embodiments is described in "*A Survey of Face Recognition Techniques*, by Jafri," which is incorporated by reference. EX1005, ¶79. Jafri, as incorporated in Gross, describes a recognition system that detects "prominent facial landmarks (i.e., the eyes, nose, and mouth)" using *pixel groupings* to identify those image *features.* EX1008, 43, 51, FIG. 19 (illustrating pixel groupings around nose, eye, lips); EX1003, ¶¶93-94; *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." (internal citations omitted).

e. [1.4]: determining, by the processing circuitry from the extracted features, a property characteristic classification for the property characteristic, wherein determining the property characteristic classification includes applying the pixel groupings for the property characteristic to a first machine learning classifier trained to identify property characteristics from a set of pixel groupings;

Gross teaches element [1.4]. EX1003, ¶95. Gross discloses that, after it has been trained, Classifier Engine (the claimed *first machine learning classifier* for the reasons described below) performs an identification of attributes (e.g., roof elements) presented in an image. EX1005, ¶123. The specific types of the attributes (i.e., *property characteristic classification(s)*) are also captured (e.g., façade (shingle, siding), roof (pitched, flat, shingle). 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." Put differently, Gross takes the pixels of features (i.e., *pixel groupings*) extracted from images (described in [1.3]), feeds them through its Classifier Engine (i.e., *applies them to a first machine learning classifier*) to identify the property attribute (*property characteristic*) and its type (*property characteristic classification*). EX 1005,

¶¶120, 123. As discussed for element [1.2], "processing circuitry" executes the process performed by Classifier Engine. EX1005, ¶161. Thus, Gross teaches *determining, by the processing circuitry from the extracted features* (extracted in limitation [1.3]), *a property characteristic classification* (e.g., pitched) *for the property characteristic* (e.g., roof), *wherein determining the property characteristics includes applying the pixel groupings* (extracted in [1.3]) to Classifier Engine 150. EX1003, ¶¶95-96.

Gross's Classifier Engine 150 is *a first machine learning classifier trained to identify property characteristics from a set of pixel groupings*. Gross discloses 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. *Id*. 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 the training results in extraction of specific features characterized by a "***distinct set of pixels***, shapes … or other mathematically derivable feature" (i.e., a set of pixel groupings). EX1005, ¶78. Thus, Classifier Engine is *a machine learning classifier* that is *trained to identify property characteristics from a set of pixel groupings* (features characterized by the pixel groupings). EX1003, ¶97; EX1005, ¶¶77, 123.

f. [1.5]: determining, by the processing circuitry based on the identified property characteristic and the extracted features, a condition classification for the property characteristic, wherein identifying the condition classification includes applying the pixel groupings for the property characteristic to a second machine learning classifier trained to identify property characteristic conditions from a set of pixel groupings;

Gross teaches, or renders obvious, element [1.5]. EX1003, ¶98. Gross discloses identifying and classifying "conditions/impairments … associated with a particular building attribute" (i.e., *determining a condition classification for the property characteristic*). EX1005, ¶60. Gross describes examples of structure attributes (property characteristics) and related conditions (condition classifications), including: roof (new, holes/cracks); and façade (new, holes). EX1005, ¶¶60-69. The examples provided are a partial list and other individual structure attribute/condition pairings can be identified by Classifier Engine. EX1005, ¶70.

After Classifier Engine is trained, it can identify indicators in attributes "of an irregularity, defect, damage or the like" and compute a condition score/rating for the detected attribute (e.g., a "poor" condition rating). 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 other mathematically derivable feature from the image." EX1005,

¶¶78, 120. In other words, the *pixel groupings for the (identified) property characteristic* are further analyzed to *determin[e]* the *condition classification* for that identified characteristic. For the reasons provided for element [1.2] and [1.4], "processing circuitry" executes the process performed by Classifier Engine. Thus, Gross teaches *determining, by the processing circuitry based on the identified property characteristic and the extracted features, a condition classification* (e.g., missing tile) *for the property characteristic* (e.g., roof)*, wherein identifying … includes applying the pixel groupings for the property characteristic to a second machine classifier*. EX1003, ¶99.

Gross teaches Classifier Engine is *a machine learning classifier*. EX1005, ¶77; *see* element [1.4]. Although Gross does not explicitly disclose its condition qualifiers are classified via a different machine learning classifier than was used to identify attributes, Gross does explicitly disclose "it may be useful to employ multiple classifiers … to identify the attributes and classify the structure." EX1005, ¶80. 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 (*property characteristics*) discussed above for Element [1.4], such as a "roof" or "façade." Gross also discloses 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. EX1003, ¶100.

In light of these teachings, a POSA would have understood Gross teaches, or renders obvious, the use of *a second machine learning classifier*, as claimed, to classify property characteristic conditions because customized classifiers are more accurate or more appropriate for different vendors. EX1003, ¶100. A POSA would have been motivated to employ a second machine classifier to identify a condition classification because Gross explicitly suggests different classifiers can be used and that classifiers can be customized for different purposes. EX1005, ¶80, claim 26. Moreover, a POSA would have recognized the reason Gross suggests using different classifiers is so 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. *See* EX1005, ¶¶80-81; *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, ¶¶100-102; *KSR*, 550 U.S. at 416.

Therefore, Gross teaches, or renders obvious, *a second machine learning classifier trained to identify* (using image processing techniques) *property*

characteristic conditions (e.g., missing tile) *from a set of pixel groupings*. For the reasons provided for element [1.4], this second machine learning classifier would be *trained to identify property characteristic conditions from a set of pixel groupings.* EX1005, ¶77 (describing training Classifier Engine with reference images). A POSA would have understood or found obvious that this second machine learning classifier employs image processing after it has been trained and that determining the condition classification includes *applying the pixel groupings for the property characteristic condition* to Classifier Engine 150. EX1003, ¶103; EX1005, ¶¶60-66, 126-27.

g. [1.6]: determining, by the processing circuitry based in part on the property characteristic classification and the condition classification, a risk estimate of damage to the property due to one or more disasters; and

Gross, in combination with Davis, renders obvious element [1.6]. EX1003, ¶104. 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. Gross discloses "risk assessments, etc., can be based on an evaluation of an upkeep/maintenance evidenced for a particular property" (i.e., *condition classification*). For example, a "missing/damage tile" or "holes/cracks" roof condition evidences poor upkeep and maintenance. *Id.*, ¶¶60-70, 238. Gross further discloses "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." 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). EX1005, ¶238; EX1003, ¶104.

Gross does not explicitly disclose basing its risk assessment on the property characteristic classification, but Davis describes 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," (i.e., risk assessment *based on the property characteristic classification*). EX1006, 10:19-38. In light of Davis's teachings, a POSA would have understood or found obvious to base Gross's insurance risk assessment on the property characteristic classification (e.g., type of roof), in addition to the condition classifications (e.g., an old roof) because it is common sense the risk varies depending on the specific property characteristic classification (e.g., a metal roof would have less risk of damage for certain types of disasters than a slate roof). EX1003, ¶105; *KSR*, 550 U.S. 398 at 421 ("Rigid preventative rules that deny factfinders recourse to common sense, however, are neither necessary under our case law nor consistent with it.").

These risk assessments can be *risk estimates of damage due to one or more* potential *disasters*, such as due to "arson" (i.e., *a disaster*) or other potential

hazards (e.g., trees that are too close, dilapidated ancillary structures adjacent to a structure). EX1005, ¶238; *also, e.g.*, ¶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 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 ¶106.

