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(54) **METHODS AND APPARATUS FOR AUTOMATED INSURANCE CLAIM PROCESSING USING HISTORICAL DATA**

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G06F 16/2458 (2019.01)
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(Continued)

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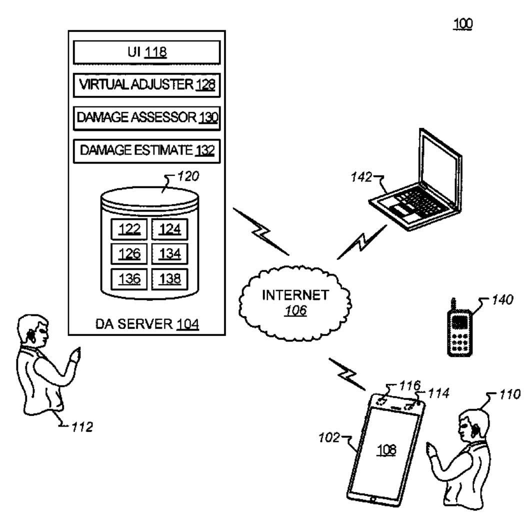
(57) **ABSTRACT**

Example methods, apparatus and articles of manufacture to process insurance claims using historical data are disclosed herein. An example method of estimating damage to a vehicle, the method includes receiving, using one or more processors, one or more images of damage to a vehicle, identifying, using one or more processors, one or more additional vehicles having damage similar