IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

ZESTY.AI, INC.,
Petitioner

v.

AON RE, INC.,
Patent Owner

Case IPR2025-00XXX
U.S. Patent No. 11,030,491

PETITION FOR *INTER PARTES* REVIEW OF U.S. PATENT NO. 11,030,491

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1017	Krizhevsky, *et al.*, "ImageNet Classification with Deep Convolutional Neural Networks," Communications of the ACM, Vol. 60, No. 6, May 2017
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1019	Bradski, "The OpenCV Library," accessible at https://www.drdobbs.com/open-source/the-opencv-library/184404319 (last accessed July 10, 2025)
1020	van der Walt, *et al*., "scikit-image: image processing in Python," *PeerJ*, June 2014
1021	"Cartographic Work in Japan 2000 – 2005," United Nations Economic and Social Council, June 2005
1022	Usery, *et al*., "Mapping Developments and GIS in the USGS, 1884-2009," International Cartographic Association, January 2009
1023	Novak, *et al*., "Anatomy of a Color Histogram," *Proceedings of the 1992 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, June 1992, pp. 599-605

Petitioner Zesty.ai, Inc. ("Petitioner") petitions for *inter partes* review, seeking cancellation of claims 1-20 of U.S. Patent No 11,030,491 ("the '491 patent," EX1001), assigned to Patent Owner Aon Re, Inc. ("Aon").

I. INTRODUCTION

The '491 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 isolate property locations/structures contained in image, extract features from an image (e.g., of a property), determine characteristics of the feature (e.g., tile roof), and classify a condition of the feature (e.g., new, damaged). The claimed property assessment concepts were known to anyone who ever performed such an assessment of a property. In fact, property assessment was performed manually—either by manually reviewing images or by inspecting the property in person—long before the '491 patent proposed applying standard image processing and known machine learning techniques to automate the process. *See, e.g.*, EX1005, ¶6 (describing prior art systems to assess buildings, including a manual inspection form "used to assess a risk of damage to a house as a result of physical disturbance, such as wind, earthquakes, etc."); *id.* at ¶7 (describing prior art camera system for surveying property). And the '491 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. Indeed, the independent claims merely implement the age old property assessment practice using generic computing components that employ conventional image processing technique and the well-known existing machine learning capabilities to extract and classify the property features and conditions. EX1003, ¶¶45-49.

In fact, the primary reference asserted herein—Gross—renders obvious virtually all of the limitations recited in the challenged claims. Gross in combination with Davis (a patent developed by State Farm) renders obvious the "risk profile" "to determine a damage risk to property" recited in dependent claims 12-15. The remaining well-known "shape-map" limitations recited in dependent claims 2-5 are rendered obvious by the Gross-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 '491 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 '491 patent is at issue in *Aon Re, Inc. v. Zesty.ai, Inc.*, Case No. 1:25-cv-00201 (D. Del.), filed February 19, 2025.

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

- U.S. Patent No. 10,529,029 (IPR2025-00XXX);
- U.S. Patent No. 10,650,285 (IPR2024-00XXX);
- U.S. Patent No. 11,195,058 (IPR2024-00XXX).

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

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

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

The undersigned and Petitioner certify that the '491 patent is available for *inter partes* review and that Petitioner is not barred or estopped from requesting *inter partes* review of any '491 patent claim on the grounds herein.

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

A. Identification of Prior Art

The '491 patent's earliest possible priority date is September 23, 2016. Without conceding that this is the correct priority date, all references relied upon herein are prior art as of September 23, 2016.

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

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

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 '491 patent. EX1003, ¶¶50, 55, 57. 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.

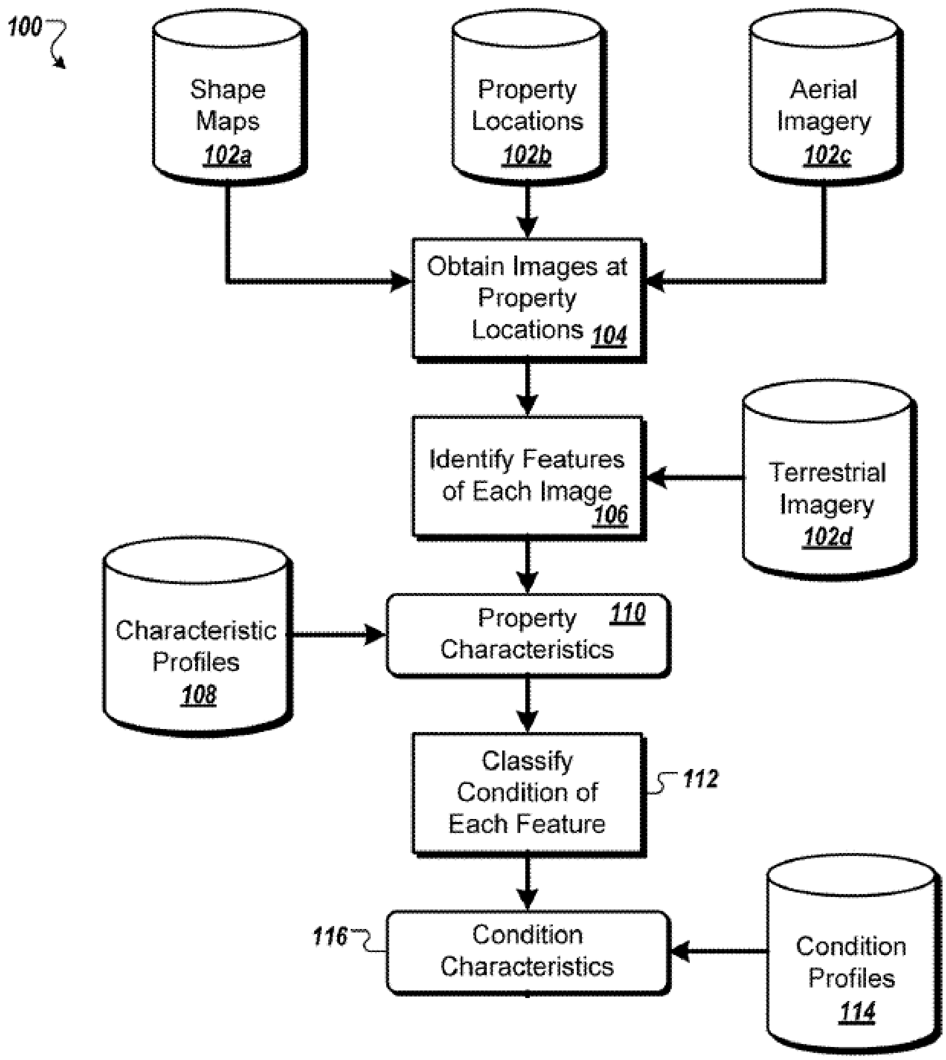
Ground	Basis	Claims	References
1	§103	1, 6-11, 16-20	Gross
2	§103	2-5	Gross and Furukuwa
3	§103	12-15	Gross and Davis

V. THE ’491 PATENT

A. Summary of the ’491 Patent

The ’491 patent discloses techniques for analyzing aerial imagery to evaluate property characteristics and condition classifications. EX1001, Abstract. For example, this might include analyzing images to determine the maintenance levels of certain property features, such as the roof. *Id.*, 1:46–51, 2:39–54. 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.*, 2:47–54; 12:29–33 (“The types of disasters can include, in some examples, earthquake, hurricane, tornado, storm surge, fire, straight line winds, or explosion. The types and estimated severity of disasters, in some embodiments, may depend upon the particular property location.”).

The ’491 patent teaches applying “machine learning analysis” to “analyze aerial imagery and automatically extract characteristics of individual properties, providing *fast and efficient automated classification* of building styles and repair conditions," in order to perform risk evaluations. *Id.*, 2:21–30, 39–47.[1] Figure 1, reproduced below, illustrates an "example system operational flow 100 for matching aerial image features to corresponding property maintenance levels" (*id.*, 6:21–23):



EX1001, FIG. 1 (cropped).

[1] Emphasis added throughout, unless otherwise noted.

As shown in Figure 1, the system first obtains images, including e.g., "aerial imagery" and "shape map images," at property locations at step 104. Such "shape map images" can "include a block shape layout of existing properties" (e.g., "urban planning maps"). EX1001, 7:46–49. The shape map images can be used to confirm the location of a particular property in the aerial image. *Id.*, 7:58–59, FIG. 1. In the embodiment of claim 1, "boundary information" is applied to the aerial image to "isolate the property location." *Id.*, Claim 1. At step 106, the system then identifies (or "extracts") "features" of each aerial image, such as "substantially homogenous fields" and "pixel groupings" (groups of pixels). EX1001, 8:30–40. These "features" represent a characteristic of the property, such as a "rooftop" or a "tree." *Id.*, 8:34–44; *see also id.*, 2:66–3:9 ("The property characteristic of a structure such as a house, factory, or barn, in some examples, can include a rooftop, porch, chimney, or skylights. Property characteristics of manmade structures within a property location, in some examples, can include a deck, swimming pool, shed, gazebo, detached garage, tennis court, fence, retaining wall, dock, playground equipment, equipment or vehicles, or greenhouse. Property characteristics of natural features within a property location, in some examples, include trees, ponds, marshes, rivers, lakes, grasses, cliffs, or ocean shore.").

Then, at step 110, the system determines a "characteristic classification" for the identified property characteristic from the image. *Id.*, 8:40–50. For example, this may include determining the "type of rooftop" (e.g., gambrel, gable, hipped, square, flat). *Id.*, 8:40–50, 9:23–43, FIG. 2A; *see also id.*, 3:9–16 ("Further, property characteristic classifications can include shapes, materials, size (breadth and/or height, relative or actual), and/or distance of the property characteristic from other features. In some embodiments, the property characteristic classification may include existing versus not existing (e.g., in the event of determining replacement or removal of a manmade feature at a property location such as a fence)."). This classification is done using "characteristic profiles 108," which include machine learning analysis algorithms trained to classify property characteristics. *Id.*, 8:50–9:22.

At step 112, the system determines a "condition classification" of the property characteristic, such as, e.g., a "good" condition or a "bad" condition. *Id.*, 3:27–28, 10:49–57. To do so, "condition profiles 114" (e.g., machine learning analysis algorithms trained to classify conditions of property characteristics) are applied to the extracted image features from step 106. *Id.*, 10:60–11:20.

The '491 patent does not purport to have invented any new machine learning or image analysis techniques. Rather, the classification steps 110 and 112 described by the '491 patent merely apply existing machine learning and image analysis techniques. For example, the '491 patent identifies convolutional neural network (CNN) technology as one example, which the '491 patent describes as "a well-established and popular machine-learning methodology." *Id.*, 8:50–9:8. *See* EX1003, ¶¶34-39.

B. Prosecution History

The '491 patent issued from U.S. Application No. 17/155,633 ("the '633 application") without any substantive prior art examination. The '491 patent is a continuation of U.S. Application No. 16/868,113 (now U.S. Patent No. 11,195,058), which is a continuation of U.S. Application No. 16/733,888 (now U.S. Patent No. 10,650,285), which is a continuation-in-part of U.S. Application No. 15/714,376 (now U.S. Patent No. 10,529,029 ("the '029 patent"). EX1002, 22-23. The prosecution history reveals that the claims never underwent meaningful analysis against the prior art that renders them obvious. *See, generally*, EX1002.

During prosecution, the '633 application received a double-patenting rejection over the '029 patent. EX1002, 127-33. In response, the applicant filed a terminal disclaimer, after which the Examiner issued a Notice of Allowance. EX1002, 165-66, 193-99.[2] This limited prior art consideration occurred despite the

[2] The Notice of Allowance references the reasons for allowance in the 15/714,376 application (U.S. Patent 10,529,029), where the Examiner distinguished three references (Swanson, Downey, and Cuttell) without having issued a single rejection against the allowed claims of the '029 patent and without the detailed

robust prior art landscape that existed at the time of filing. *See* EX1003, ¶¶40-41.