To the extent Aon argues Gross does not teach risk assessments based on "disasters," Davis does. EX1003, ¶107. 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. Davis describes a risk analysis unit "may generate different kinds of risk information based upon the analyzed feature(s) and other information" (i.e., *property 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*). EX1006, 11:25-36;

EX1003, ¶108. 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.

A POSA would have found it obvious to modify Gross to incorporate Davis's teachings of determining a risk of property damage due to disasters for the reasons provided in Section VII.A.1.b. As explained, a POSA would have recognized the benefits in the combined Gross-Davis system to provide more specific information for a an insurer to determine the risk of property damage based on property characteristic classifications and conditions and would have been readily able to implement this predictable variation. EX1003, ¶109.

The Gross-Davis combination would, therefore, render obvious *determining by the processing circuitry* (e.g., Gross's Classifier Engine 150) *based in part on the property 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, ¶110.

h. [1.7]: returning, to the user at the remote computing device via a graphical user interface responsive to receiving the request, a condition assessment of the property characteristic including the condition classification and the risk estimate of damage to the property due to the one or more disasters.

Gross, and the Gross-Davis combination, renders obvious element [1.7]. EX1003, ¶111. As described in limitation [1.1], Gross discloses its user interface is

preferably an interactive web page, which is *a graphical user interface*. EX1005, ¶98. Gross describes a report of the results is presented to the user (*at the remote computing device*) in response to receiving the request. EX1005, ¶96. The user can be provided with "classifying details about the building structure such as highlighted, tagged or annotated version of the building structure identified in FIG. 7E … to quickly see the assessment of the property as performed by Building Classifier Engine" (i.e., *a condition assessment of the property characteristic including the condition classification*). EX1005, ¶103; EX1003, ¶111. FIG. 7E illustrates a "visual assessment report 730" that "identifies at least those attributes identified by the system as having some measure of damage, impairment, aging, weathering." EX1005, ¶130.

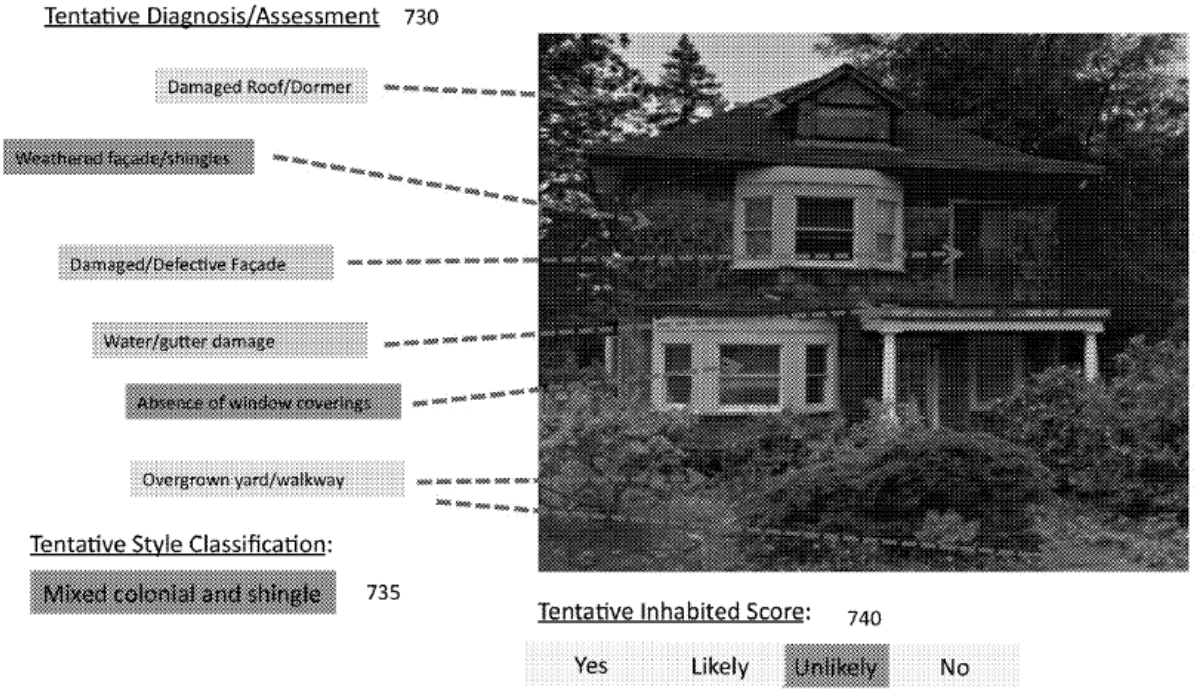


FIGURE 7E

EX1005, FIG. 7E.

This report includes *a condition assessment of the property characteristic including the condition classification* because it includes the condition classifications of property characteristics (e.g., damaged/defective façade). EX1003, ¶111.

A POSA would have been motivated to modify Gross's visual assessment report to include *the risk estimate of damage to property*—taught by Gross's insurance risk assessment and also by the Gross-Davis combination—to provide one report to convey all relevant information to the user. Conveying the information in one report would have been a simple design choice and allowed a

user (e.g., an insurance agent) to see all relevant information in one place, rather than viewing two separate reports. And such a modification to the report to include the risk assessment information would have been a predictable variation and easily implemented by a POSA. EX1003, ¶112.

3. Independent Claim 15

Claim 15 recites a non-transitory computer readable medium with limitations substantially similar to limitations in claim 1 and 8.

a. [15.P]

To the extent limiting, Gross discloses the preamble of claim 15 for the reasons provided for element [8.1]. EX1003, ¶125.

b. [15.1]

Gross teaches element [15.1] for the reasons provided for element [1.1]. EX1003, ¶126.

c. [15.2]

Gross teaches element [15.2] for the reasons provided for element [1.2] and [8.3]. EX1003, ¶127.

d. [15.3]

Gross teaches element [15.3] for the reasons provided for element [1.3]. EX1003, ¶128.

e. [15.4]: for each of the at least one property characteristic,

Gross teaches element [15.4]. This element merely requires elements [15.5] and [15.6] be executed a single time because one property characteristic is "at least one." Although not required, Gross teaches executing elements [15.5] and [15.6] for multiple property characteristics (e.g., a "roof" as a first property characteristic and a "façade" as a second property characteristic). EX1003, ¶129.

f. [15.5]

Gross teaches element [15.5] for the reasons provided for element [1.4]. EX1003, ¶130.

g. [15.6]

Gross renders obvious element [15.6] for the reasons provided for element [1.5]. EX1003, ¶131.

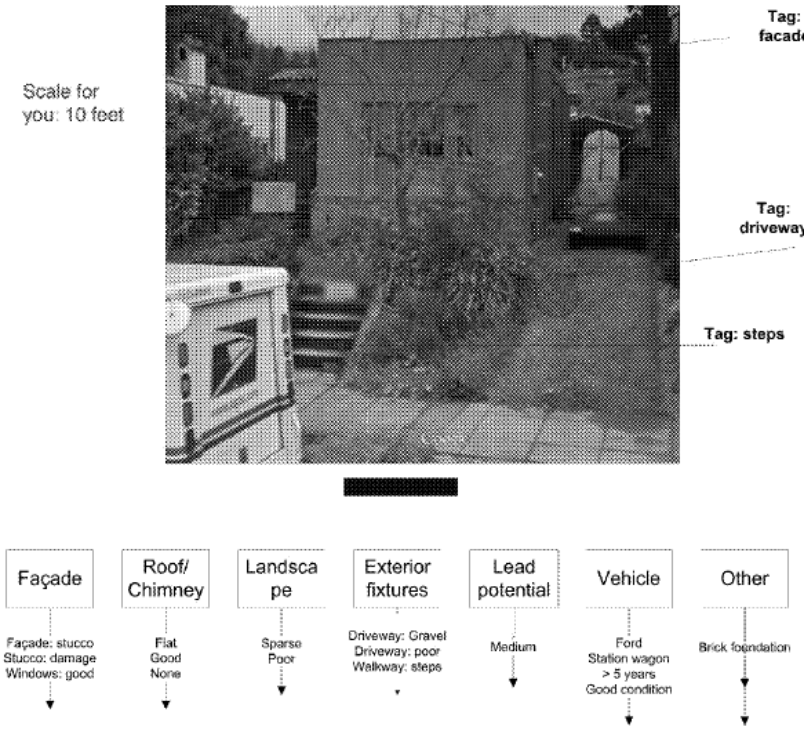
h. [15.7]

The Gross-Davis combination renders obvious element [15.7] for the reasons provided for element [1.6] and [8.7]. EX1003, ¶132.