to the damage to the vehicle based on the one or more images, determining, using one or more processors, a likelihood that a part of the vehicle is damaged based on damage associated with the one or more additional vehicles, and determining, using one or more processors, whether to include the part in a repair estimate based on the likelihood.

20 Claims, 4 Drawing Sheets



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(58) **Field of Classification Search**
USPC 705/4
See application file for complete search history.

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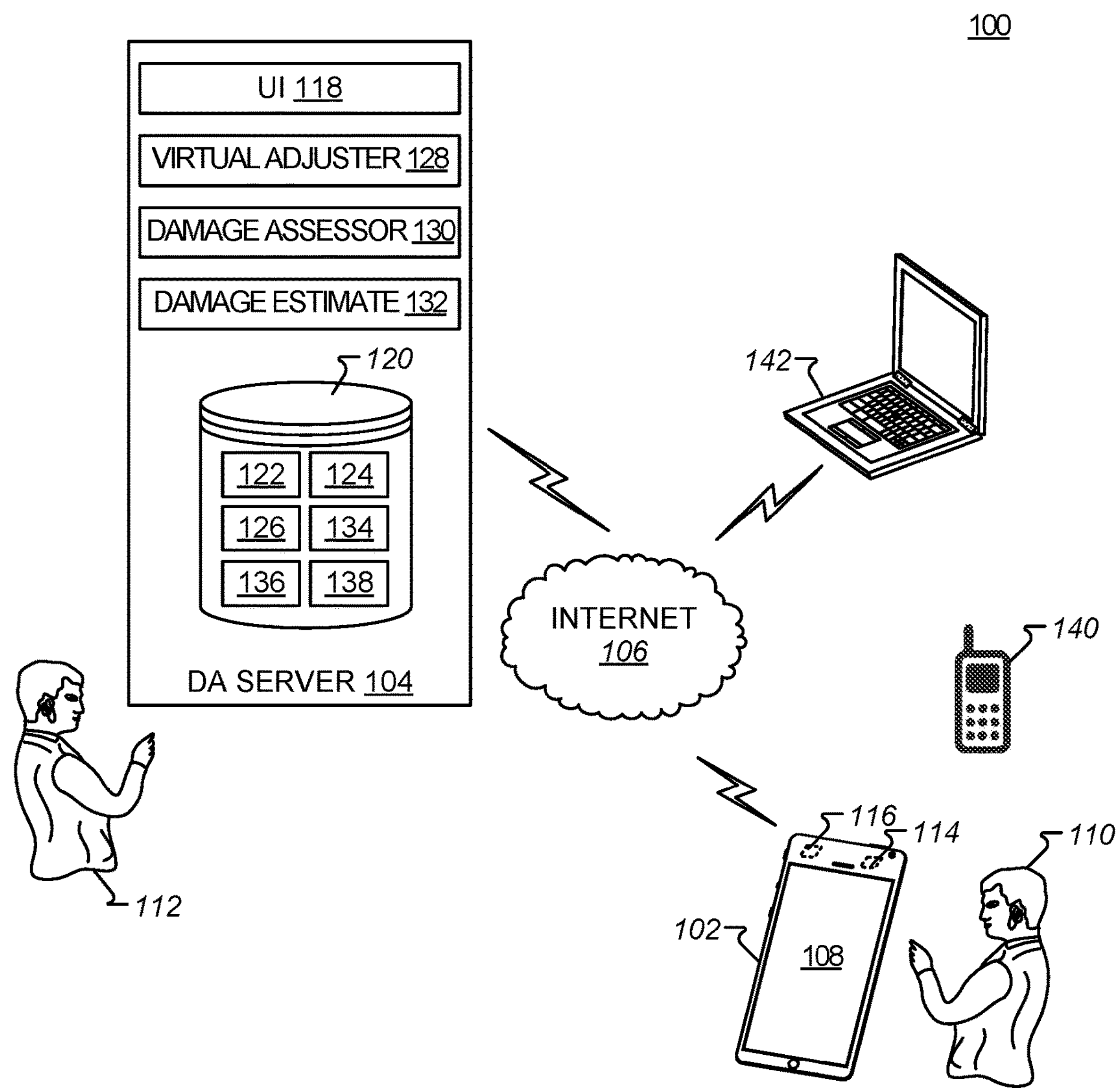
100
UI 118
VIRTUAL ADJUSTER 128
DAMAGE ASSESSOR 130
DAMAGE ESTIMATE 132
120
122
124
126
134
136
138
DA SERVER 104
INTERNET
106
142
140
116
114
110
102
108
112