C. Person of Ordinary Skill in the Art

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

D. Claim Construction

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

Solely for the purposes of this Petition, Petitioner submits that all claim terms should receive their plain and ordinary meaning in the context of the '491

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analysis typically conducted during examination. The "Reasons for Allowance" for the '029 patent also discusses an *Alice* rejection, but again there were no substantive rejections made of the claims during prosecution of the '029 patent.

patent specification. EX1003, ¶44.

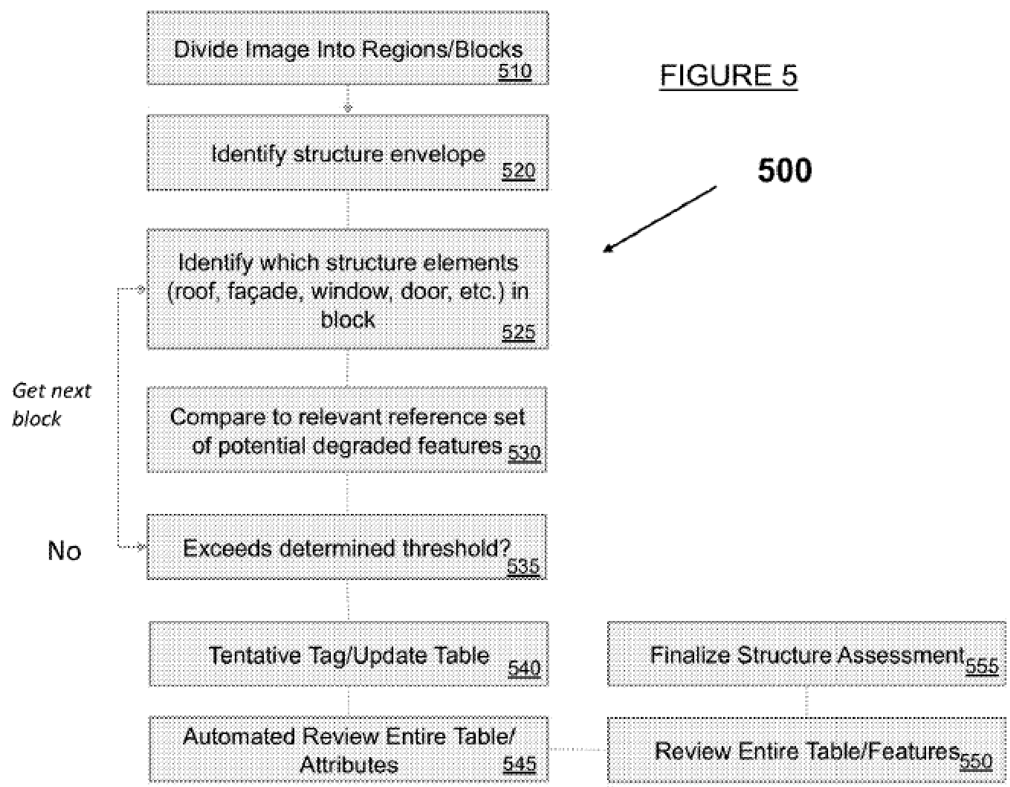
VI. OVERVIEW OF THE APPLIED REFERENCES

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 '491 patent, Gross teaches that these tools are useful in the area of insurance, among others. *Id.*, ¶¶2, 5, 186, 237-238.

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

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



EX1005, FIG. 5.

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

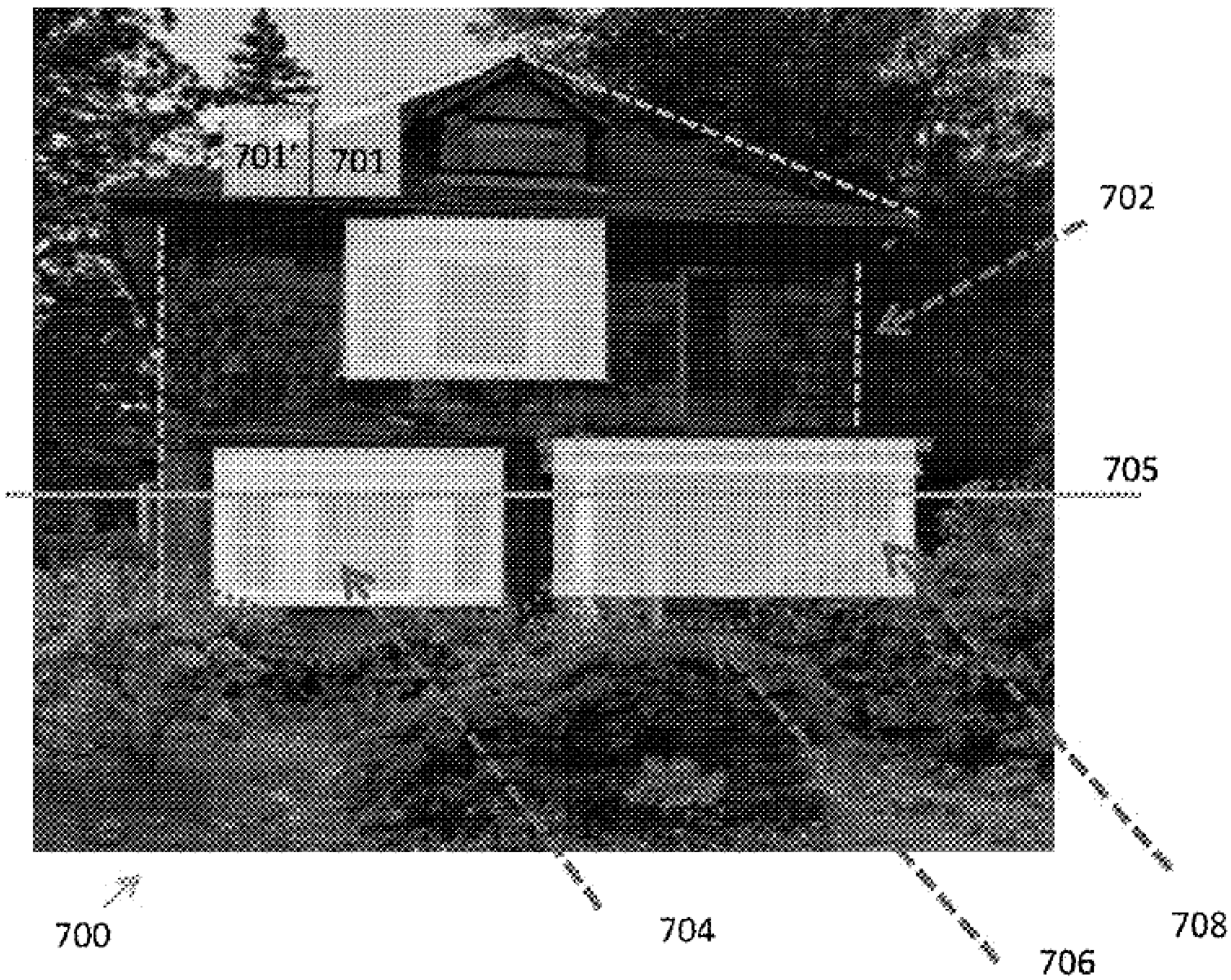


FIGURE 7B

EX1005, FIG. 7B.

At step 520 of the method of Figure 5, Gross's system identifies a "building envelope 702" (which as seen in Figure 7B is essentially an outline of the building) by detecting edges of structures in the image. EX1005, ¶122, FIG. 7B; EX1003, ¶53. Such "boundaries" (e.g., edges) of other objects in the property (e.g., landscaping, trees, etc.) can also be determined. EX1005, ¶122. The image blocks include "structural elements" (e.g., a roof, tree, etc.), which are determined (alongside a "type" of the structural element (e.g., pitched roof, shingle roof, etc.) at step 525. *Id.*, ¶123. As one example, "the first block 701 may be coded to denote that an attribute {roof} with type {pitched} and {shingle} is contained" therein. *Id.* As Gross explains, and similar to the '491 patent, identifying the structural element and its classification "can be performed in any number of ways by Classifier Engine … including by pattern recognition techniques and statistical image processing using models." *Id*.

Again similar to the '491 patent, Gross's system then employs Classifier Engine to determine a "condition" of the determined structural element at steps 530 and 535, such as a "good" condition or a "poor" condition. *Id*., ¶¶126–127, 141. The condition classification is then stored into memory at step 540. *Id*., ¶127. This assessment process is repeated for one or more extracted image blocks for the image and the final assessment data is reviewed and finalized at steps 545, 550, and 555. *Id*., ¶¶129–133. *See* EX1003, ¶¶50-54.

B. Davis

Davis discloses a computer-implemented method for determining property features from aerial images and analyzing the property features to determine an estimated risk of damage to the property. EX1006, Abstract. Davis's system "allow[s] an insurance provider to more accurately and efficiently underwrite risk for a home insurance policy" and "reduc[e] the number, frequency and/or cost of

… risk mitigation requests." *Id.*, 1:64–2:3. A policyholder user (e.g. "the owner of [a] property") may first request "a risk mitigation program." *Id.*, 7:53–60. In response, Davis's system, like the '491 patent, obtains and processes an aerial image of the property associated with the request. *Id*. Davis's system then processes the aerial image to "determine one or more features of the property," using techniques such as feature extraction. *Id.*, 18:27–34.

Davis's system also performs "object detection/identification," for example, to "identify a particular tree" of a property or "a type of roof" on a house on a property from the aerial image. *Id.*, 18:36–39, 48–52; 9:24–29. Subsequently, Davis's system employs "other image analysis techniques" (e.g., image classification) to determine classifications of the detected object, such as "a size of at least a portion of the tree[,] a species of the tree, an orientation of a portion of the tree with respect to the structure or object," "distances of tree trunks and/or branches from homes or other structures located on the properties," or "a type of roof on a structure." *Id.*, 18:27–39; 9:22–29, 3:38–46. Based on these determinations, Davis's system then analyzes a risk of damage to a structure on the property (e.g., a house). *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 employee (e.g., agent) of an insurance provider … and/or to the policyholder." *Id.*, 20:40–42, 59–64. *See* EX1003, ¶¶55-56.

C. Furukawa

Furukawa describes techniques for processing image data (e.g., satellite 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 by image processing means" (e.g., via "building external shape information detecting means 6") or "obtains the same from … existing map data." EX1007, 6:43–46, 32:65–33:7. Furukawa's system then 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 then modifies the map data to obtain an alternate, updated raster image. *See, e.g.*, EX1007, 35:50–57, 30:56–31:53. *See* EX1003, ¶¶57.

VII. GROUNDS OF UNPATENTABILITY

A. Ground 1: Gross renders obvious claims 1, 6-11, and 16-20

Claims 1, 6-11, and 16-20 would have been obvious over Gross. EX1003, ¶¶14, 58.