4. Claim 2

Claim 2 depends from claim 1 and further recites, "*wherein the property characteristic classification is rooftop shape.*"

Gross teaches this claim. EX1003, ¶¶133-134. Gross's Figure 12 depicts examples of structural features that can be identified, such as roof shapes, e.g., "flat" in Figure 12. EX1005, ¶21; *also* EX1001, 20:28-29, FIG. 2A (identifying exemplary rooftop shapes as gambrel, gable, hipped, square, flat).



EX1005, FIG. 12.

Gross discloses additional attributes, such as façade and windows, along with specific types (e.g., façade (siding, brick). EX1005, ¶57.

5. Claim 3

Claim 3 depends from claim 2 and further recites, "*wherein the first machine learning classifier is trained with a set of aerial training images having known rooftop shapes such that the machine learning classifier is configured to determine the rooftop shape from a plurality of rooftop shapes*."

Gross teaches this claim. EX1003, ¶¶135-137. Gross discloses Classifier Engine "is trained with the template consisting of the training set of reference images 144 and tags as created and logged in database 152 … using a variety of

techniques, including statistical processing, neural networks." EX1005, ¶77. These "reference images 144" include "conditions/impairments … associated with a particular building attribute," and with respect to roofs, Gross provides various examples of roof shapes and conditions for training Classifier Engine. *Id*., ¶¶57, 61.

Thus, Gross teaches *the first machine learning classifier* (e.g., Classifier Engine) *is trained with a set of aerial training images* (e.g., "reference images 144") *having known rooftop shapes* (e.g., "pitched," "flat") *such that the machine learning classifier is configured to determine the rooftop shape* (e.g., "flat") *from a plurality of rooftop shapes.*

6. Claim 4

Claim 4 depends from claim 1 and further recites, "*wherein at least one of the first machine learning classifier and the second machine learning classifier is a Network in Network (NIN) classifier*."

Gross teaches this claim. EX1003, ¶¶138-139. Gross discloses "[f]eature extraction algorithms are well-known in the art" and "[u]sing conventional image processing, each attribute (and related condition qualifier) may be reduced in dimensionality and characterized by a distinct set of pixels." EX1005, ¶¶78-79. These "conventional image processing" techniques and "well-known" "feature extraction algorithms" included a Network in Network classifier. EX1003, ¶139.

The ’029 patent’s own Background section notes the Network in Network model as “[o]ne model used for deep learning.” EX1001, 1:50–54.

7. Claim 5

Claim 5 depends from claim 1 and further recites, “*wherein determining the risk estimate comprises applying a disaster risk profile corresponding to a) a first disaster of the at least one disaster and b) the property characteristic*.”

As explained, Gross discloses risk assessments “can be based on an evaluation of an upkeep/maintenance evidenced for a particular property; in this respect correlations may be developed between property condition ratings … and … severity.” EX1005, ¶238. These risk assessments can be risk estimates due to one or more potential disasters, such as due to “arson” or other potential hazards. EX1005, ¶238; *also, e.g.*, ¶63 (listing “water damage” as an example condition assessment). In other words, these correlations may associate maintenance condition ratings of a property attribute (e.g., a roof in “poor” condition) with higher risk of damage (e.g., from arson). EX1005, ¶238. Gross describes prior art systems that assess “a risk of damage to a house as a result of physical disturbance such as wind, earthquakes” EX1005, ¶6.

Gross, thus, teaches this claim. EX1003, ¶¶140-142. Obtaining a “risk assessment” for a disaster using “correlations … developed between property condition ratings … and … severity” would involve *applying a disaster risk profile*

(e.g., the "correlations") to *a first disaster of the at least one disaster* (e.g. "arson") and *the property characteristic* (e.g., the attributes associated with the "property condition ratings") because the correlations are correlating the risk of damage for a specific disaster with the analyzed "condition rating" of a property attribute/structure. EX1005, ¶¶238, 78.

Davis also teaches this claim. Davis describes risk analysis unit may "utilize certain types of a priori knowledge to determine risk," which "may be incorporated as rules stored in data storage 40." EX1006, 10:22–24. Davis describes risk analysis unit "may access rules specifying that certain tree species are more prone to failure than others … with respect to particular conditions such as high winds, wet soils, lightning, insect infestations." These rules may also specify whether trees of certain species more likely to catch fire. EX1006, 11:25–39. Risk analysis unit applies the "access[ed] rules" to a disaster of interest (e.g., wildfire) and a property characteristic (e.g., roof) to "estimate a likelihood that damage will occur to some portion of the property." EX1006, 11:30–34. Applying "access[ed] rules" specifying a likelihood of disaster based on a property characteristic is *applying a disaster risk profile*. EX1003, ¶143.

It would have been obvious to modify Gross to incorporate Davis's teachings of applying rules to a disaster and a property characteristic when determining a risk of property damage due to disasters for the reasons provided in

Section VII.A.1.b. As explained, a POSA would have recognized the benefits in the combined Gross-Davis system to provide more specific information for an insurer to determine the risk of property damage based on property characteristic classifications and conditions and would have been readily able to implement this predictable variation. EX1003, ¶144.

The Gross-Davis combination would, therefore, render obvious this claim. EX1003, ¶145.

8. Claim 6

Claim 6 depends from claim 1 and further recites, "*wherein the pixel groupings comprise at least one of angles, outlines, and substantially homogenous pixel fields defining the property characteristic*."

As discussed, 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—expressly discloses extracting features and computing geometric relationships (e.g., "distances, areas and angles") to represent pixel groupings of facial features. EX1008, 43; 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. Thus, Gross teaches this claim. EX1003, ¶¶146-147.

9. Claim 7

a. [7.1]: The method of claim 1, wherein identifying the condition classification for the property characteristic comprises: generating, from the pixel groupings, a pixel intensity distribution of the property characteristic; and

Gross renders obvious this element. EX1003, ¶148. Gross discloses "the dark or irregular color [of a group of pixels representing a roof] may cause a roof element to score poorly" during condition determination. EX1005, ¶126. This disclosure demonstrates Gross's system analyzes pixel color and brightness characteristics—i.e., pixel intensity—to assess property conditions. EX1003, ¶148.

Gross further teaches its analysis involves using conventional image processing, where each attribute (and related condition qualifier) may be reduced in dimensionality and characterized by proportions or other mathematically derivable feature from the image. EX1005, ¶78. A POSA would have understood or found obvious *generating, from the pixel groupings, a pixel intensity distribution* constitutes exactly this type of "conventional image processing" that produces "mathematically derivable feature[s]" for condition assessment. EX1003, ¶149.