FIG. 1

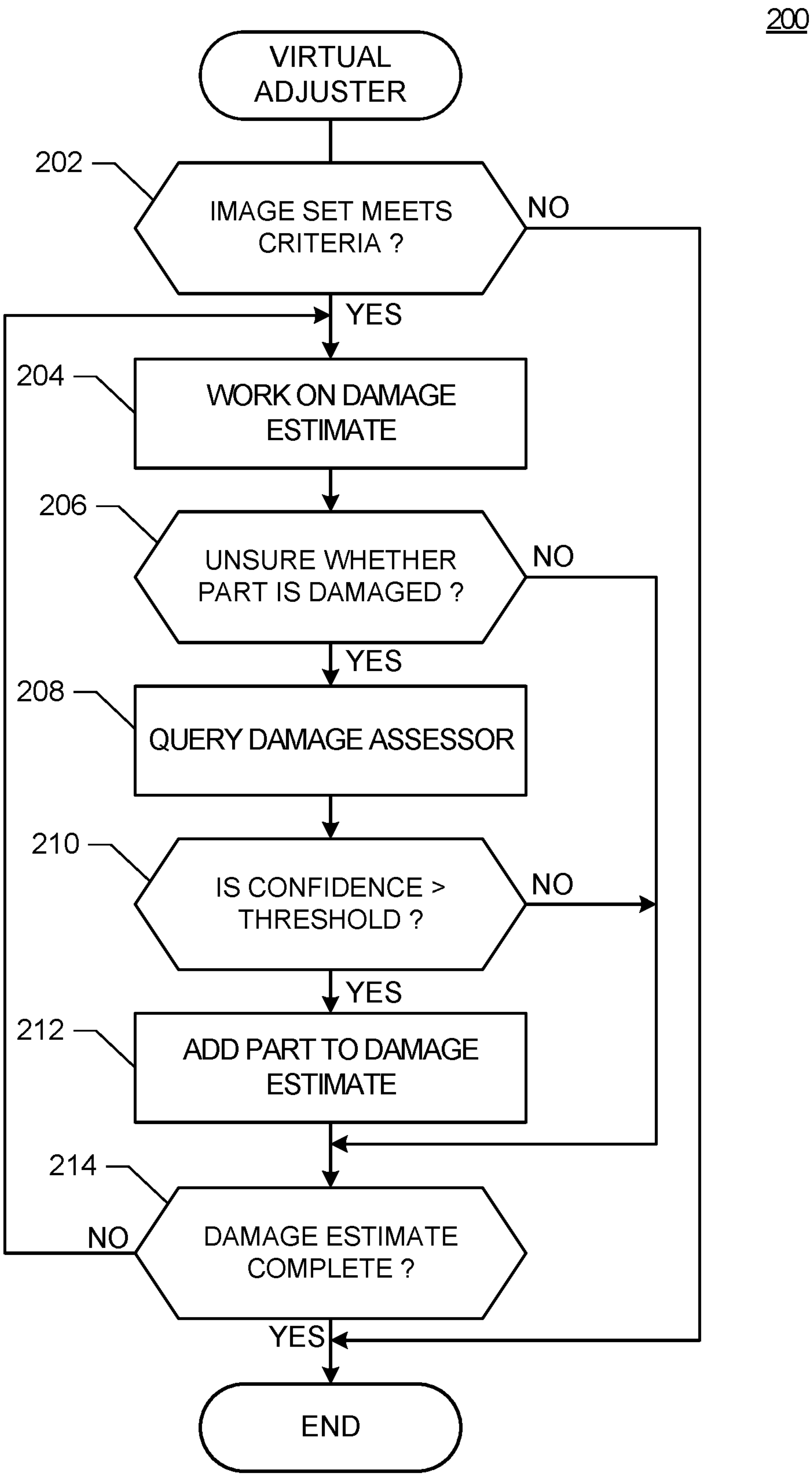
200
VIRTUAL ADJUSTER
202
IMAGE SET MEETS CRITERIA ?
NO
YES
204
WORK ON DAMAGE ESTIMATE
206
UNSURE WHETHER PART IS DAMAGED ?
NO
YES
208
QUERY DAMAGE ASSESSOR
210
IS CONFIDENCE > THRESHOLD ?
NO
YES
212
ADD PART TO DAMAGE ESTIMATE
214
DAMAGE ESTIMATE COMPLETE ?
NO
YES
END