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

As explained above, Gross discloses training a Classifier Engine 150 and using it to assess and rate properties. EX1005, ¶57, FIG. 2. Gross describes specific details on how its Classifier Engine 150 is trained with reference images and uses conventional image processing techniques to extract attributes of a property and classify conditions of the attributes. *See* EX1005, ¶¶77-93; EX1003, ¶¶59-60. Gross further describes that, after it has been trained, Classifier Engine 150 may be used to identify attributes (and their types and conditions) contained in an image of a property to be assessed. *See* EX1005, ¶¶120-129, FIG. 5; EX1003, ¶61. Gross describes that "the identification of such attributes (and their types) can be performed in any number of ways by Classifier Engine 150. EX1005, ¶123. For example, Classifier Engine 150 may be trained to assess whether the following exemplary structure attributes, attribute types, and conditions/impairments are contained in an image: roof {new, missing/damage tile, shingle metal, holes/cracks, unevenness, brightness (moss mold)}; façade (new, missing, shingles/siding, breaks, holes, discontinuities, discoloration, warping, paint bubbles/blistering/peeling—aging, weathering, water damage}; and other exemplary attributes/types/conditions. EX1005, ¶¶60-70; EX1003, ¶61.

A POSA reading Gross would have understood that the image processing and attribute classification techniques used to train Classifier Engine 150 were intended to also be utilized in its building attribute/condition assessment process. EX1003, ¶62. Indeed, that is the whole point of Gross—to use its trained classifier to determine building attributes and condition assessments. Both processes involve analyzing property images to identify attributes (such as roof elements, window elements, etc.), their types (e.g. for a roof – shingle, metal, tile), and conditions (e.g., for a roof – missing/damage tile, holes/cracks). EX1003, ¶62. A POSA would have recognized that Classifier Engine 150 would employ the same, or very similar, techniques as those used during training to process images to identify and classify attributes contained therein. EX1003, ¶62; *see also* EX1005, ¶245 (Gross describing that "conventional steps that would be included … have been omitted"). Such implementation would merely amount to combining (as intended) Gross's disclosure of the image processing elements used to train the Classifier Engine with its disclosure of image processing used in its building attribute/condition assessment process according to known methods to yield predictable results with a reasonable expectation of success. EX1003, ¶63; *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 417 (2007).

2. Independent Claim 1

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

To the extent limiting, Gross discloses the preamble. EX1003, ¶64.

Gross discloses "training [a] Classifier Engine … and using it to assess and rate" properties. EX1005, ¶57. "[A]n identification is performed" by Classifier Engine "to determine structural elements presented in a first block" of an image, "including such attributes as roof elements, window elements, façade elements, etc." EX1005, ¶123. These attributes are *features of a property location comprising a structure*, as claimed, because they are physical parts of a structure, such as a house or building. EX1003, ¶¶65-66.

Gross also discloses that Classifier Engine identifies conditions associated with a particular attribute. EX1005, ¶60. For example, the Classifier Engine may automatically assess the condition of a roof (*feature of a property location*) as "new," "missing/damage tile," and/or "holes/cracks." EX1005, ¶61. In some instances, "severity weightings (i.e., a scaling factor of any convenient range (1-10, or the like) for the identified condition" may also be assigned by Classifier Engine. EX1005, ¶70; *see also id.*, ¶126 (Gross's description that a "condition score is computed [by Classifier Engine] for the detected attribute."). Gross further discloses that "with sufficient training an automated classifier could participate in the process, if not perform the entire process of classifying structural features." EX1005, ¶145; *also id.* ¶¶174, 176. Thus, Gross discloses *automatically assessing feature of a property location*. EX1003, ¶67.

b. [1.1]: 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. These "executable software routines" are executed via "*processing circuitry*." EX1003, ¶68. Gross further discloses that its "applications can be embodied in tangible, machine readable form for causing a computing system to execute appropriate operations in accordance" with the teachings. EX1005, ¶56. Thus, Gross teaches element [1.1]. EX1003, ¶68.

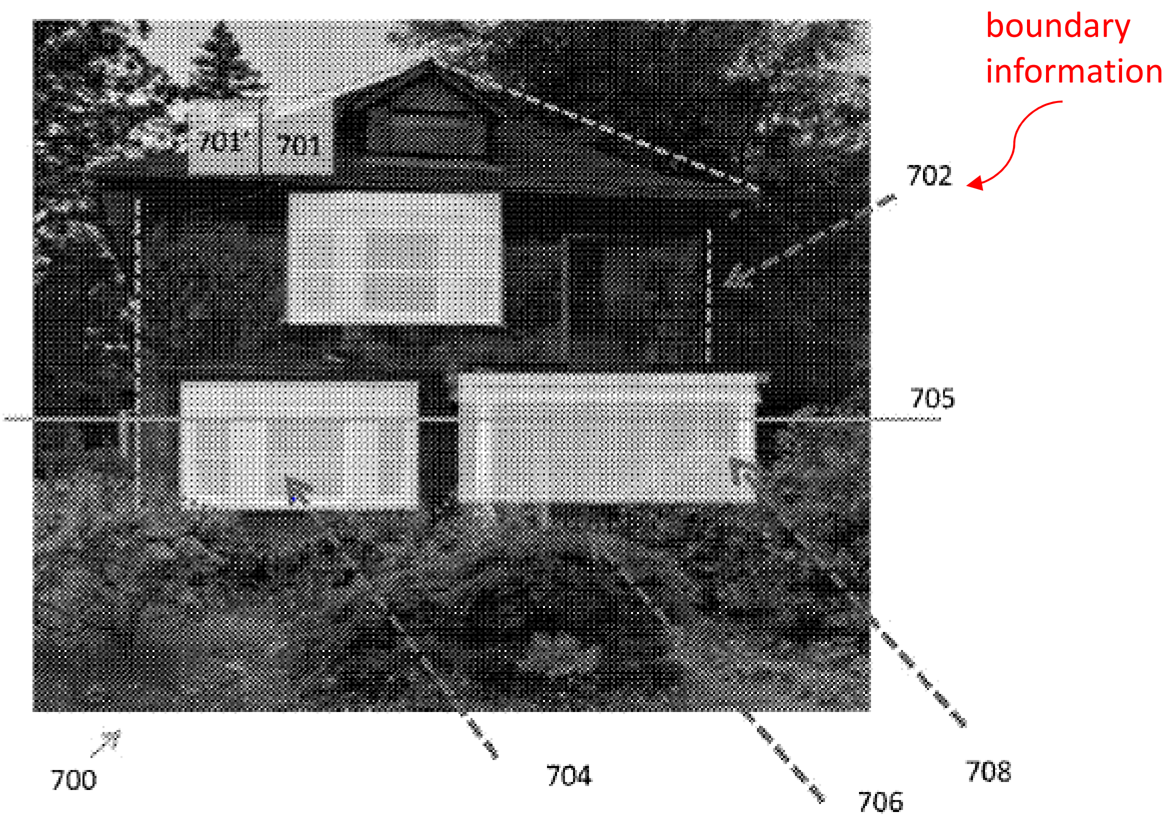
c. [1.2]: access a plurality of images of the property location including the structure;

Gross teaches element [1.2]. EX1003, ¶¶69-71. In particular, Gross describes "aerial drones, satellite, balloon and similar technology" can be used that "capture[s] structure image data from a variety of perspectives" (i.e., *a plurality of images of the property location including the structure*) and "can facilitate building out a comprehensive image database." EX1005, ¶164. The building image data is stored in a structure image database. EX1005, ¶165.

Gross further describes "a data acquisition process" used by a classifier (e.g., Classifier Engine 150) and that "the purpose "of this specialized computing module is to acquire appropriate image data for structures within a target area." EX1005, ¶161. Classifier engine retrieves (*accesses*) an image 700 from a database to begin the building attribute/condition assessment process and the image data that is retrieved is for the target address. EX1005, ¶¶120-21, 164.

d. [1.3]: apply boundary information to one or more images of the plurality of images to isolate the property location or the structure thereon within each respective image; and

Gross teaches element [1.3]. EX1003, ¶72. Gross describes identifying a "building envelope 702" by image processing adapted to detect edges of structures. EX1005, ¶122. The building envelope functions as *boundary information*, which is applied *to isolate the structure* within the image because it detects the edge of the structure and isolates the structure within the image. EX1003, ¶72. Other than in independent claims 1 and 11, the '491 patent does not describe applying boundary information to isolate a structure within an image. Figure 7B of Gross (depicted below) illustrates the boundary information (building envelope 702), which isolates the structure.



EX1005, FIG. 7B (annotated); EX1003, ¶72.

Thus, Gross teaches *apply[ing] boundary information to one or more images of the plurality of images to isolate … the structure thereon.* EX1003, ¶73.

Gross also teaches *apply[ing] boundary information to isolate the property location* too. EX1003, ¶74. Gross discloses "a data acquisition process 1600 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 describes additional data could be gleaned "from public records which identify the layout of building envelopes on each lot." EX1005, ¶143. Gross further discloses using “[i]nformation identifying a beginning and end of each individual street, road, alley” “from any convenient database or similar source” to retrieve “image data” for a “target address in question.” EX1005, ¶¶162, 164; *see also id.,* FIG. 10. Both the data in public records that identifies the layout of building envelopes on each lot (i.e., identifies lot locations) and the information identifying beginning and end of streets/roads/alleys constitutes boundary information because it is used to isolate the location of the target address from other properties in the area. EX1003, ¶75. Thus, Gross teaches *applying boundary information to* isolate the location of the “target address in question.” EX1003, ¶75.

e. [1.4]: classify a condition of one or more property features of the property location, wherein classifying comprises, for each feature of the one or more features,

Gross teaches element [1.4]. EX1003, ¶76. Gross discloses classifying “conditions/impairments … associated with a particular building [structure] attribute.” EX1005, ¶60. The structure attributes are *property features of the property location* because, like the ’491 patent they are characteristics located on the property (*see, e.g.*, EX1001, 2:39-45, 8:36-38). EX1003, ¶76. Gross describes examples of structure attributes (i.e., *property features*) and related *conditions*, including: roof (new, missing/damage tile, holes/cracks); façade (new, missing, holes); and support (leaning/damaged columns). EX1005, ¶¶60-69. The examples provided are just a partial list and other individual structure attribute/condition pairings can be identified by Classifier Engine. EX1005, ¶70.

For the reasons provided for elements [1.5]-[1.7], Gross teaches *wherein classifying comprises, for each feature of the one or more features*, the limitations set forth in [1.5]-[1.7] are performed for at least one feature, which is all that is required by the claim (i.e., "classify a condition of *one* or more *property features*"). EX1003, ¶77.

f. [1.5]: extracting the respective feature from each image of at least one image of the one or more images,

Gross teaches or renders obvious element [1.5]. EX1003, ¶78. Gross discloses objects can be analyzed in image patterns, using a variety of techniques, including statistical processing and neural networks, which can be used to detect and *extract* features of attributes. EX1005, ¶77. An 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, etc." EX1005, ¶¶121, 123. A POSA would have understood or found obvious this identification *extracts the respective feature* from the image because image features representing specific structural elements (i.e., *property features* such as roof, window, etc.) are extracted from the image (using the disclosed image analysis techniques, such as neural networks). EX1003, ¶79.

g. [1.6]: applying a set of machine learning analysis algorithms to at least a portion of each image of the at least one image to determine a set of characteristics of the respective property feature, wherein each algorithm of the first set of machine learning analysis algorithms is trained to identify one or more characteristics of the set of characteristics, and

Gross teaches, or renders obvious, element [1.6]. EX1003, ¶80. Gross discloses that, after it has been trained, Classifier Engine 150 (which includes the claimed "*machine learning analysis algorithms*") identifies "structural elements" (i.e., *property features*) presented in an image. EX1005, ¶123. The specific types of the attributes (i.e., *characteristics of the property feature*) are also captured "(i.e., façade (shingle, siding, brick), … roof {pitched, double pitched, hipped, flat, metal, tile, shingle, slate, parapet, dormer, mansard, fascia, brackets, eaves, pent, pediment, etc.})". EX1005, ¶57. For example, a first block of the image "may be coded [by Classifier Engine] to denote that an attribute {roof} with type {pitched} and {shingle} is contained" in the image. EX1005, ¶123. To do this, Classifier Engine "employs image processing" and the "identification of such attributes (and their types) can be performed in any number of ways by Classifier Engine 150 after it has been trained." EX1005, ¶¶120, 123. Thus, Gross teaches applying its Classifier Engine to at least a portion of an image *to determine a set of characteristics* (e.g., "pitched") *of the respective property feature* (e.g., roof). EX1003, ¶80.