Pixel intensity refers to the brightness level of pixels in an image and is a

fundamental parameter for characterizing and comparing grayscale and colored images. EX1003, ¶150. Given Gross's teaching that "dark or irregular color" affects condition scoring, a POSA would have found it obvious to systematically generate a pixel intensity distribution from pixel groupings of an image to quantify these color/brightness characteristics for input into Gross's Classifier Engine. *Id.* This represents a predictable variation that a POSA could have readily implemented by feeding a pixel intensity distribution from extracted pixel groupings into Gross's Classifier Engine. *Id.*; *KSR*, 550 U.S. at 417. Therefore, Gross renders obvious, *generating, from the pixel groupings* (e.g., extracted image features), *a pixel intensity distribution of the property characteristic* (e.g., roof). EX1003, ¶150; EX1005, ¶¶78, 126.

b. [7.2]: determining, by applying the second machine learning classifier, the condition classification based on the pixel intensity distribution of the property characteristic.

Gross teaches this element. EX1003, ¶151. As explained, Gross discloses during the condition determination, "the dark or irregular color [of a group of pixels representing a roof] may cause a roof element to score poorly." EX1005, ¶126. Determining the condition is poor based on finding a "dark or irregular color" is determining the condition classification *based on the pixel intensity distribution* of the property characteristic. EX1003, ¶151. Thus, Gross further teaches *determining, by applying the second machine learning classifier* (e.g.,

Classification Engine)*, the condition classification* (e.g., poor condition) *based on the pixel intensity distribution of the property characteristic* (e.g., dark or irregular color). *Id.*

10. Claim 16

Claim 16 depends from claim 15 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to obtaining the aerial image of the geographic region, determine, based upon the at least one property characteristic, a preferred image type corresponding to each property characteristic of the at least one property characteristic*."

Gross teaches or renders obvious this claim. EX1003, ¶¶168-169. Gross discloses a data acquisition process "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 when retrieving this "image data," 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 "this will also facilitate building out a comprehensive image database." *Id*. Gross explains obtaining images "at different angles, elevations and profiles" helps "increase building coverage and feature currency/accuracy." *Id*., ¶148.

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. For example, an image that would "increase building coverage" of the roof of a property and increase the "accuracy" of the roof condition classification could 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). *Id*., ¶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 characteristic being classified. *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 of the geographic region*. EX1003, ¶¶170-171.

11. Claim 17

a. [17.1]: The non-transitory computer readable medium of claim 16, wherein: the at least one property characteristic comprises two or more property characteristics; and

Gross teaches this element. EX1003, ¶¶172-173. For instance, Gross discloses the condition classification process—in addition to identifying a first element (e.g., "roof elements")—"is done repeatedly … to identify any number of

elements … in poor condition." EX1005, ¶¶123, 127.

b. [17.2]: the instructions, when executed by the processing circuitry, cause the processing circuitry to, responsive to determining the preferred image type corresponding to a first property characteristic of the at least one property characteristic is a terrestrial image, obtain a terrestrial image of the geographic region including the property.

Gross teaches or renders obvious this element for at least the reasons provided for element [17.1]. Gross discloses obtaining images "at different angles, elevations and profiles" helps "increase building coverage and feature currency/accuracy." EX1005, ¶148. Gross discloses identifying and classifying multiple structural elements of a property, including "window elements." *Id*., ¶123. In light of these teachings, a POSA would have understood or found obvious an image that would "increase building coverage" of a window element of a property and increase the "accuracy" of the window condition classification was a side-profile image of the property at street elevation (as opposed to an aerial image of the property shot from above), since such an image type would have a higher chance of containing pixels corresponding to a window element. EX1005, ¶148. A POSA would have understood or found obvious a side-profile image of a property at street elevation is "a terrestrial image," since such an image is taken at street elevation Thus, Gross teaches [17.2]. EX1003, ¶¶174-175.

12. Claim 18

Claim 18 depends from claim 15 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to access one or more known property characteristics, wherein determining the at least one risk estimate comprises determining the at least one risk estimate further based on the one or more known property characteristics*."

Gross teaches this element for at least the reasons provided for element [1.6]. EX1003, ¶176. 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.'" EX1005, ¶118. Gross 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. Obtaining occupancy information from "public records" requires the system to access, at least in part, the "public records" for the occupancy information, which is *accessing one or more known property characteristics* (e.g., the occupancy information). EX1003, ¶177; EX1005, ¶118.

Additionally, Gross discloses determining "policy premiums, risk assessments, etc., can be 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." *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. Then, developing a risk estimate correlation value from property occupancy would be *applying a known property characteristic* (e.g., applying occupancy information accessed from "public records" to a mathematical model) when determining a risk estimate. EX1003, ¶178. Thus, Gross teaches this claim. EX1003, ¶179.

13. Claim 19

Claim 19 depends from claim 18 and further recites, "*wherein the one or more known property characteristics comprise at least one of a property age, a property elevation, a property slope, a year built, a year renovated, and a building height*."

Gross renders this element obvious. EX1003, ¶¶180-181. As explained with respect to claim 18, Gross discloses determining "policy premiums, risk assessments, etc., can be based on an evaluation of an upkeep/maintenance evidenced for a particular property," and developing correlations for "occupancy estimates." EX1005, ¶238. In addition to "occupancy data," Gross discloses accessing and correlating property characteristics, including "internal details (size,

# of bedrooms, # rooms, etc.)." *Id.*, ¶81.

The claimed *property characteristics* represent obvious variations from a finite set of well-known property details. Gross's disclosure of "internal details" such as "size, # of bedrooms, # rooms" indicates that the system was designed to incorporate various standard property characteristics. *Id.* There are only a limited number of fundamental property characteristics routinely used in property assessment systems, including the basic physical characteristics (e.g., size, building height, property elevation, property slope), temporal characteristics (e.g., property age, year build, year renovated), and structural characteristics (e.g., # of bedrooms and # rooms) disclosed by Gross. EX1003, ¶182.

Given Gross's teaching to use "internal details" and other property data for risk correlation, it would have been obvious to incorporate any of these well-known characteristics from the finite universe of standard property assessment parameters. Each of the claimed characteristics—*property age, property elevation, property slope, year built, year renovated, and building height*—represents predictable variations that a POSA would have been motivated to include based on their known relevance to property risk assessment. *Id.* The selection of any particular combination of these characteristics would have been obvious to try given the limited number of fundamental property details available and Gross's teachings. EX1003, ¶183; *KSR*, 550 U.S. at 421.

14. Claim 20

a. [20.1]: The non-transitory computer readable medium of claim 15, wherein: receiving identification of the property and the at least one property characteristic comprises receiving, via a network from a remote computing device, the identification of the property; and

Gross teaches element [20.1] for the reasons provided for element [1.1]. Additionally, Gross discloses its "software modules … can be implemented … using … servers connected to a network (such as the Internet)." EX1005, ¶56. Thus, Gross teaches this element. EX1003, ¶184.

b. [20.2]: the instructions, when executed by the processing circuitry, cause the processing circuitry to provide, via the network to a graphical user interface at the remote computing device in real-time responsive to receiving the at least one property characteristic, the at least one risk estimate.

The Gross-Davis combination renders obvious element [20.2] for the reasons provided for elements [1.7] and [20.1]. EX1003, ¶185.

B. Ground 2: Gross renders obvious claims 8 and 11-14.

Claims 8 and 11-14 would have been obvious over Gross. EX1003, ¶¶14, 113.