FIG. 2

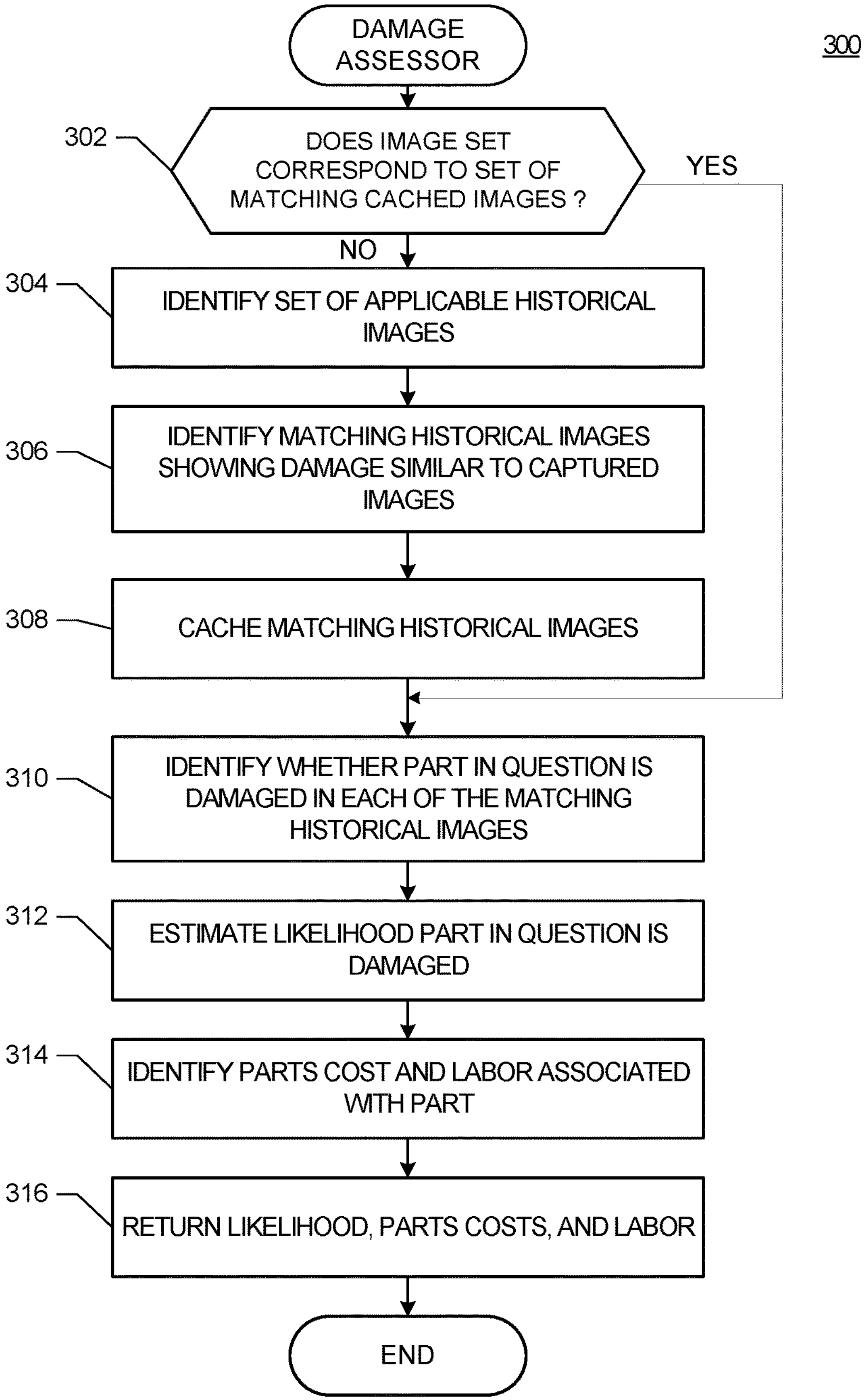
300
DAMAGE ASSESSOR
302
DOES IMAGE SET CORRESPOND TO SET OF MATCHING CACHED IMAGES ?
YES
NO
304
IDENTIFY SET OF APPLICABLE HISTORICAL IMAGES
306
IDENTIFY MATCHING HISTORICAL IMAGES SHOWING DAMAGE SIMILAR TO CAPTURED IMAGES
308
CACHE MATCHING HISTORICAL IMAGES
310
IDENTIFY WHETHER PART IN QUESTION IS DAMAGED IN EACH OF THE MATCHING HISTORICAL IMAGES
312
ESTIMATE LIKELIHOOD PART IN QUESTION IS DAMAGED
314
IDENTIFY PARTS COST AND LABOR ASSOCIATED WITH PART
316
RETURN LIKELIHOOD, PARTS COSTS, AND LABOR
END