Gross's Classifier Engine includes *a set of machine learning analysis algorithms*, *wherein each algorithm is trained to identify one or more characteristics of the set of characteristics*. EX1003, ¶81. In particular, Gross discloses its Classifier Engine is trained with reference images and that objects in the image are analyzed using neural networks to detect and extract features. EX1005, ¶77. For example, Classifier Engine is trained to identify a roof feature and a set of characteristics associated with the roof ("pitched, double pitched, hipped, flat, metal, tile, shingle, slate, parapet, dormer, mansard"). EX1005, ¶57; EX1003, ¶81. Gross further describes that "[f]or better accuracy it may be useful to employ multiple classifiers trained with different algorithms." EX1005, ¶80. In light of Gross's teachings, a POSA would, therefore, would have understood, or found obvious, Classifier Engine includes *a set of machine learning analysis algorithms* (and a POSA would have understood a set could be a set of one) that is *trained to identify one or more characteristics of the set of characteristics* (e.g., trained to identify a roof is pitched, double pitched, hipped, etc.). EX1003, ¶81; EX1005, ¶¶77, 123.

a. [1.7]: applying another machine learning analysis algorithm to at least a portion of each image of the at least one image to classify a condition of the respective property feature, wherein the condition is classified as a respective classification of a set of possible classifications, and the another machine learning analysis algorithm is trained to identify one or more conditions of property locations and/or structures

thereon having the set of characteristics of the respective property feature.

Gross teaches, or at least renders obvious, element [1.7]. EX1003, ¶82. Gross discloses identifying and classifying "conditions/impairments … associated with a particular building attribute" (i.e., *classifies a condition of the respective property feature*). EX1005, ¶60. Gross describes examples of structure attributes (i.e., *property features*) and related condition classification, including: roof (new, missing/damage tile, holes/cracks); façade (new, missing, holes); and support (leaning/damaged columns). EX1005, ¶¶60-69. The examples provided are just a partial list and other individual structure attribute/condition pairings can be identified by Classifier Engine. EX1005, ¶70.

After the Classifier Engine is trained, it can identify indicators in attributes "of an irregularity, defect, damage or the like" and compute a condition score for the detected attribute. EX1005, ¶¶123, 126. Thus, Gross teaches applying its Classifier Engine (i.e., *another machine learning analysis algorithm* for reasons explained below) to at least a portion of an image *to classify a condition of the respective property feature* (e.g., roof has a "missing tile"), *wherein the condition is classified as a respective classification of a set of possible classifications* (e.g., new, missing/damage tile, holes/cracks). EX1003, ¶83.

Additionally, for the reasons provided for element [1.6], Gross teaches that its Classifier Engine includes *a set of machine learning analysis algorithms*.

EX1003, ¶84; EX1005, ¶77. And although Gross does not explicitly disclose that its conditions of property conditions are classified via *another* machine learning analysis algorithm than that used to identify attributes, Gross does explicitly disclose that "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 (*machine learning analysis algorithm*) to identify conditions, such as "damaged/exposed roof elements" and "broken—façade," EX1005 ¶¶85, 91, which correspond to the attributes (*property feature*) discussed above for Element [1.4], such as a "roof" or "façade." Gross also discloses that different classifiers (i.e., *another machine learning analysis algorithm*) 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.

In light of these teachings, a POSA would have understood that Gross teaches, or renders obvious, the use of *another machine learning algorithm*, as claimed, to classify a condition of the property feature because customized algorithms are more accurate or more appropriate for different vendors. EX1003, ¶84. A POSA would have been motivated to employ another machine learning analysis algorithm to identify a condition classification because Gross explicitly suggests that different classifiers (i.e., different machine learning analysis algorithms) can be used and that classifiers can be customized for different purposes. EX1003, ¶85; EX1005, ¶80, claim 26. Moreover, a POSA would recognize that the reason Gross suggests using different classifiers (*another machine learning analysis algorithm*) is so that it would then be trained with "additional data" that optimizes and improves the accuracy of their classifications, such as in this case the classification of a condition of property features. EX1003, ¶¶85-86; *See* EX1005, ¶¶80-81; *see also id.*, ¶84 (identifying "types of attributes and conditions that can be used to train the classifier"). A POSA would have readily implemented the predictable variation of Gross's Classifier Engine to use multiple machine learning analysis algorithms—a first set of algorithms used to determine characteristic of the property feature and another machine learning analysis algorithm used to identify conditions of those features/characteristics. EX1003, ¶86; *see KSR*, 550 U.S. at 416 ("If a person of ordinary skill can implement a predictable variation, § 103 likely bars its patentability."). Therefore, Gross teaches, or at least renders obvious, the claimed *another machine learning analysis algorithm* that is *trained to identify one or more conditions of property locations and/or structures thereon* (e.g., trained to identify the condition of a roof, which is a condition of a structure on the property) *having the set of characteristics of the respective property feature* (e.g., a roof with characteristics "tile" and "parapet."). EX1003, ¶87; EX1005, ¶¶60-61, 123, 126.

3. Independent Claim 11

a. [11.P]: A method for automatically assessing risk damage to a property, the method comprising:

To the extent limiting, Gross discloses element [11.P] for the reasons provided for element [1.P]. EX1003, ¶88. Gross further discloses its assessment system can be used for insurance risk assessments and that correlations can "be developed between property condition ratings, occupancy estimates and number of claims filed, type of claim, severity, etc." EX1005, ¶248 In other words, Gross teaches its methods can *automatically assess risk damage to a property*. EX1003, ¶88.

a. [11.1]: accessing, by processing circuitry, a plurality of images of a property location including a structure

Gross teaches element [11.1] for the reasons provided for element [1.1] and [1.2]. EX1003, ¶89.

b. [11.2]: applying, by the processing circuitry, boundary information to one or more images of the plurality of images to isolate the property location or the structure thereon within each respective image; and

Gross teaches element [11.2] for the reasons provided for element [1.1] and [1.3]. EX1003, ¶90.

c. [11.3]: classifying, by the processing circuitry, a condition of one or more property features of the property location, wherein classifying comprises, for each feature of the one or more property features,

Gross teaches element [11.3] for the reasons provided for element [1.1] and

[1.4]. EX1003, ¶91.

d. [11.4]: adjusting each image of the at least one image to obtain an adjusted image for analyzing the respective feature,

Gross teaches element [11.4]. EX1003, ¶92. Gross discloses that "customized image processing operations (rotations, noise clean up, etc.) may also be performed" (i.e., image adjustment operations) as part of an image pre-processing (i.e., before the image analysis). EX1005, ¶76. These image processing operations adjust the image *to obtain an adjusted image for analyzing the respective feature.* EX1003, ¶92.

a. [11.5]: applying a set of machine learning analysis algorithms to at least a portion of each image of the at least one adjusted image to determine a set of characteristics of the respective property feature, wherein each algorithm of the first set of machine learning analysis algorithms is trained to identify one or more characteristics of the set of characteristics, and

Gross teaches, or renders obvious, element [11.5] for the reasons provided for element [1.6]. EX1003, ¶93.

b. [11.6]: applying another machine learning analysis algorithm to at least a portion of each image of the at least one image to classify a condition of the respective property feature, wherein the condition is classified as a respective classification of a set of possible classifications, and the another machine learning analysis algorithm is trained to identify one or more conditions of property locations and/or structures

thereon having the set of characteristics of the respective property feature.

Gross teaches, or renders obvious, element [11.6] for the reasons provided for element [1.7]. EX1003, ¶94.

4. Claim 6

a. [6.1] The system of claim 1, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to determine at least one property characteristic of the structure including one or more of an occupancy type, a number of stories, or a siding type,

Gross teaches element [6.1]. EX1003, ¶95. Gross describes that further information that can be determined by its Classifier Engine includes "[i]information on the … number of stories" (i.e., *property characteristic of the structure including … a number of stories*). EX1005, ¶146. Gross also describes that its Classifier Engine can determine the type of façade of the structure (i.e., *siding type*), such as shingle, brick, and stone. EX1005, ¶57. And Gross describes its Classifier Engine can identify whether structures are inhabited or not (i.e., *occupancy type*). EX1005, ¶¶118, 131.

b. [6.2] wherein: determining the at least one property characteristic comprises, for each characteristic of the at least one property characteristic, selecting a given image of the at least one image for determining the respective characteristic, and

Gross teaches, or renders obvious, element [6.2]. EX1003, ¶96. For the reasons provided for elements [1.2] and [1.5], Gross describes that its attribute/condition assessment process retrieves an image from the database for the target address. Thus, Gross teaches *selecting a given image … for determining the respective characteristic* through its description of selecting an image for the target address. EX1005, ¶164; EX1003, ¶96.

Gross further describes images can be obtained "to increase building coverage and feature currency/accuracy." EX1005, ¶148. And Gross describes that "[w]hile some images may allow only for one/two dimensional measurements … additional data could be gleaned from other perspectives obtained by other image capturing systems" (i.e., other images). In other words, Gross discloses that multiple images of the same structure exist, and that different data would be "gleaned" from each of these different images. And although Gross doesn't explicitly state how its system would know which data would be gleaned from which image, a POSA would have understood or found obvious that regardless of how Gross's system made this determination, Gross's system would have some mechanism for determining which specific images to analyze among its various "perspectives" of a structure to "glean" the aforementioned "additional data". EX1003, ¶97. In this manner , a POSA would have understood or found obvious that Gross's comprehensive image database of images from various perspectives would allow the classifier to use certain, preferred types of images for certain property classification tasks. EX1003, ¶97; EX1005, ¶164. 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), while a POSA would understand Classifier Engine would select an alternative image to increase the accuracy of the "siding type" or "number of stories." EX1003, ¶97.

c. [6.3] applying a machine learning analysis algorithm trained to identify the respective property characteristic to the given image to determine the respective characteristic.

Gross teaches element [6.3]. EX1003, ¶98. For the reasons described in element [1.6], Gross teaches applying a machine learning analysis algorithm trained to determine a set of characteristics of the property feature. Gross similarly describes its Classifier Engine (*machine learning analysis algorithm*) is trained to identify *property characteristics*, such as *occupancy type*, *number of stories*, and façade (*siding type*) (*see* element [6.1]). *See* EX1005, ¶¶57, 63, 118, 146; EX1003, ¶98.

5. Claim 7

Claim 7 depends from claim 6 and further recites, "*wherein the given image corresponding to a first property characteristic of the at least one property characteristic is a terrestrial image*."

Gross teaches, or renders obvious, this claim. EX1003, ¶¶99-100. Gross discloses images "at different angles, elevations and profiles" helps "increase building coverage and feature currency/accuracy." EX1005, ¶148. Gross illustrates several *terrestrial images* of properties, such as in Figure 7B. EX1005, FIG. 7B; EX1003, ¶100. For the reasons described in element [6.1], Gross teaches its Classifier Engine determines *a number of stories* and *a siding type*. In light of Gross's explicit teachings, a POSA would have understood or found obvious that a "terrestrial image" (obtained e.g., by "crowdsourcing") would "increase building coverage" and "increase feature accuracy" for the classification of *siding type* and *a number of stories* because such image type would have a higher chance of containing pixels necessary to identify the siding (façade) elements and the number of stories of a structure. EX1003, ¶101.