1. Independent Claim 8

Claim 8 recites a system with a majority of limitations substantially similar to limitations in claim 1.

a. [8.P]

To the extent limiting, Gross discloses the preamble of claim 8 for the reasons provided for element [1.P]. EX1003, ¶113.

b. [8.1] 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

Gross discloses "the critical steps identified in this process can be implemented into executable software routines and modules using any number of ways by skilled artisans." EX1005, ¶161. A POSA would have understood or found obvious these "executable software routines" are executed via *processing circuitry*. Gross further discloses 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. Thus, Gross teaches element [8.1]. EX1003, ¶114.

c. [8.2]

Gross teaches element [8.2] for the reasons provided for element [1.1]. EX1003, ¶115.

d. [8.3]

Gross teaches element [8.3] for the reasons provided for element [1.2]. Gross further teaches the aerial image is obtained from a remote date source through its description aerial image data is retrieved for a target address and

preferably "obtained from a third party vendor." EX1005, ¶164; EX1003, ¶116.

e. [8.4]

Gross teaches element [8.4] for the reasons provided for element [1.3]. EX1003, ¶117.

f. [8.5]

Gross teaches element [8.5] for the reasons provided for element [1.4]. EX1003, ¶118.

g. [8.6]

Gross renders obvious element [8.6] for the reasons provided for element [1.5]. EX1003, ¶119.

h. [8.7]: determine, in real-time responsive to receiving the property classification request and using the property characteristic classification and the condition classification, a replacement cost for replacing the property characteristic.

Gross teaches or renders obvious element [8.7]. EX1003, ¶120. 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 "repair or improvement figures" teach, or at least render obvious, *a replacement cost for replacing the property characteristic* (e.g., attribute, such as a roof) because it is common sense that replacing a defective attribute "improves" the attribute. *KSR*, 550 U.S. at 421.

Gross teaches its determination of the replacement cost uses: *the condition classification* ("summing over all the attribute *conditions*"); and *the property characteristic classification* because repair and improvement figures depend on the classification of that attribute (e.g., a tile roof replacement has a different cost than a slate roof). EX1003, ¶121; EX1005, ¶134.

Further, Gross teaches, or renders obvious, its determination *is in real-time responsive to receiving the property classification request*. For the reasons discussed in element [1.1] and [1.7], Gross renders obvious an interactive user interface, which generates a report responsive to a property condition classification request. And, for the reasons discussed in element [1.1], Gross teaches, or renders obvious, *a property condition classification request* received from a user that allows the user to initiate performance of the attribute/condition assessment process, and the system then returns the graphical user interface discussed in element [1.7]. If the user's request initiates the assessment process, the process occurs *responsive to receiving the request*. Thus, Gross teaches, or renders obvious, Classifier Engine performs its analysis *in real-time* because Gross depicts its building attribute/condition assessment process retrieves the images, performs the assessment, and returns the assessment report to a human operator (user) for immediate review. EX1005, ¶¶120-34, FIG. 5 (illustrating real-time steps of the property condition assessment process). Gross confirms Classifier Engine can

perform its analysis *in real-time* (including the "generated" determination of replacement costs, which is based on the condition assessment), describing that a user may use a smartphone to capture a structure image for "rapid, on the spot identification and review of property details." EX1005, ¶108; *also id.*, ¶109 (without "explicit geolocation data the user's image data of the property can easily be broken down and analyzed for attributes, features, etc. by Classifier Engine 150 to identify likely matches …, even if it takes more time"). EX1005, ¶109; EX1003, ¶¶122-24.

2. Claim 11

Claim 11 depends from claim 8 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to compare a current condition classification of the property characteristic to a stored historic condition classification of the property characteristic*."

Gross teaches this claim. EX1003, ¶¶152-153. Gross discloses using "long term evaluations over defined time periods … to identify changes in a property condition." EX1005, ¶134. Gross accomplishes this by storing the "final structure assessment data" (i.e., historic condition classifications) "in database 142" during the feature coding (e.g., condition assessment) process. EX1005, ¶133; *also id*., ¶141 (describing how "the presence of [a building] feature, type and condition is

coded and collected and stored in digital form.”).

Gross explains “the coding process” that obtains the property assessments for the “long term evaluations” described above “may be targeted primarily or solely for identifying structural improvements,” such as the presence of a new fence or new roof.” *Id*., ¶¶134, 146. Given the recorded “structure assessment data,” a POSA would have understood or found obvious the way one would identify these “structural improvements” (e.g., a new roof was added) would be through a comparison between assessment data of current, updated images of a property and prior, stored historic assessment data of the same property. These comparisons would indicate the *change in condition* of the property structure and whether it was a positive change (i.e., improvement) or otherwise. Thus, Gross teaches this claim. EX1003, ¶¶154-155; EX1005, ¶¶134, 146, 61.

3. 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, in real-time responsive to receiving the property condition classification request, determine whether repairs have been made to the property based on the comparison of the current condition classification to the historic condition classification of the property characteristic*.”

Gross teaches this claim. EX1003, ¶¶156-157. As explained, a POSA would

have understood or found obvious performing "long term evaluations … to identify changes" would involve comparisons between assessment data of current, updated images of a property and prior, historic assessment data of the same property. For example, a current assessment of a roof condition can be compared to a historic assessment of a roof condition to identify "the presence of a … new roof" (i.e., a "repair[] … to the property"). EX1005, ¶146. Gross also discloses its "coding process may be targeted primarily or solely for identifying [such] structural improvements." *Id*. Given these teachings and the reasons discussed in element [8.7], a POSA would have understood or found obvious that these structural improvement identifications occurred *in real-time responsive to receiving the property condition classification request*. A POSA could have readily implemented the predictable variation of determining structural repairs in real-time in response to a condition classification request to Gross's Classifier Engine. EX1003, ¶157; *KSR*, 550 U.S. at 417.

Thus, Gross teaches *instructions* (e.g., instructions on "the computing system") that *cause the processing circuitry to, in real-time responsive to receiving the property condition classification request* (e.g., in response to a classification request made at Gross's interactive user interface), *determine whether repairs* (e.g., "structural improvements") *have been made to the property based on the comparison of the current condition classification* (e.g., "good" condition roof) *to*

the historic condition classification of the property characteristic (e.g., "damaged" roof). EX1003, ¶158; EX1005, ¶¶134, 146, 61, 98.

4. Claim 13

Claim 13 depends from claim 8 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to identifying the one or more of the plurality of features, assess orthogonality of the aerial imagery*."

Gross teaches this claim. EX1003, ¶¶159-160. Gross teaches *assess[ing] orthogonality of the aerial image*. *Id.* 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 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, 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, ¶¶160-61.

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." EX1009, 8:59–9:1. Such implementation would merely amount to combining Gross's disclosure of pre-processing techniques with its disclosure of orthogonality assessment according to known methods to yield predictable results. EX1003, ¶¶162-163; *KSR*, 550 U.S. at 417. Because Gross's pre-processing process occurs "prior to training" (and using) Classifier Engine, the orthogonality assessment would also occur *prior to identifying the one or more of the plurality of features*. EX1005, ¶76. Thus, Gross teaches this claim. EX1003, ¶163.

5. 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, responsive to assessing that the orthogonality of the aerial imagery does not correspond to a true orthophoto form, cause correction of the aerial*

imagery to the true orthophoto form."

Gross teaches this claim for at least the reasons provided for claim 13. EX1003, ¶¶164-165. Gross teaches *caus*[ing] *correction of the aerial image to the true orthophoto form*. *Id.* As described above, orthogonality of an image refers to the degree to which a camera's optical axis is perpendicular to the imaged surface. *Id.* 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.*; *also*, *e.g.*, EX1001, 20:57–62 (describing "generat[ing] a true orthophoto form" of an image "if the aerial imagery is not orthogonal").

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, ¶166.