FIG. 3

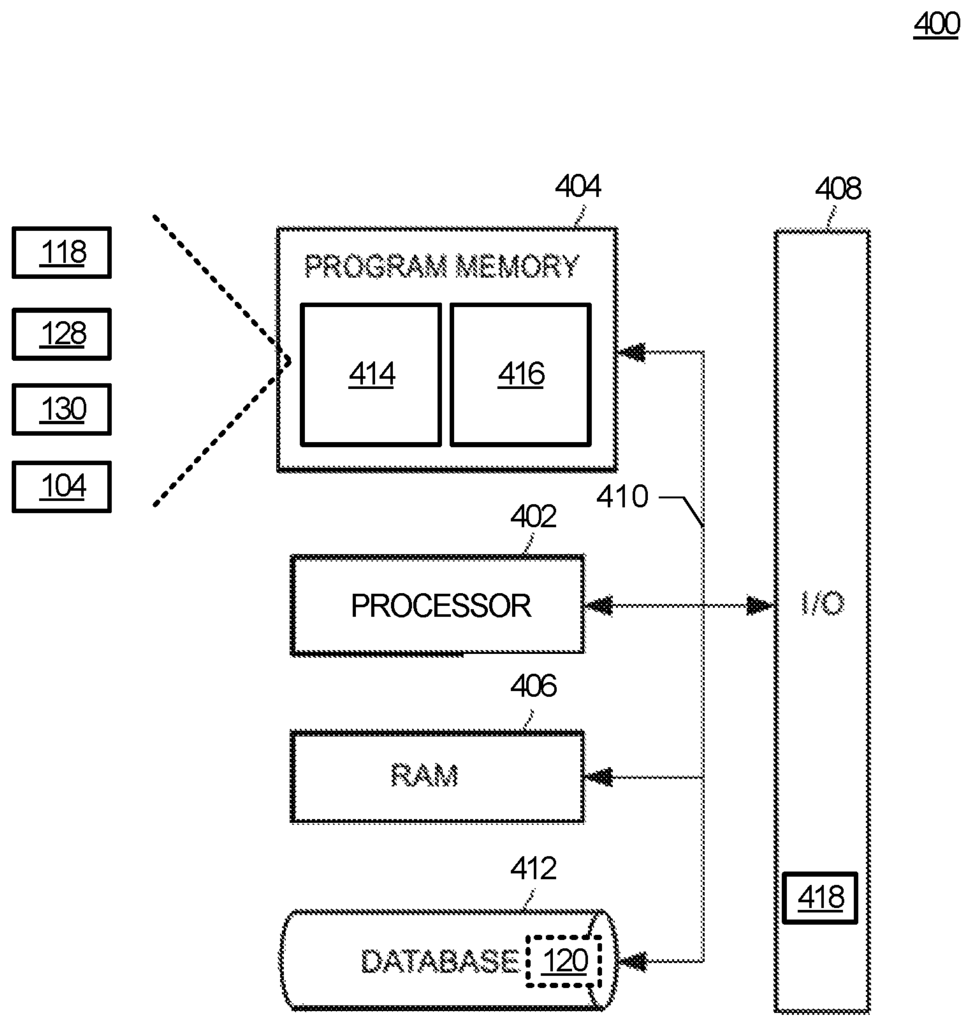
400
404
408
118
128
130
104
PROGRAM MEMORY
414
416
410
402
PROCESSOR
I/O
406
RAM
412
418
DATABASE
120

FIG. 4

METHODS AND APPARATUS FOR AUTOMATED INSURANCE CLAIM PROCESSING USING HISTORICAL DATA

RELATED APPLICATION

This patent claims the benefit of and priority to U.S. Provisional Patent Application Ser. No. 62/815,711, which was filed on Mar. 8, 2019. U.S. Provisional Patent Application Ser. No. 62/815,711 is hereby incorporated herein by reference in its entirety.

FIELD OF THE DISCLOSURE

This disclosure relates generally to insurance claim processing, and, more particularly, to methods, apparatus and articles of manufacture to process insurance claims using historical data.

BACKGROUND

Damage may occur to a vehicle under a number of circumstances. For example, acts of nature such as inclement weather, animals, and/or human-involved accidents may cause damage to a vehicle. The damage may be unsightly or even dangerous and, thus, require restorative repairs.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram of an example system to capture images of damage and to estimate a cost to repair the damage.

FIG. **2** is a flowchart representative of an example method, hardware logic or machine-readable instructions for implementing the example virtual appraiser of FIG. **1**, in accordance with disclosed embodiments.

FIG. **3** is a flowchart representative of an example method, hardware logic or machine-readable instructions for implementing the example damage assessor of FIG. **1**, in accordance with disclosed embodiments.

FIG. **4** is a block diagram of an example computing system that may be used to carry out the various user interfaces, methods, functions, etc., for processing insurance claims using historical data, in accordance with disclosed embodiments.

The figures depict embodiments of this disclosure for purposes of illustration only. One skilled in the art will readily recognize from the following discussion that alternate embodiments of the structures and methods illustrated herein may be employed without departing from the principles set forth herein.

In general, the same reference numbers will be used throughout the drawing(s) and accompanying written description to refer to the same or like parts. The figures are not to scale. Connecting lines or connectors shown in the various figures presented are intended to represent example functional relationships and/or physical or logical couplings between the various elements.