6. Claim 8

Claim 8 depends from claim 1 and further recites, "*wherein a first feature of the at least one feature of the property location comprises a natural feature*."

Gross teaches this claim. EX1003, ¶¶102-103. Gross describes that "the presence, type and condition of … landscaping" (i.e., *natural feature*) can be collected and assessed as part of its classification process. EX1005, ¶141. For example, the landscaping features and related condition pairs that may be identified and classified includes trees and shrubs. EX1005, ¶68.

7. Claim 9

Claim 9 depends from claim 8 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to determine a distance between the natural feature and the property location*."

Gross teaches this claim. EX1003, ¶¶104-105. Specifically, Gross discloses its classification system can be used by property insurers. Gross teaches data captures and processed by its assessment system (Classifier Engine) can include hazards, such as "trees that are too close." EX1005, ¶238. Trees that have a distance which is too close to the property structure are hazards. In order to determine if a tree is "too close" and therefore a hazard, the distance between the tree (i.e., *natural feature*) and the property must be assessed. Thus, Gross teaches or renders obvious determining *a distance between the natural feature* (tree) *and the property location*. EX1003, ¶105; EX1005, ¶238.

8. Claim 10

Claim 10 depends from claim 1 and further recites, "*wherein assessing a first feature of the at least one feature of the property location comprises comparing the classification of the first feature to a historic condition classification of the first feature*."

Gross teaches this claim. EX1003, ¶¶106-107. Gross discloses using "long term evaluations over defined time periods … to identify changes in a property condition." EX1005, ¶134. Gross accomplishes this by storing the "final structure assessment data" (i.e., *historic condition classification*) "in database 142" during the feature coding (e.g., condition assessment) process. EX1005, ¶133; *see also id.*, ¶141 (describing how "the presence of [a building] feature, type and condition is coded and collected and stored in digital form," including "the presence, type and condition of facades, roofs, awnings," and more).

Gross also explains "the coding process" that obtains the property assessments for the "long term evaluations" described above "may be targeted primarily or solely for identifying structural improvements, such as the presence of a new fence, new roof, new paint job." *Id.*, ¶¶134, 146. Given the recorded "structure assessment data," a POSA would have understood or found obvious that the way one would identify these "structural improvements" (e.g., that a new roof was added) would be through a comparison between assessment data of current, updated images of a property and prior, stored historic assessment data of the same property. EX1003, ¶108; EX1005, ¶146. These comparisons would indicate the change in condition of the property structure and whether it was a positive change (i.e., improvement) or otherwise. EX1003, ¶108.

Thus, Gross teaches *comparing the classification of the first feature* (e.g., "good" condition roof) *to a historic condition classification* (e.g., "damaged" roof) as part of *assessing a first feature.* EX1003, ¶109; EX1005, ¶¶134, 146

9. Claim 16

Claim 16 depends from claim 11 and further recites, "*wherein adjusting each image comprises adjusting color of the at least one image*."

Gross renders obvious this claim. EX1003, ¶¶110-111.

Gross teaches that Classifier Engine may analyze color in images to assess property conditions through its description that "dark or irregular color [of a group of pixels representing a roof] may cause a roof element to score poorly" during condition determination. EX1005, ¶126; EX1003, ¶112. As described in element [11.4], Gross further describes that "customized image processing operations" may be applied to images. EX1005, ¶76. A POSA would have understood or found obvious that adjusting color of the image is one of "a finite number of identified, predictable" image adjustment operations that could be used and that many (if not most) image operations (e.g., adjusting contrast, brightness, hue, saturation, color balance, exposure, and sharpness) adjust the color of an image in some fashion. EX1003, ¶113; *see KSR*, 550 U.S. at 402-03 (use of a finite number of identified, predictable solutions is likely the product of ordinary skill and common sense). A POSA could have readily implemented well-known color adjustment techniques and would have been motivated to do so to adjust color of the image before determining characteristics and conditions of property features to provide better accuracy in the assessment process. EX1003, ¶113.

10. Claim 17

Claim 17 depends from claim 11 and further recites, "*wherein the set of machine learning analysis algorithms are part of a neural network*."

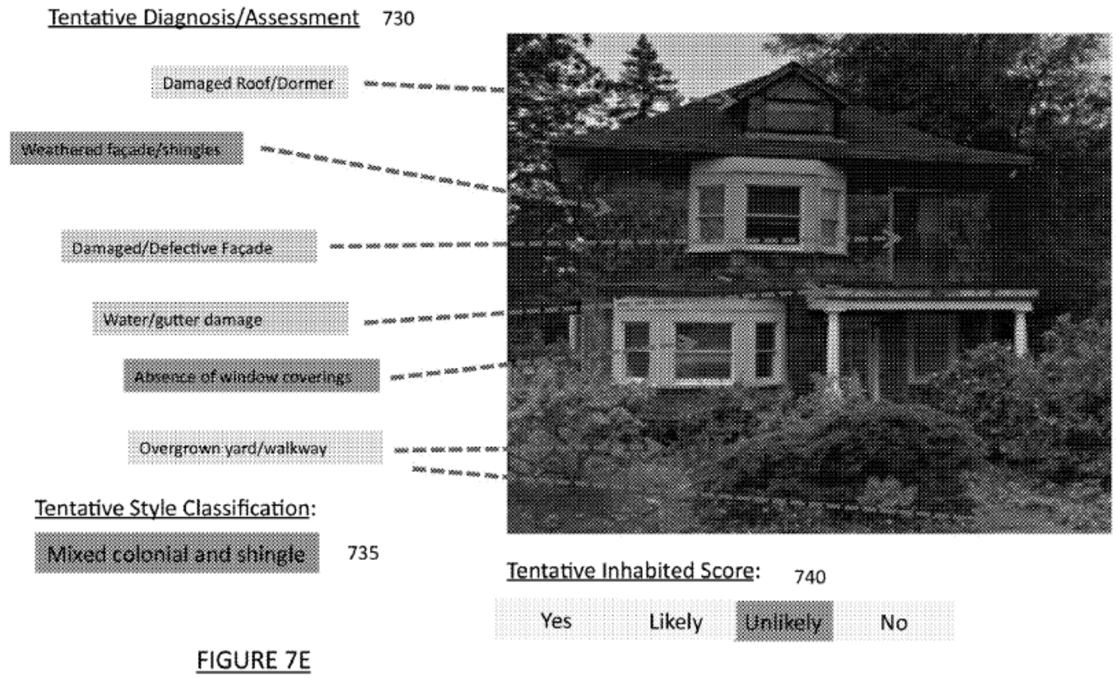
Gross teaches or renders obvious this claim. EX1003, ¶¶114-115. For the reasons set forth in elements [1.6] and [11.5], Gross teaches its Classifier Engine includes *a set of machine learning analysis algorithms*. EX1003, ¶116. Gross describes Classifier Engine uses neural networks to detect and extract features. EX1005, ¶77. Gross notes that 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. Gross—through the incorporated Jafri material—describes using "a hybrid neural network solution" to analyze image patterns. EX1008, 49; *see also Cook Biotech Inc. v. Acell, Inc.*, 460 F.3d 1365, 1376 (Fed. Cir. 2006) (incorporation by reference "provides a method for integrating material from various documents into a host document … by citing such material in a manner that makes clear that the material is effectively part of the host document as if it were explicitly contained therein." (quoting *Advanced Display Sys., Inc. v. Kent State Univ.*, 212 F.3d 1272, 1282 (Fed. Cir. 2000)). Thus, Gross teaches Classifier Engine (*set of machine learning analysis algorithms*) *are part of a neural network*. EX1003, ¶116.

11. Claim 18

Claim 18 depends from claim 11 and further recites, "*presenting, to a user at a computing device via a network, a graphical user interface comprising information regarding the set of characteristics and the condition of each feature of the at least one property feature*."

Gross teaches this claim. EX1003, ¶¶117-118.

Specifically, Gross describes its system 110 engages with users employing computing devices 112 and, in a preferred embodiment, system 110 is part of a website (i.e., *a graphical user interface*) which can be accessed through a conventional browser. EX1005, ¶43. Gross describes that a report of the results is *present[ed] to a user* (*at a computing device via a network*). EX1005, ¶96. The user can be provided with "classifying details about the building structure such as highlighted, tagged or annotated version of the building structure identified in FIG. 7E … to quickly see the assessment of the property as performed by Building Classifier Engine 150" (i.e., *information regarding the set of characteristics and the condition of each feature*). EX1005, ¶103; EX1003, ¶119. Figure 7E (depicted below) presents an embodiment of this visual assessment report and illustrates exemplary *set of characteristics* (e.g., a "dormer" roof, "shingle" façade) and *condition of property features* (e.g., "damaged" roof; "damaged/defective façade).



EX1005, FIG. 7E.

Gross further discloses that "[t]his data is presented in a list and visual form for a human reviewer." EX1005, ¶130. This "visual assessment report" is *a graphical user interface comprising information regarding the plurality of characteristics and the condition of each feature of the at least one property feature*. EX1003, ¶120. Although in the example shown in Figure 7E, the visual assessment report may not depict a plurality of characteristics for a feature, this is just an example of a report. Gross teaches *a set of characteristics* may be assessed for a feature for reasons set forth in element [1.6] (e.g., for a roof, "dormer" and "shingle"). And Gross describes "the user can be provided with additional classifying details about the building structure … identified in FIG. 7E" to allow the user "to quickly see the assessment of the property" (EX1005, ¶103)—i.e., Gross teaches its report can include the *set of characteristics* identified in its assessment process. EX1003, ¶120.

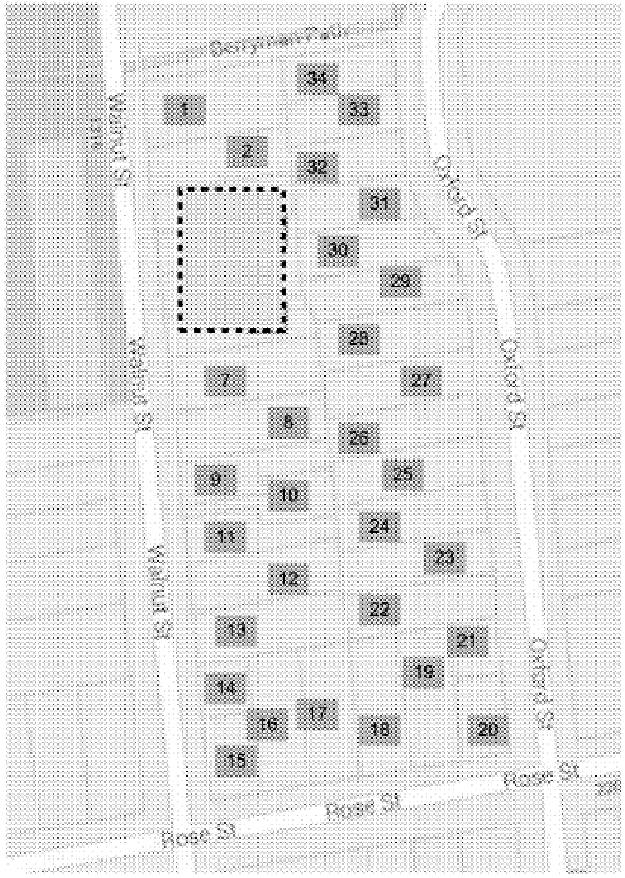
12. Claim 19

Claim 19 depends from claim 11 and further recites, "*presenting, to a user at a computing device via a network, a graphical user interface comprising a map view presenting the structure and at least a portion of the property location, wherein the map view comprises information regarding risk in view of the condition of each feature of the at least one property feature and/or cost in view of the condition of each feature*."