Thus, Gross teaches *instructions* (e.g., instructions on "the computing system") that *cause the processing circuitry to, responsive to assessing that the*

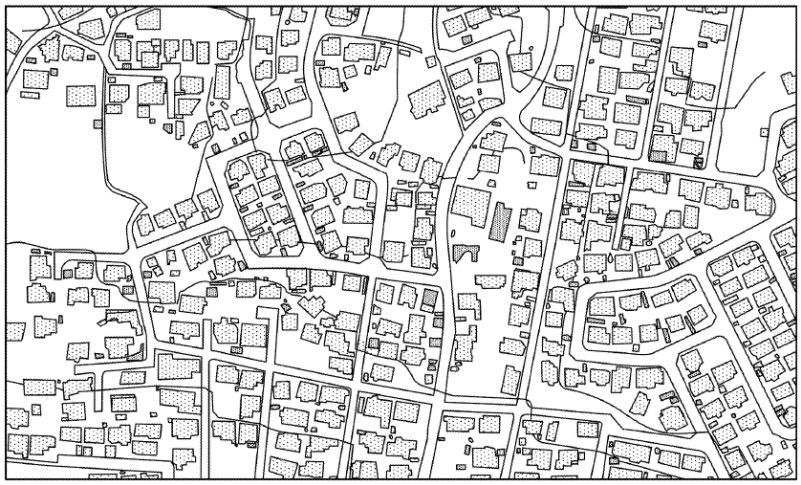
orthogonality of the aerial imagery does not correspond to a true orthophoto form (e.g., determining that the vertical axis of a particular aerial image does not match the actual vertical axis of its scene)*, cause correction of the aerial imagery to the true orthophoto form* (e.g., adjusting scale or relative angle of the aerial image). EX1003, ¶167.

C. Ground 3: The combination of Gross and Furukawa renders obvious claims 9 and 10.

1. Claim 9

a. [9.1]: The system of claim 8, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to identifying the one or more of the plurality of features: obtain a shape map image including the property;

Gross and Furukawa render obvious this element. EX1003, ¶¶14, 186-187. The ’029 patent describes “shape map images” as being “used to confirm [a] location of a particular property,” such as being “overlaid with a corresponding aerial image 102c to match properties with images.” EX1001, 7:21–25. Figures 5A and 5C of the ’029 patent respectively depict an example “shape map image” and an example result of overlaying shape outlines with an aerial image.



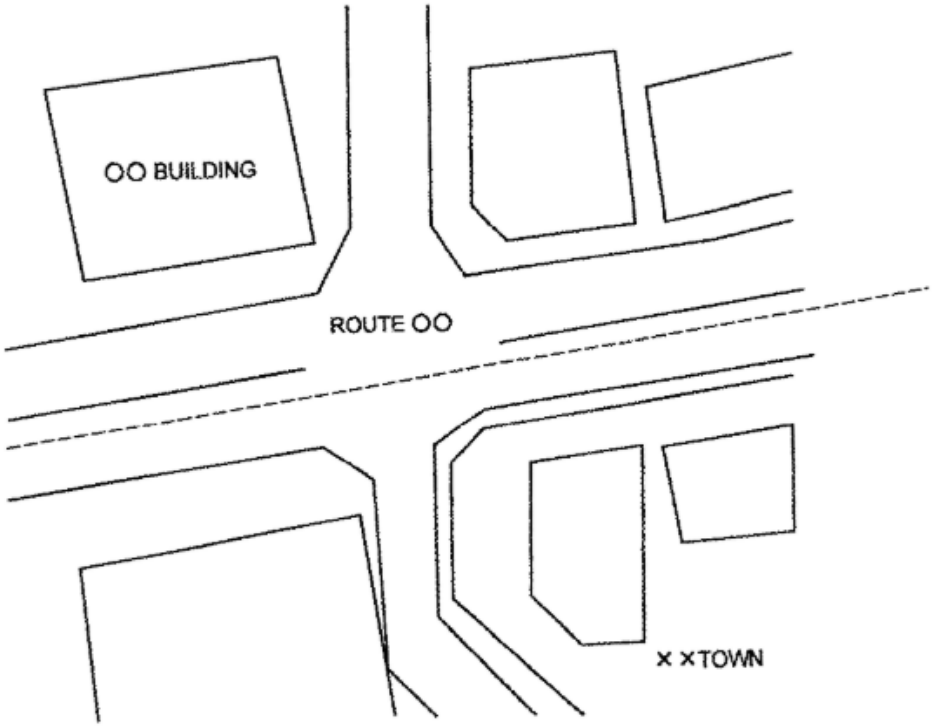
EX1005, FIG. 5A (top), FIG. 5C (bottom).

Gross discloses a data acquisition process used by a classifier (e.g., Classifier Engine) as it would be implemented on a customized structure assessment. EX1005, ¶161. Gross explains the purpose of this process "is to acquire appropriate image data for structures within a target area." *Id*. Gross further discloses how "for [a] target address in question," the system obtains and uses "[i]nformation identifying a beginning and end of each individual street, road,

alley" "from any convenient database or similar source." *Id*., ¶¶162, 164; EX1003, ¶¶188-190.

Gross also discloses obtaining "boundaries established by street address ranges" and "public records which identify the layout of building envelopes on each lot" as part of this process. *Id*., ¶¶143, 163. As this data acquisition process obtains the image input(s) for the assessment process of the classifier, this obtaining is also *prior to identifying the one or more of the plurality of features*. EX1005, ¶¶161–163; EX1003, ¶191.

Furukawa teaches instructions to *obtain a shape map image*. EX1003, ¶192. Furukawa teaches obtaining map data that includes "information of the external shape of buildings" which is stored and provided by a "map data storing means 4." EX1007, 15:19–31. Figure 7 of Furukawa depicts an example of such map data:



EX1007, Figure 7.

Furukawa further explains the "map data" depicted in Figure 7 includes "shapes of buildings" as "raster data … of those data showing shapes of buildings," and can also include identification information, such as "names of administrative districts/roads/buildings and the like" and location information, such as "latitude and longitude." EX1007, 12:26–39. This map data is a *shape map image including the property*, because, similar to the '029 patent it plots out the shapes of various structures in an area and includes their location information. EX1003, ¶192. And, similar to the '029 patent, which describes that the shape map data may be obtained from external sources (e.g., Geospatial Information Authority of Japan or Zenrin Co. Ltd. of Japan), Furukawa also describes its map data may

be obtained from many products that are commercially available. *Compare* EX1001, 7:14-20, *with* EX1007, 8:62-66; EX1003, ¶¶192-193.

A POSA would have been motivated to modify Gross to incorporate Furukawa's teachings of obtaining map data, because Gross and Furukawa provide a teaching, suggestion, and motivation to do so. Gross teaches the need for address confirmation, describing how "building image[s] and tentative address[es] are tentatively tagged" during the classification process, and how "this address information" should be "confirmed" to ensure the system "contain[s] accurate information for a particular address." EX1005, ¶¶165, 170. Gross's teaching tentative address information should require confirmation would have suggested to a POSA the benefit of incorporating additional data sources for verification purposes. A solution to this need is supplied by Furukawa, which teaches the use of "map data" containing building shape and identification information and location information for the structures that could serve as the confirmation mechanism Gross contemplates. Thus, the prior art provided both Gross's problem of building address confirmation and Furukawa's map data solution, creating a teaching and motivation for their combination. EX1003, ¶¶194-195; *KSR*, 550 U.S. at 418–421.