DETAILED DESCRIPTION

In the event that damage to property (e.g., a motor vehicle, a car, a truck, a motorcycle, a boat, etc.) arises from a damage-causing event, claim adjusters are tasked with assessing the extent of the damage to determine an estimate of the cost to complete repairs. Generally speaking, the adjuster must obtain measurements and images of damage

(e.g., the size of a damaged area, which components of the vehicle that are damaged, etc.) as well as other relevant information to assess the extent of the damage. A damaged vehicle may require multiple assessments to get an accurate evaluation of the damage. This process of receiving one or more assessments may be time-consuming and costly.

To reduce or eliminate some or all of these, or other problems of conventional insurance claim processing, example methods, apparatus and articles of manufacture to process insurance claims using historical data are disclosed. Disclosed examples use images captured of damage and historical damage information for other vehicles to estimate components that are likely to be damaged, and to estimate the cost associated with repairing these components. While, for sake of clarity, examples are described herein with respect to damage to vehicles, aspects of this disclosure also relate to damage to other forms of property (e.g., a house, a garage, etc.). Further, while examples are described herein with reference to insurance claims, disclosed methods, apparatus, and articles of manufacture may be used to estimate what is required to repair damage, carry out an improvement, etc. that is not related to an insurance claim.

Reference will now be made in detail to non-limiting examples, some of which are illustrated in the accompanying drawings.

FIG. **1** is a block diagram of an example system **100** to capture images of damage, and to estimate a cost to repair the damage. The system **100** may include front end components (e.g., a client device **102**) and backend components (e.g., a damage assessment (DA) server **104**) in communication with each other via one or more computer networks, such as the Internet **106**, a local area network (LAN), a metropolitan area network (MAN), a wide area network (WAN), a mobile, a wired network, a Wi-Fi® network, a cellular network, a wireless network, a private network, a virtual private network, etc.

While not shown for clarity of illustration, the system **100** of FIG. **1** (e.g., the client device **102**, the DA server **104**, etc.) include various software, machine-readable instructions, or computer-executable instructions, and hardware components (e.g., a processor) that may execute the software or instructions to capture images of reported or claimed damage, and to estimate a cost to repair the damage. The software or instructions may be stored on non-transitory or tangible computer- or machine-readable storage memories or disks for execution on the system **100**. The software or instructions may be stored in various locations, including separate repositories or physical locations. The software or instructions may perform the various tasks associated with capturing images of reported or claimed damage, and estimating a cost to repair the damage, as herein described. The system **100** also includes data communication components for communicating between devices.

The client device **102**, among other things, provides a user interface (UI) **108** (e.g., a graphical user interface (GUI), an application, a plugin, a web browser, etc.) that enables a person **110** to use the client device **102** to take images of reported or claimed damage, provide the images to the DA server **104**, interact with the DA server **104**, interact with a human adjuster or agent **112**, etc. The client device **102** includes an imaging sensor (e.g., a camera **114**), or is coupled to an imaging device (e.g., a camera), that enables the person **110** to capture images of their reported or claimed damage with the client device **102** using, for example, the UI **108**, a button of the client device **102**, etc. The client device **102** includes a non-transitory machine-readable storage memory **116** or disks for storing captured images.

Example client devices **102** include, but are not limited to, a personal computer, a smartphone, a tablet computer, a camera, or other suitable computing device. In some examples, the client device **102** is a drone (i.e., an unmanned aerial vehicle having an imaging sensor coupled thereto), or the client device **102** is communicatively coupled to a drone. The UI **108** may communicate with the DA server **104** through, for example, the Internet **106**.

The DA server **104**, among other things, provides a UI **118** (e.g., a GUI, an application, a web browser, etc.) that enables a person (e.g., the adjuster or agent **112**) to use the DA server **104** to estimate the cost to repair damage, interact with the person **110**, etc. The DA server **104** includes a repository **120** for storing images **122** of damage from a damage-causing event, and a database **124** of images of damage arising from other damage-causing events. The database **124** may also store calculated damage information, processes or algorithms (e.g., machine learning algorithm(s) **126**) for calculating damage estimates, data that may be necessary for evaluating damages to vehicles, etc. In some examples, the repository **120** is implemented separately from the DA server **104** and accessed via a public or private network (e.g., the Internet **106**).