Gross renders obvious this claim. EX1003, ¶¶121-122. Gross discloses that "risk assessments, etc., can be based on an evaluation of an upkeep/maintenance evidenced for a particular property." EX1005, ¶238. Gross further discloses "correlations may be developed between property condition ratings" (i.e., the *condition of a property feature* described above in element [1.7]) and insurance metrics such as "type of claim, severity." EX1005, ¶238. Thus, Gross teaches *information regarding the risk* (its risk assessment) *in view of the condition of at least one property feature* (property condition rating, such as a roof in "poor" condition; or trees that are too close to a structure as described in claim 9). EX1003, ¶122.

And for the reasons described in claim 18, Gross teaches *presenting, a graphical user interface comprising information regarding the set of characteristics and the condition of each feature of the at least one property feature*. Gross does not explicitly disclose that the information presented in the graphical user interface includes the *risk in view of the condition of at least one property feature.* A POSA would have been motivated to modify the visual assessment report (*graphical user interface*) disclosed by Gross to include *information regarding the risk in view of the condition of the property feature*—taught by Gross's insurance risk assessment—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, ¶123.

Gross also does not explicitly disclose its graphical user interface comprises a *map view*. However, Gross does illustrate a *map view* in Figure 10 that "shows a typical city sized block in a residential neighborhood which can be assessed … in accordance with embodiments of the present teachings." EX1005, ¶137.



EX1005, FIG. 10.

Gross also describes another "interface 350" that "can take any convenient form known in the art, including by identifying the locations of listings on a map (virtual pins)." EX1005, ¶103. With respect to this interface, Gross discloses that "the use can be provided with additional classifying details about the building structure such as highlighted, tagged or annotated version of the building structure," which "allows the user to quickly see the assessment of the property as performed by Building Classifier Engine 150." EX1005, ¶103. A POSA would have been motivated to further modify Gross's visual assessment report to display in a *map view*, such as shown in Figure 10 and taught by "interface 350," so that the information for all the properties being assessed is displayed in a single report for ease of viewing by the user. EX1005, ¶103; EX1003, ¶¶124-125. Using a "map view" to convey the information would have been a simple design choice and a predictable variation easily implemented by a POSA. EX1003, ¶125.

13. Claim 20

Claim 20 depends from claim 11 and further recites, "*wherein the another machine learning analysis algorithm is trained to identify a first condition of one or more conditions of the property feature having at least two characteristics, wherein the at least two characteristics comprises at least two of the following: a type of material of the property feature, a distance between the property feature and another feature at the property location, and a shape of the property feature*."

Gross teaches this claim. EX1003, ¶¶126-127. For the reasons set forth in element [1.7] and [11.6], Gross teaches *another machine learning analysis algorithm trained to identify a first condition of one or more conditions of the property feature.* Gross also discloses additional attributes and characteristics that can be identified, "such as façade, eaves, windows, balcony, porch, arch, piers, columns, lattices, false timbering, ornamental, etc. along with specific types (i.e., façade (shingle, siding, brick, stone, horizontal boards, vertical boards, etc.) roof {pitched, double pitched, hipped, flat, metal, tile, shingle, slate, parapet, dormer, mansard, fascia, brackets, eaves, pent, pediment, etc.} and so on).” *Id.*, ¶57. The examples include *a type of material of the property feature and a shape of the property feature*—e.g., characteristics of a roof (*property feature*) can be identified as flat (*a shape of the property feature*) and metal (*a type of material of the property feature*). EX1005, ¶57; EX1003, ¶127.

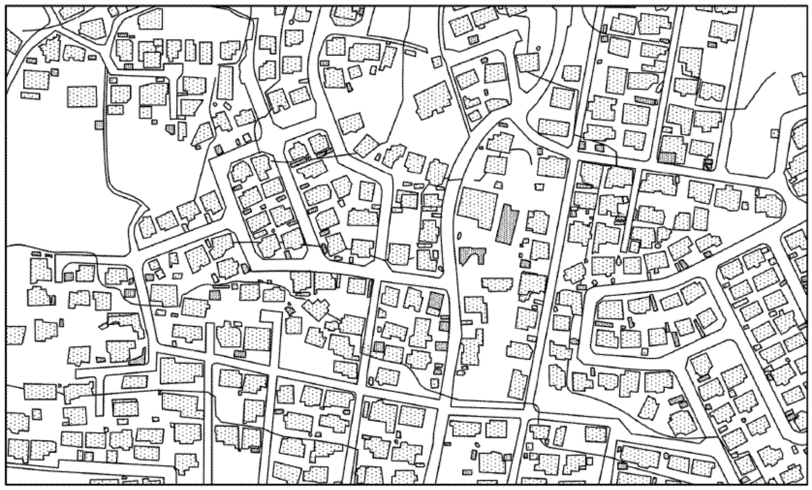
B. Ground 2: The combination of Gross and Furukawa renders obvious claims 2-5.

Claims 2-5 would have been obvious over Gross and Furukawa. EX1003, ¶¶14, 128.

1. Claim 2

Claims 2 depends from claim 1 and further recites, “*wherein the boundary information comprises a shape map*.”

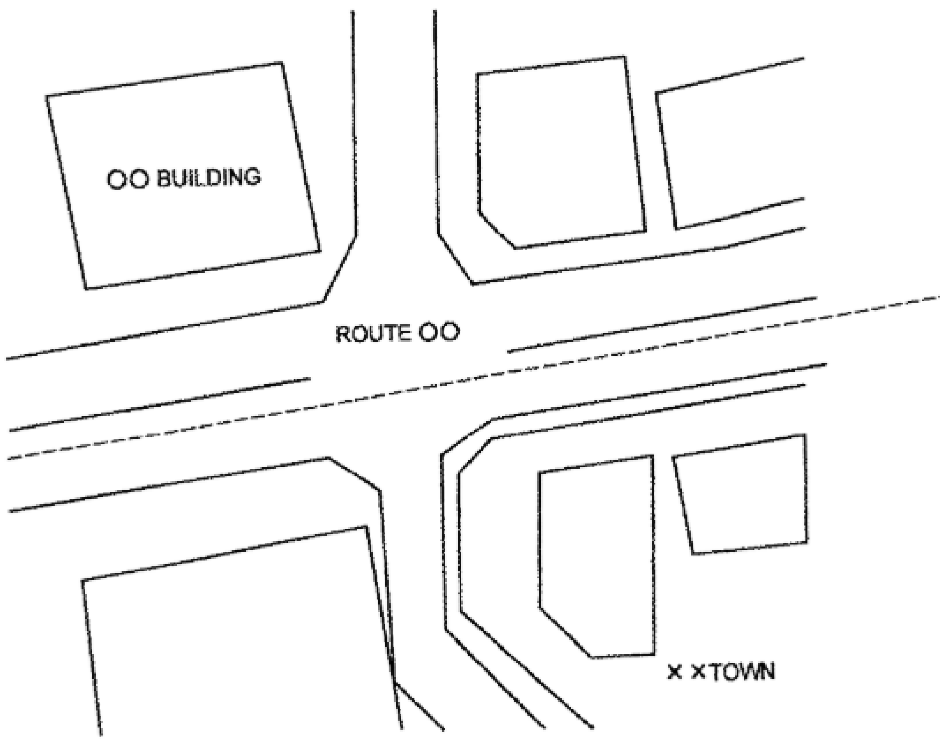
The combination of Gross and Furukawa teaches, or at least renders obvious, this claim. EX1003, ¶¶129-130. The ’491 patent describes a “shape map” as being “used to confirm [a] location of a particular property,” such as being “overlaid with a corresponding aerial image 102c to match properties with images.” EX1001, 7:58–62. Figures 5A and 5C of the ’491 patent (shown below) respectively depict an example “shape map” and an example result of overlaying shape outlines with an aerial image.



EX1005, FIG. 5A (top), FIG. 5C (bottom); EX1003, ¶¶131-132.

As explained in element [1.3], Gross describes a "building envelope" (the claimed *boundary information*) that *isolate[s] a property structure*. EX1003, ¶¶133. And for the reasons set forth in element [1.3], Gross further teaches applying different *boundary information to isolate the property location*. EX1003, ¶133. Gross does not explicitly disclose that its "[i]nformation" used to isolate the location of the "target address in question" is *a shape map*. EX1005, ¶¶162, 164.

Furukawa teaches *boundary information compris[ing] a shape map*. EX1003, ¶134. In particular, 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, FIG 7.

Furukawa further explains how 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 *boundary* *information compris[ing] a shape map*, because, similar to the ’491 patent it plots out the boundaries and shapes of various structures in an area and includes their location information. EX1003, ¶135. And, similar to the ’491 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, 7:51-57, *with* EX1007, 8:62-66; EX1003, ¶135.

A POSA would have been motivated to modify Gross to incorporate Furukawa’s teachings of using map data, because Gross and Furukawa provide a teaching, suggestion, and motivation to do so. EX1003, ¶¶136-137. 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 that tentative address information should require confirmation would have suggested to a POSA the benefit of incorporating additional data sources for such verification purposes. EX1003, ¶137. But Gross doesn’t describe how the address confirmation would occur and that would have motivated a POSA to seek out such solutions. 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 would serve as the confirmation mechanism Gross contemplates. EX1003, ¶138. 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, ¶138; *see KSR*, 550 U.S. at 418–421.

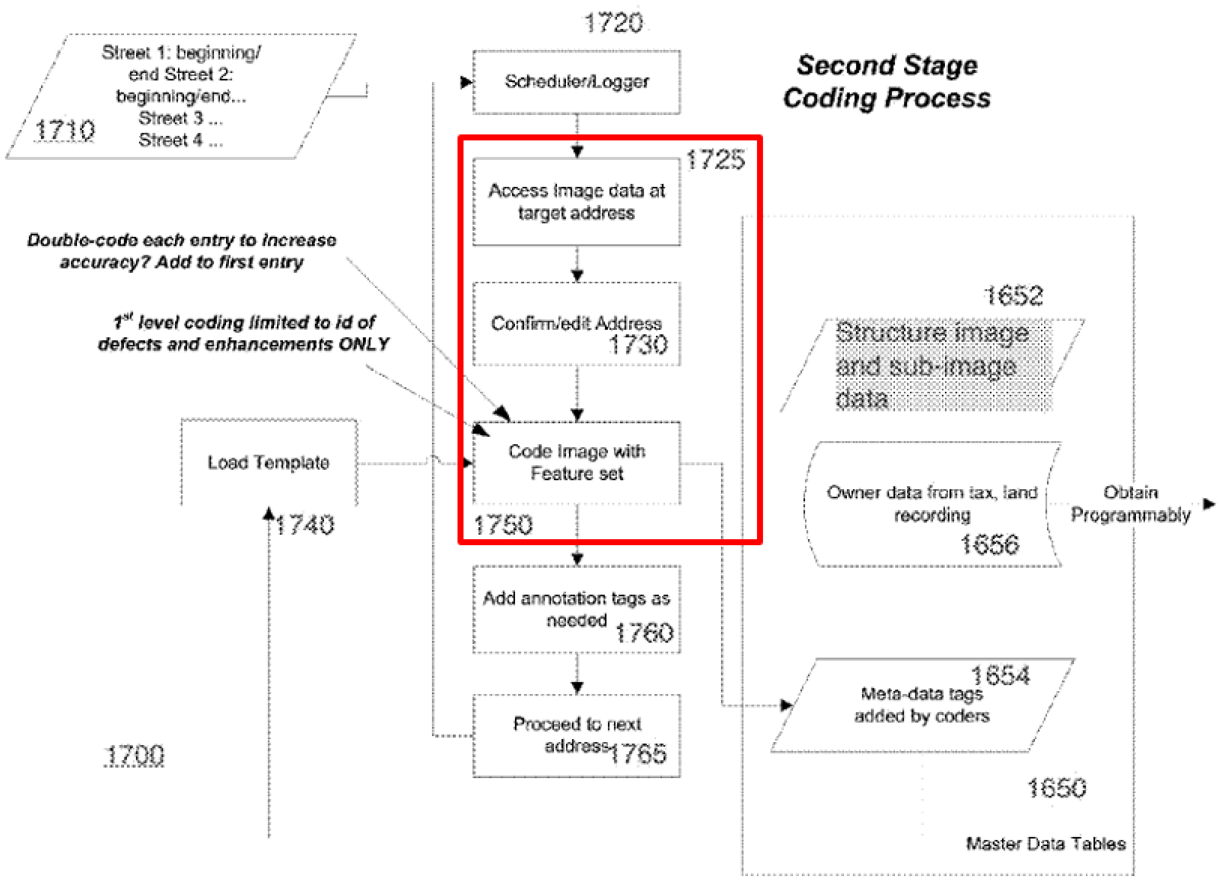
Therefore, the Gross-Furukawa combination teaches *boundary information compris[ing] a shape map* (e.g., map data including "information of the external shape of buildings"). EX1003, ¶139; EX1007, 15:19–31.