Thus, the Gross-Furukawa combination renders obvious this element. EX1003, ¶196; EX1007, 15:19–31.

b. [9.2]: overlay the aerial image with the shape map image; and

The Gross-Furukawa combination renders obvious this element. EX1003, ¶197. As explained in element [9.1], Furukawa's system obtains map data that includes "information of the external shape of buildings" which is stored and provided by a "map data storing means." EX1007, 15:19–31. Furukawa's system "analyzes … obtained satellite stereo images, and extracts vector information showing the external shape for the photographed building," which Furukawa describes is performed by a "building external shape information detecting means." EX1007, 32:65–33:7.

Furukawa's system performs a process that superimposes the map data with the satellite images. Furukawa teaches a "building external shape information comparing/combining means 7 compares and combines the information of the external shape of buildings of the map data … with the information of the external shape of buildings extracted by the building external shape information detecting means." EX1007, 32:17–24. During this process, "a pair of the information of the external shape of buildings, which exist at locations only a little way from each other and of which difference in areas is smaller than a predetermined value and ratio of the common part is larger than a predetermined value, is made to correspond to each other as information indicating the same building." EX1007, 23:56–24:2. In other words, the shape outline obtained from the satellite image and

the shape outline obtained from the map data are overlaid with each other, from which values such as area differences and overlap ratios may be calculated. EX1003, ¶¶198-99.

A POSA would have found it obvious to modify Gross to incorporate Furukawa's teachings of superimposing stored map data with shape information extracted from an aerial image to solve Gross's need to identify the address of the property structure, as described in element [9.1]. The prior art provided both Gross's problem of building address confirmation and Furukawa's map data solution, creating a reason for the combination. EX1003, ¶200.

The Gross-Furukawa combination would, therefore, render obvious *overlaying* (e.g., "combining") *the aerial image* (e.g., Gross's aerial image) *with the shape map image* (e.g., map data including "information of the external shape of buildings"). EX1003, ¶201; EX1007, 32:17–24, 15:19–31.

c. [9.3]: determine whether a boundary of the property as identified by the shape map matches a boundary of the property as illustrated in the aerial image.

The Gross-Furukawa combination renders obvious this element. EX1003, ¶202. Furukawa discloses a "building external shape information comparing/combining means" combines and compares extracted shape information for a building with stored map data. EX1007, 32:17–24. The comparison process determines whether the boundaries—depicted by the extracted shape information

and the map data—match, by evaluating factors including location proximity, area differences, and overlap ratios. When these evaluation factors match within "predetermined value[s]," the system considers the depicted boundaries as matching and "indicating the same building." *Id*.

A POSA would have found it obvious to modify Gross to incorporate Furukawa's boundary comparison teachings for at least the same reasons provided for element [9.1]. The prior art provided both Gross's problem of building address confirmation and Furukawa's map data solution, creating a teaching and motivation for their combination. EX1003, ¶203.

Thus, the Gross-Furukawa combination renders obvious *determining whether a boundary of the property as identified by the shape map* (e.g., "information of the external shape of buildings of the map data") *matches* (e.g., area difference below a threshold, overlap ratio above a threshold) *a boundary of the property as illustrated in the aerial image* (e.g., extracted "vector information showing the external shape of the photographed building"). EX1003, ¶204; EX1007, 21:22–23, 21:58–59.

2. Claim 10

Claim 10 depends from claim 9 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, upon determining that the shape map does not match the boundary of*

the corresponding property, obtain an alternate aerial image of the property."

The Gross-Furukawa combination renders obvious this claim. EX1003, ¶¶205-206. As explained for claim 9, Furukawa's boundary comparison process determines whether boundaries match by evaluating factors including location proximity, area differences, and overlap ratios. EX1007, 23:56–24:2. When these factors do not meet "predetermined value[s]," the system would recognize a mismatch. *Id*.

Gross provides the teaching and motivation for *obtaining an alternative aerial image of the property* when mismatches occur in the combined system. EX1003, ¶207. Gross maintains multiple images of structures in its database. "[I]mage data … for the building structure is retrieved for the target address in question" and can be "obtained from a third party vendor" or "generated as needed" using various methods such as "aerial drones, satellite, balloon and similar technology." EX1005, ¶164. These methods "can obtain image data [at] different elevations" and "at different times." *Id*. Gross teaches its "structure image database" contains primary images for a structure, as well as "structure sub-images, which are based on automatically dividing the original image into separate blocks, or separate areas corresponding to distinct building elements." *Id*., ¶165.

Second, Gross renders obvious image matching processes that involve accessing multiple images when initial matches fail. Gross explains that to

"identify the property," the system scans through a "range of image data" or uses Classifier Engine 150 "to identify likely matches from the preexisting stock of building structures in database 142." EX1005, ¶109. Gross further teaches "image matching for building structures can be accomplished in any number of ways by adapting existing recognition algorithms to recognize the types of objects of interest." EX1005, ¶108. A POSA would have found obvious these matching algorithms involve iterating through available images (i.e., *obtaining alternate images*), because the algorithm would evaluate alternate available images from the database until a match was found. EX1003, ¶¶208-209.

A POSA would have been motivated to modify the Gross-Furukawa combination to obtain alternate aerial images upon determining a boundary mismatch, because doing so would allow the Gross-Furukawa system to more frequently perform classification on the building that is actually at the target address. Gross's teaching building and address information should be "confirmed" to ensure the system "contain[s] accurate information for a particular address" naturally suggests trying alternate image sources when an initial verification fails. EX1005, ¶170. Gross's teachings that multiple images of the same property can be captured "at different times" and "elevations" and its system maintains a database with multiple image options would have suggested to a POSA that alternate images would be available (and beneficial) for when initial matching fails. EX1005, ¶164.

Because Gross teaches "image matching for building structures can be accomplished in any number of ways," a POSA would have found it obvious or common sense to try alternative approaches (including using alternate images) when one approach failed. EX1003, ¶¶210-211; EX1005, ¶108; *KSR*, 550 U.S. at 421.

VIII. CONCLUSION

The challenged claims are unpatentable and IPR is warranted.

Respectfully submitted,

STERNE, KESSLER, GOLDSTEIN & FOX PLLC

/XX/

Daniel S. Block (Reg. No. 68,395)
Jennifer Meyer Chagnon (Reg. No. 55,440)
Justin D. Wang (Reg. No. 81,975)
Attorneys for Petitioner Zesty.ai, Inc.

Date: August 1, 2025

1101 K Street, NW, 10th Floor
Washington, DC 20005
(202) 371-2600

Claims Appendix – U.S. Patent No. 10,529,029

Claim 1

Element	
[1.P]	A method for automatically categorizing a repair condition of a property characteristic, comprising:
[1.1]	receiving, from a user at a remote computing device, a request for a property condition classification, wherein the property classification request includes identification of a property and at least one property characteristic;
[1.2]	obtaining, by processing circuitry of a computing system responsive to receiving the request, an aerial image of a geographic region including the property;
[1.3]	extracting, by the processing circuitry, one or more of a plurality of features from the aerial image corresponding to the property characteristic, wherein the extracted features include pixel groupings representing the property characteristic;
[1.4]	determining, by the processing circuitry from the extracted features, a property characteristic classification for the property characteristic, wherein determining the property characteristic classification includes applying the pixel groupings for the property characteristic to a first machine learning classifier trained to identify property characteristics from a set of pixel groupings;
[1.5]	determining, by the processing circuitry based on the identified property characteristic and the extracted features, a condition classification for the property characteristic, wherein identifying the condition classification includes applying the pixel groupings for the property characteristic to a second machine learning classifier trained to identify property characteristic conditions from a set of pixel groupings;
[1.6]	determining, by the processing circuitry based in part on the property characteristic classification and the condition classification, a risk estimate of damage to the property due to one or more disasters; and
[1.7]	returning, to the user at the remote computing device via a graphical user interface responsive to receiving the request, a condition assessment of the property characteristic including the condition

	classification and the risk estimate of damage to the property due to the one or more disasters.