The DA server **104** includes a virtual adjuster **128** and a damage assessor **130** to determine an automated damage estimate **132** (e.g., an estimate of the cost(s) to repair reported or claimed damage caused by a customer's damage-causing event). The virtual adjuster **128** uses the images **122** captured by the person **110** using their client device **102**. The virtual adjuster **128** uses the images **122** to determine the likelihood that a part is damaged and, if damaged, the cost to repair. The virtual adjuster **128** queries the damage assessor **130** to determine the likelihood (e.g., as a percentage) that a part is damaged. In some examples, the damage assessor **130** runs on a first server (e.g., the DA server **104**), with the repository **120** and the virtual adjuster **128** running on a second server.

The virtual adjuster **128** determines (e.g., calculates) the damage estimate **132** based on a customer's images **122** of their damage, and the database **124** of historical images of damage for other damage-causing events or other damage related information. A damage estimate **132** can be in the form of a monetary value for the cost of repairs, a numeric score indicating the severity of the damage, etc. A damage estimate can be an assessment of the damage to any vehicle (car, motorcycle, truck, etc.) of any make/model/year.

The damage assessor **130** identifies in the historical images **124** a set of historical images of vehicles that are similar to the captured images (e.g., same make/model of vehicle, same type of damage, e.g., side impact to passenger front door, etc.) and have similar damage. The damage assessor **130** identifies in the set of historical images those that most closely match (e.g., same location on door, same depth of dent, etc.) the damage being assessed. For those that most closely match, the damage assessor **130** uses damage records (e.g., insurance claim records) to estimate the probability that certain parts are damaged. For example, 70% of the vehicles associated with the matching damage have part X damaged. In some examples, the damage assessor **130** implements the machine learning algorithm(s) **126** to identify applicable historic images and determine the likelihood of parts being damaged. In some examples, the adjuster **112** uses the damage assessor **130** while preparing an estimate to identify the likelihood that parts are damaged.

In some examples, previously created damage estimates **132** are used to determine other damage estimates **132**. Further, the damage estimate **132** can be evaluated or compared to actual damages to determine the accuracy of the damage estimate **132**. The analysis of the damage estimate **132** can be implemented to refine machine learning algorithms **126** for determining future damage estimates **132**.

In some examples, the machine learning algorithm(s) **126** are refined (e.g., continually) through machine learning, and many different machine learning algorithm(s) **126** can be created and applied to create the damage estimate **132**. For example, machine learning algorithm(s) **126** may be made for specific makes or models of vehicles. In some examples, the machine learning algorithm(s) **126** are configured to calculate damage estimates **132** to particular areas of vehicles (e.g., the fender, the bumper, etc.). In some examples, two or more machine learning algorithms **126** are used in combination to determine damage estimates.

The repository **120** may, additionally or alternatively, store manufacturer's data **134**, insurance data **136**, and repair data **138** that the virtual adjuster **128** or the damage assessor **130** can use to determine damage estimates **132**. The manufacturer's data **134** may include data for creating damage estimates **132** from data provided by vehicle manufacturers. The manufacturer's data **134** may include data indicative of the price of components of a vehicle. In some examples, the damage assessor **130** analyzes one or more images of a damaged vehicle to determine which components may have been damaged. If the damage assessor **130** determines that a component is likely damaged beyond repair, the damage assessor **130** may retrieve data indicating the price of replacement from the manufacturer's data **134**. In some examples, the damage assessor **130** is also able to retrieve the price of components from third-party databases of parts manufacturers or other resources.

The manufacturer's data **134** may also include data such as 3-D models of vehicles. In some examples, the virtual adjuster **128** or the damage assessor **130** analyzes one or more received images of the vehicle in comparison to the one or more 3-D models (corresponding to a vehicle of a similar make/model/year) to determine which component(s) of the vehicle are likely damaged, and to determine the extent of the damage to the components. The manufacturer's data **134** may also include other data relevant to vehicles that may be used by the virtual adjuster **128** or the damage assessor **130** to create damage estimates **132**.