2. Claim 3

Claim 3 depends from claim 1 and further recites, "*wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to select the one or more images as a subset of the plurality of images responsive based at least in part on the boundary information*."

The Gross-Furukawa combination teaches, or at least renders obvious, this claim. EX1003, ¶¶140-141. Gross teaches *select[ing] the one or more images as a subset of the plurality of images*. EX1003, ¶141. As described above in element [1.2], Gross discloses maintaining and accessing multiple images of structures in its database (i.e., a *plurality of images*). For example, Gross discloses how "image 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 further teaches that 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.

Gross further discloses how during a structure classification process, "image data for a particular target address is obtained at step 1725, along with a tentative address tag" and how the address tag is "confirmed at step 1730" to ensure the system "contain[s] accurate information for a particular address." EX005, ¶170. Then at step 1750, the system proceeds to "identify, classify and rate a condition of features" in the image. *Id*., 172. This process is illustrated in Figure 17 of Gross (annotated below).



EX1005, FIG. 17 (annotated).

This confirmation process is *select[ing] the one or more images as a subset of the plurality of images*, because in the combination of Gross and Furukawa, the images with confirmed address tags would be used for classification at step 1750 (as opposed to images whose address tags cannot be confirmed). EX1003, ¶142.

As described above, Furukawa provides a solution for confirming addresses associated with an image of a property using map data that includes "information of the external shape of buildings" (*boundary information*) and "identification information." EX1003, ¶143; EX1007, 15:19–31. In particular, Furukawa's system first "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 6." EX1007, 32:65–33:7.

Furukawa's system then determines whether this boundary (extracted from the satellite images) matches the boundary of the same building in the stored map data. Specifically, Furukawa teaches that 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 6." 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 system determines whether the boundaries 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 claim 2. EX1003, ¶¶144-146. As explained, 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, ¶146.

Thus, the Gross-Furukawa combination teaches, or at least renders obvious, *select[ing]* (e.g., proceeding with classification) *the one or more images* (e.g., images with confirmed address tags) *as a subset of the plurality of images* (e.g., images of a property location) *responsive based at least in part on the boundary information* (e.g., boundary in "satellite image" matching a boundary from "map data"). EX1003, ¶147; EX1007, 15:19–31, 32:65–33:7.

3. Claim 4

Claim 4 depends from claim 3 and further recites, "*wherein selecting the one or more images comprises identifying the one or more images as most closely matching the boundary information*."

The Gross-Furukawa combination teaches or at least renders obvious this claim. EX1003, ¶¶148-149. As described in claim 3, Furukawa's system determines whether a boundary extracted from the satellite images matches the boundary of the same building in the stored map data 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." EX1007, 32:17–24, 23:56–24:2.

A POSA would have found it obvious and been motivated to modify Gross to incorporate Furukawa's boundary matching teachings for at least the same reasons provided for claims 2 and 3. EX1003, ¶150. As explained, 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, ¶150.

Thus, the Gross-Furukawa combination teaches, or at least renders obvious, *wherein selecting the one or more images* (e.g., proceeding with classification) *comprises identifying the one or more images as most closely matching the boundary information* (e.g., boundary in "satellite image" matching a boundary from "map data"). EX1003, ¶151; EX1007, 15:19–31, 32:65–33:7.

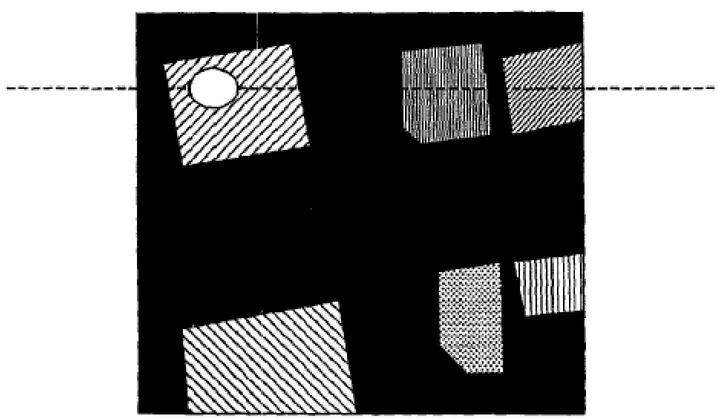
4. Claim 5

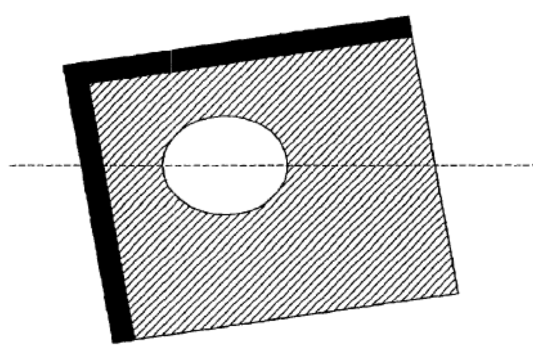
Claim 5 depends from claim 1 and further recites, "*wherein applying the boundary information comprises cropping each respective image*."

The Gross-Furukawa combination renders obvious this claim. EX1003, ¶¶152-153. For instance, Gross discloses how "[d]uring or after the coding [e.g., classification] process, the image for the structure can be automatically divided by an image processing system into different sub-images of different size," "which correspond to distinct building elements" and can be "selected by the coder" "using a conventional image cropping tool, or automatically identified and bounded by an automated classifier" (i.e., *cropping*). EX1005, ¶174; *see also* EX1005, ¶76 (describing how Gross's images "may be cropped" as part of an image pre-processing or normalization process). Gross explains that this cropping process is performed "to identify the element and its condition" and "be used in reports [and] responding to queries." EX1005, ¶174. Gross does not explicitly describe whether these teachings necessarily involve *applying boundary information*.

To the extent that Aon may argue that the "selected by the coder" and "identif[y] and bound" descriptions in Gross do not teach *cropping* when *applying boundary information*, Furukawa teaches this. EX1003, ¶¶154-155. For instance, Furukawa describes obtaining "three-dimensional data images" (e.g., "DEM (Digital Elevation Map) Data") and "superimposing the map data on the three-dimensional data in such a manner that the same points match each other." EX1007, 13:1:3, 1:17–18, 7:5. As described in claim 2, the "map data" in Furukawa includes "information of the external shape of buildings," which is *boundary information* that defines the perimeter of a building structure. EX1007, 15:19–31. Furukawa further describes how "[a]fter the map data is superimposed on the three-dimensional [data], the three-dimensional data included in a closed area surrounded by vector data is set for each building as an area corresponding to the building by the area setting means 32." EX1007, 13:4–7. For each building in the map data, the three-dimensional data is set to the area within the external shape of the building as the candidate area of each building. EX1007, 9:13–17, 10:18-24; EX1003, ¶154.

Figure 6A of Furukawa depicts an "example three-dimensional data image" (EX1007, 7:5), and Figure 8A depicts an example "three-dimensional data set by area setting means" (EX1007, 7:10), both of which are reproduced below:





EX1007, FIG. 6A (top), FIG. 8A (bottom).

Here, the “area setting means” is *cropping* the *image* when *applying the boundary information*, because it is using (i.e., *applying*) the “closed area surrounded by vector data” (i.e., the map data’s *boundary information*) to obtain “the candidate area of each building” from the “three-dimensional data image.” EX1003, ¶155; EX1007, 13:4–7, 7:5, 9:13–17.

A POSA would have found it obvious and been motivated to modify Gross’s classification system to incorporate Furukawa’s boundary-based cropping techniques because the combined Gross-Furukawa system would provide more precise and accurate identification of individual building structures within images. EX1003, ¶156. The modification would have been a predictable variation of Gross, because Gross explicitly contemplates using “automated classifier[s]” to “identif[y] and bound” building elements, and Furukawa’s superimposition and area setting techniques represent straightforward applications of known image processing and geographic data integration methods that a POSA would routinely use to enhance the automated classification and bounding capabilities contemplated by Gross. EX1003, ¶156; EX1005, ¶174; EX1007, 15:19–31, 13:1:3; *see KSR*, 550 U.S. at 417. A POSA would also have readily been able to implement Furukawa’s techniques in Gross because both systems similarly use automated image processing to analyze building structures, with Gross providing the framework for structure classification, and Furukawa providing complementary techniques for isolating structures using established boundary data. EX1003, ¶156.

Thus, the Gross-Furukawa combination teaches, or at least renders obvious, *wherein applying the boundary information* (e.g., map data including "information of the external shape of buildings") *comprises cropping each respective image* (e.g., "set[ting] the three-dimensional data included in the area within the external shape of the building as the candidate area of each building"). EX1003, ¶157; EX1007, 13:1-3, 9:13–17, 15:19–31.

C. Ground 3: The combination of Gross and Davis renders obvious claims 12-15.

Claims 12-15 would have been obvious over Gross and Davis. EX1003, ¶¶14, 158.

1. Claim 12

Claim 12 depends on claim 11 and further recites, "*applying, by the processing circuitry, a risk profile corresponding to at least one risk to the property location or the structure thereon in view of the classification of the condition of each of the one or more property features to determine a damage risk to the property location*."

The Gross-Davis combination renders obvious this claim this claim. EX1003, ¶¶159-160. Gross discloses that "risk assessments, etc., 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 insurance metrics such as "type of claim, severity." EX1005, ¶238. These risk assessments are determinations of *a damage risk to the property location*. EX1003, ¶160. And Gross teaches risk profiles through its description that these correlations may associate maintenance condition ratings of a property attribute (i.e., the *condition of a property feature* described above in element [1.7], such as a roof in "poor" condition or trees that are too close to a structure as described in claim 9) with higher risk of damage (e.g., from arson). EX1005, ¶238. Obtaining a "risk assessment" for a disaster using "correlations … developed between property condition ratings … and … severity" would involve *applying a risk profile* (e.g., the "correlations") *corresponding to at least one risk* (e.g. "arson") and *the classification of the condition of property features* (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.

To the extent Aon may argue the correlations are not *risk profiles*, Davis explicitly discloses such *risk profiles*. EX1003, ¶161. 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. 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. Davis describes "risk analysis unit 34 may access rules specifying that dead branches … are prone to cause at least a certain amount of damage." EX1006, 10:31-34. Davis further describes other risk information based on a chance that a dead or dying tree will fall over and a branch in close proximity to a chimney will cause damage due to backdraft. EX1006, 11:30-38. These rules may also specify whether trees of certain species more likely to catch fire. *See* EX1006, 11:25–39; EX1003, ¶161. Risk analysis unit 34 then applies the "access[ed] rules" to "estimate a likelihood that damage will occur to some portion of the property." EX1006, 11:30–34. In other words, Davis more explicitly teaches its risk analysis unit *appl[ies]* rules (*a risk profile*) *corresponding to a condition of a property feature* (tree location/condition) *to determine a damage risk to the property location*. EX1003, ¶161.