Claim 2

Element	
[2]	The method of claim 1, wherein the property characteristic classification is rooftop shape.

Claim 3

Element	
[3]	The method of claim 2, wherein the first machine learning classifier is trained with a set of aerial training images having known rooftop shapes such that the machine learning classifier is configured to determine the rooftop shape from a plurality of rooftop shapes.

Claim 4

Element	
[4]	The method of claim 1, wherein at least one of the first machine learning classifier and the second machine learning classifier is a Network in Network (NIN) classifier.

Claim 5

Element	
[5]	The method of claim 1, wherein determining the risk estimate comprises applying a disaster risk profile corresponding to a) a first disaster of the at least one disaster and b) the property characteristic.

Claim 6

Element	
[6]	The method of claim 1, wherein the pixel groupings comprise at least one of angles, outlines, and substantially homogenous pixel fields defining the property characteristic.

Claim 7

Element	
[7.1]	The method of claim 1, wherein identifying the condition classification for the property characteristic comprises: generating, from the pixel groupings, a pixel intensity distribution of the property characteristic; and
[7.2]	determining, by applying the second machine learning classifier, the condition classification based on the pixel intensity distribution of the property characteristic.

Claim 8

Element	
[8.P]	A system for automatically categorizing a repair condition of a property characteristic, comprising:
[8.1]	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
[8.2]	receive, from a user at a remote computing device, a property condition classification request, wherein the property classification request includes identification of a property and at least one property characteristic;
[8.3]	obtain, from a remote data source responsive to receiving the property classification request, an aerial image of a geographic region including the property;
[8.4]	extract one or more of a plurality of features from the aerial image corresponding to the property characteristic, wherein the extracted features include pixel groupings representing the property characteristic;
[8.5]	determine, from the extracted features, a property characteristic classification, wherein determining the property characteristic classification includes applying the pixel groupings for the property characteristic to a first machine learning classifier trained to identify property characteristics from a set of pixel groupings;

[8.6]	determine, based on the identified property characteristic and the extracted features, a condition classification for the property characteristic, wherein identifying the condition classification includes applying the pixel groupings for the property characteristic to a second machine learning classifier trained to identify property characteristic conditions from a set of pixel groupings; and
[8.7]	determine, in real-time responsive to receiving the property classification request and using the property characteristic classification and the condition classification, a replacement cost for replacing the property characteristic.

Claim 9

Element	
[9.1]	The system of claim 8, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to identifying the one or more of the plurality of features: obtain a shape map image including the property;
[9.2]	overlay the aerial image with the shape map image; and
[9.3]	determine whether a boundary of the property as identified by the shape map matches a boundary of the property as illustrated in the aerial image.

Claim 10

Element	
[10]	The system of claim 9, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, upon determining that the shape map does not match the boundary of the corresponding property, obtain an alternate aerial image of the property.

Claim 11

Element	
[11]	The system of claim 8, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to compare a

	current condition classification of the property characteristic to a stored historic condition classification of the property characteristic.

Claim 12

Element	
[12]	The system of claim 11, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, in real-time responsive to receiving the property condition classification request, determine whether repairs have been made to the property based on the comparison of the current condition classification to the historic condition classification of the property characteristic.

Claim 13

Element	
[13]	The system of claim 8, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to identifying the one or more of the plurality of features, assess orthogonality of the aerial imagery.

Claim 14

Element	
[14]	The system of claim 13, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, responsive to assessing that the orthogonality of the aerial imagery does not correspond to a true orthophoto form, cause correction of the aerial imagery to the true orthophoto form.

Claim 15

Element	
[15.P]	A non-transitory computer readable medium having instructions stored thereon, wherein the instructions, when executed by processing circuitry, cause the processing circuitry to:
[15.1]	receive, from a user at a remote computing device, a property condition classification request, wherein the property classification

	request includes identification of a property and at least one property characteristic;
[15.2]	obtain, from a remote data source responsive to receiving the property classification request, an aerial image of a geographic region including the property;
[15.3]	extract from one or more of a plurality of features from the aerial image corresponding to each property characteristic of the at least one property characteristic, wherein the extracted features include pixel groupings representing the respective property characteristic;
[15.4]	for each of the at least one property characteristic,
[15.5]	determine, from the extracted features for the respective property characteristic, a respective property characteristic classification, wherein determining the respective property characteristic classification includes applying the pixel groupings for the respective property characteristic to a first machine learning classifier trained to identify property characteristics from a set of pixel groupings, and
[15.6]	determine, based on the respective identified property characteristic and the respective extracted features, a respective condition classification for the respective property characteristic, wherein identifying the respective condition classification includes applying the respective pixel groupings for the respective property characteristic to a second machine learning classifier trained to identify property characteristic conditions from a set of pixel groupings; and
[15.7]	determine, in real-time responsive to receiving the property classification request and using the property characteristic classification of each property characteristic and the condition classification of each property characteristic, at least one risk estimate representing risk of damage due to disaster.

Claim 16

Element	
[16]	The non-transitory computer readable medium of claim 15, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to, prior to obtaining the aerial image of the geographic region, determine, based upon the at least one property

	characteristic, a preferred image type corresponding to each property characteristic of the at least one property characteristic.

Claim 17

Element	
[17.1]	The non-transitory computer readable medium of claim 16, wherein: the at least one property characteristic comprises two or more property characteristics; and
[17.2]	the instructions, when executed by the processing circuitry, cause the processing circuitry to, responsive to determining the preferred image type corresponding to a first property characteristic of the at least one property characteristic is a terrestrial image, obtain a terrestrial image of the geographic region including the property.

Claim 18

Element	
[18]	The non-transitory computer readable medium of claim 15, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to access one or more known property characteristics, wherein determining the at least one risk estimate comprises determining the at least one risk estimate further based on the one or more known property characteristics.

Claim 19

Element	
[19]	The non-transitory computer readable medium of claim 18, wherein the one or more known property characteristics comprise at least one of a property age, a property elevation, a property slope, a year built, a year renovated, and a building height.

Claim 20

Element	
[20.1]	The non-transitory computer readable medium of claim 15, wherein:

	receiving identification of the property and the at least one property characteristic comprises receiving, via a network from a remote computing device, the identification of the property; and
[20.2]	the instructions, when executed by the processing circuitry, cause the processing circuitry to provide, via the network to a graphical user interface at the remote computing device in real-time responsive to receiving the at least one property characteristic, the at least one risk estimate.

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 13,998 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,

STERNE, KESSLER, GOLDSTEIN & FOX PLLC

/XX/

Daniel S. Block
Registration No. 68,395
Counsel for Petitioner Zesty.ai, Inc.

Date: August 1, 2025

1101 K Street, NW, 10th Floor
Washington, DC 20005
(202) 371-2600

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. 10,529,029** and associated Exhibits 1001-1023 were served in their entireties upon the Patent Owner on August 1, 2025, via FedEx® Express at the following addresses:

FINCH & MALONEY PLLC
50 Commercial St.
Suite 300
Manchester, NH 03101
UNITED STATES
Patent Owner's Correspondence Address of Record for U.S. Patent No. 10,529,029

Respectfully submitted,

STERNE, KESSLER, GOLDSTEIN & FOX PLLC

/XX/

Daniel S. Block
Registration No. 68,395
Counsel for Petitioner Zesty.ai, Inc.

Date: August 1, 2025

1101 K Street, NW, 10th Floor
Washington, DC 20005
(202) 371-2600