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 applying a risk profile to determine a damage risk because the combined Gross-Davis system would provide an efficient method for the insurer to determine the risk of property damage and to adjust risk profiles as needed. EX1003, ¶162. The modification would have been a predictable variation of Gross, because Gross explicitly contemplates developing "correlations," and Davis's specific risk correlation techniques—implemented through "rules stored in [a] data storage"—represent straightforward applications of known data correlation and rule-based processing methods that a POSA would routinely use to establish the correlations contemplated by Gross. EX1003, ¶162; EX1006, 10:23–25; *see KSR*, 550 U.S. at 417 ("If a person of ordinary skill can implement a predictable variation, §103 likely bars its patentability."). And a POSA would have readily been able to implement Davis's techniques in Gross because both systems similarly use image analysis and machine learning to analyze features of properties to determine insurance risk. EX1003, ¶162.

The Gross-Davis combination would, therefore, render obvious *applying a disaster risk profile* (e.g., the "access[ed] rules") *corresponding to at least one risk to the property location* (e.g., risk from wildfire) *in view of the classification of the condition of each of the one or more property features* (e.g., a roof in poor condition, a tree that is too close to the structure) *to determine a damage risk to the property location*. EX1003, ¶163.

2. Claim 13

Claim 13 depends on claim 12 and further recites, "*wherein the at least one risk comprises a fire or an explosion*."

The combination of Gross and Davis teaches this claim. EX1003, ¶¶164-165. Gross describes risk assessment due to a "risk of arson" (*a fire*). EX1005, ¶238. And Davis describes analyzing features of property "to determine whether particular homes are at high risk of fire damage." EX1006, 11:18-25. For the reasons described in claim 12, the Gross-Davis combination teaches the risk assessment is based on *the classification condition of the one or more property features* (e.g., whether property contains dead or dying trees or trees that are too close to a structure). EX1003, ¶165; *see* EX1006, 11:25-36.

3. Claim 14

Claim 14 depends on claim 12 and further recites, "*wherein applying the risk profile comprises modeling vulnerability of the property location to damage in view of the at least one risk*."

The Gross-Davis combination renders obvious this claim. EX1003, ¶166-167. For the reasons described in claim 12, Gross-Davis renders obvious *applying a risk profile corresponding to at least one risk to the property location or the structure thereon*. As discussed, Gross describes its risk correlations are "developed between property condition ratings … and type of claim, severity, etc." EX1005, ¶238. Gross's development of risk correlations teaches *modeling vulnerability of the property location to damage in view of the at least one risk* (e.g., a risk correlation modeling vulnerability of the property due to arson because the property condition is not occupied). EX1003, ¶167; *see* EX1005, ¶238.

Davis also teaches *modeling vulnerability of the property location to damage in view of the at least one risk*. EX1003, ¶168. For example, Davis describes its risk analysis unit may estimate a likelihood that damage will occur to the property (i.e., *modeling vulnerability of the property location to damage*), such as a percent chance that a branch in close proximity to a chimney will cause damage due to backdraft (*in view of the at least one risk*). EX1006, 11:32-29.

Thus, the Gross-Davis combination renders obvious this claim. EX1003, ¶169.

4. Claim 15

a. [15.1] The method of claim 12, further comprising: determining, by the processing circuitry, a characteristic of a neighboring structure at the property location in addition to the structure;

Gross teaches element [15.1]. EX1003, ¶170. Gross describes that structural element fields (classified by Classifier Engine as part of its assessment process) for a property include "an identification of each structural element presented in the property" and "a condition of such element." EX1005, ¶¶115-16. Gross discloses a particular property "may have multiple structural elements" and the "same information" (classification/assessment information) "is made for appurtenant elements … including for example ancillary buildings, fences, garages, vehicles, foliage, etc." (i.e., *neighboring structures*). EX1005, ¶116. In other words, Gross teaches *determining a characteristic of a neighboring structure*. EX1003, ¶170. Examples of *neighboring structures* include the appurtenant elements (e.g., garage, retaining wall, fence), and natural structures, such as trees and landscaping.

EX1005, ¶¶67-68.

b. [15.2] wherein applying the risk profile comprises applying the risk profile in view of the classification of the condition of a first feature of the one or more property features and the characteristic of the neighboring structure.

The Gross-Davis combination renders obvious element [15.2]. EX1003, ¶171. As described above, Gross discloses that "correlations may be developed between property condition ratings" (i.e., the *conditions* described in element [1.6]) and insurance metrics such as "number of claims filed, type of claim, severity, etc." EX1005, ¶238. And Davis describes that "risk analysis unit 34" "may analyze the feature(s) to determine a risk of damage to at least a portion of the property" and the rules may, for example, depend "on the type of roof construction" (i.e., *appl[ies] a risk profile in view of the characteristic of the structure*). EX1006, 10:19-38.

In light of Davis's teachings, a POSA would have understood or found obvious that in addition to the *applying a risk profile in view of the classification of the condition of the first feature of the structure* (e.g., a tree that is too close as described in claim 9), the insurance risk assessment taught by Gross-Davis (*applying the risk profile*) would have also been based, at least in part, on *the characteristic of the neighboring structure* (e.g., characteristic of a roof of a structure) because it is common sense the risk varies depending on the characteristics of a structure (e.g., a metal roof would have less risk of damage for certain types of disasters than a slate roof). EX1003, ¶172; *see KSR*, 550 U.S. 398 at 421 (factfinders may consider common sense in obviousness inquiry).

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. 11,030,491

Claim 1

Element	
[1.P]	A system for automatically assessing features of a property location comprising a structure, the system comprising:
[1.1]	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
[1.2]	access a plurality of images of the property location including the structure;
[1.3]	apply boundary information to one or more images of the plurality of images to isolate the property location or the structure thereon within each respective image; and
[1.4]	classify a condition of one or more property features of the property location, wherein classifying comprises, for each feature of the one or more features,
[1.5]	extracting the respective feature from each image of at least one image of the one or more images,
[1.6]	applying a set of machine learning analysis algorithms to at least a portion of each image of the at least one image to determine a set of characteristics of the respective property feature, wherein each algorithm of the first set of machine learning analysis algorithms is trained to identify one or more characteristics of the set of characteristics, and
[1.7]	applying another machine learning analysis algorithm to at least a portion of each image of the at least one image to classify a condition of the respective property feature, wherein the condition is classified as a respective classification of a set of possible classifications, and the another machine learning analysis algorithm is trained to identify one or more conditions of property locations and/or structures thereon having the set of characteristics of the respective property feature.

Claim 2

Element	
[2]	The system of claim 1, wherein the boundary information comprises a shape map.

Claim 3

Element	
[3]	The system of claim 1, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to select the one or more images as a subset of the plurality of images responsive based at least in part on the boundary information.

Claim 4

Element	
[4]	The system of claim 3, wherein selecting the one or more images comprises identifying the one or more images as most closely matching the boundary information.

Claim 5

Element	
[5]	The system of claim 1, wherein applying the boundary information comprises cropping each respective image.

Claim 6

Element	
[6.1]	The system of claim 1, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to determine at least one property characteristic of the structure including one or more of an occupancy type, a number of stories, or a siding type,
[6.2]	wherein: determining the at least one property characteristic comprises, for each characteristic of the at least one property characteristic, selecting a given image of the at least one image for determining the respective characteristic, and

[6.3]	applying a machine learning analysis algorithm trained to identify the respective property characteristic to the given image to determine the respective characteristic.

Claim 7

Element	
[7]	The system of claim 6, wherein the given image corresponding to a first property characteristic of the at least one property characteristic is a terrestrial image.

Claim 8

Element	
[8]	The system of claim 1, wherein a first feature of the at least one feature of the property location comprises a natural feature.

Claim 9

Element	
[9]	The system of claim 8, wherein the instructions, when executed by the processing circuitry, cause the processing circuitry to determine a distance between the natural feature and the property location.

Claim 10

Element	
[10]	The system of claim 1, wherein assessing a first feature of the at least one feature of the property location comprises comparing the classification of the first feature to a historic condition classification of the first feature.

Claim 11

Element	
[11.P]	A method for automatically assessing risk damage to a property, the method comprising:

[11.1]	accessing, by processing circuitry, a plurality of images of a property location including a structure;
[11.2]	applying, by the processing circuitry, boundary information to one or more images of the plurality of images to isolate the property location or the structure thereon within each respective image; and
[11.3]	classifying, by the processing circuitry, a condition of one or more property features of the property location, wherein classifying comprises, for each feature of the one or more property features,
[11.4]	adjusting each image of the at least one image to obtain an adjusted image for analyzing the respective feature,
[11.5]	applying a set of machine learning analysis algorithms to at least a portion of each image of the at least one adjusted image to determine a set of characteristics of the respective property feature, wherein each algorithm of the first set of machine learning analysis algorithms is trained to identify one or more characteristics of the set of characteristics, and
[11.6]	applying another machine learning analysis algorithm to at least a portion of each image of the at least one image to classify a condition of the respective property feature, wherein the condition is classified as a respective classification of a set of possible classifications, and the another machine learning analysis algorithm is trained to identify one or more conditions of property locations and/or structures thereon having the set of characteristics of the respective property feature.

Claim 12

Element	
[12]	The method of claim 11, further comprising applying, by the processing circuitry, a risk profile corresponding to at least one risk to the property location or the structure thereon in view of the classification of the condition of each of the one or more property features to determine a damage risk to the property location.

Claim 13

Element	

[13]	The method of claim 12, wherein the at least one risk comprises a fire or an explosion.

Claim 14

Element	
[14]	The method of claim 12, wherein applying the risk profile comprises modeling vulnerability of the property location to damage in view of the at least one risk.

Claim 15

Element	
[15.1]	The method of claim 12, further comprising: determining, by the processing circuitry, a characteristic of a neighboring structure at the property location in addition to the structure;
[15.2]	wherein applying the risk profile comprises applying the risk profile in view of the classification of the condition of a first feature of the one or more property features and the characteristic of the neighboring structure.

Claim 16

Element	
[16]	The method of claim 11, wherein adjusting each image comprises adjusting color of the at least one image.

Claim 17

Element	
[17]	The method of claim 11, wherein the set of machine learning analysis algorithms are part of a neural network.

Claim 18

Element	

[18]	The method of claim 11, further comprising presenting, to a user at a computing device via a network, a graphical user interface comprising information regarding the set of characteristics and the condition of each feature of the at least one property feature.

Claim 19

Element	
[19]	The method of claim 11, further comprising presenting, to a user at a computing device via a network, a graphical user interface comprising a map view presenting the structure and at least a portion of the property location, wherein the map view comprises information regarding risk in view of the condition of each feature of the at least one property feature and/or cost in view of the condition of each feature.

Claim 20

Element	
[20]	The method of claim 11, wherein the another machine learning analysis algorithm is trained to identify a first condition of one or more conditions of the property feature having at least two characteristics, wherein the at least two characteristics comprises at least two of the following: a type of material of the property feature, a distance between the property feature and another feature at the property location, and a shape of the property feature.

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

1. This Petition for *Inter Partes* Review complies with the type-volume limitation of 14,000 words, comprising 12,573 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. 11,030,491** 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. 11,030,491

Respectfully submitted,

STERNE, KESSLER, GOLDSTEIN & FOX PLLC

/XX/

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