The insurance data **136** may include data from insurance providers such as claims data, accident reports, or other data that may be used to estimate damage to a vehicle. In some examples, the insurance data **136** is used to determine damage estimates **132**. In some examples, the insurance data **136** may be used to access actual damage that may be used, in conjunction with the damage estimate **132**, to refine one or more machine learning algorithm(s) **126**. For example, the insurance data **136** may include a claim with one more images of a vehicle which may be used to determine the damage estimate **132**. Additionally or alternatively, the insurance data **136** may include a claim with one or more images of a vehicle and a cost of repair for the vehicle which may be used as for comparison to determine damage estimates **132** for another vehicle.

The repair data **138** may include data from one or more sources indicative of the cost of repair for vehicles. The repair data **138** may include images, labor costs, location data, dealership data, parts data, or any other data that may be useful for estimating damage to a vehicle.

In some examples, the person **110** interacts with the DA server **104**, the adjuster or agent **112**, or another agent (not shown) associated with an insurance company via a telephone **140** or a personal computer (PC) **142**.

While the example DA server **104** and/or, more generally, the example system **100** to capture images of reported or claimed damage, and to estimate a cost to repair the damage are illustrated in FIG. **1**, one or more of the elements, processes and devices illustrated in FIG. **1** may be combined, divided, re-arranged, omitted, eliminated or implemented in any other way. Further, the DA server **104** and/or, more generally, the system **100** may include one or more elements, processes or devices in addition to, or instead of, those illustrated in FIG. **1**, or may include more than one of any or all of the illustrated elements, processes and devices.

A flowchart **200** representative of example processes, methods, software, computer- or machine-readable instructions, etc. for implementing the virtual adjuster **128** is shown in FIG. **2**. The processes, methods, software and instructions may be an executable program or portion of an executable program for execution by a processor such as the processor **402** of FIG. **4**. The program may be embodied in software or instructions stored on a non-transitory computer- or machine-readable storage medium such as a compact disc (CD), a hard drive, a digital versatile disk (DVD), a Blu-ray disk, a cache, a flash memory, a read-only memory (ROM), a random access memory (RAM), or any other storage device or storage disk associated with the processor **402** in which information is stored for any duration (e.g., for extended time periods, permanently, for brief instances, for temporarily buffering, and/or for caching of the information). Further, although the example program is described with reference to the flowchart illustrated in FIG. **2**, many other methods of implementing the example virtual adjuster **128** may alternatively be used. For example, the order of execution of the blocks may be changed, and/or some of the blocks described may be changed, eliminated, or combined. Additionally, or alternatively, any or all of the blocks may be implemented by one or more hardware circuits (e.g., discrete and/or integrated analog and/or digital circuitry, an application specific integrated circuit (ASIC), a programmable logic device (PLD), a field programmable gate array (FPGA), a field programmable logic device (FPLD), a logic circuit, etc.) structured to perform the corresponding operation without executing software or instructions.

The example process starts with the virtual adjuster **128** determining whether a set of captured images complies with a set of criteria (block **202**). For example, the virtual adjuster **128** determines whether the images **122** were taken from a prescribed set of positions and angles, with appropriate lighting, etc. The set of images may be from an initial capture of images, for a set of additional images requested by the adjuster or agent **112**, additional images provided by the person **110**, etc. To this end, the example process of FIG. **2** may be successively carried out more than once for different sets of images.

If the set of images comply with the criteria (block **202**), the virtual adjuster **128** starts work on a damage estimate (block **204**). If it is unclear whether a part is damaged (block **206**), the virtual adjuster **128** calls (e.g., queries) the damage assessor **130** to determine the likelihood or confidence (e.g., percentage) that the part is damaged (block **208**). In some examples, the damage assessor **130** is called for each part of the vehicle that could have been damaged by the damage-causing event.

If the confidence satisfies a criteria (e.g., exceeds a threshold) (block **210**), the virtual adjuster **128** adds the part in question to the damage estimate **132** as, for example, a line item (block **212**). When the damage estimate **132** is complete (block **214**), control exits from the example process of FIG. **2**, otherwise, control returns to block **204** to continue work on the damage estimate **132**.

A flowchart **300** representative of example processes, methods, software, computer- or machine-readable instructions for implementing the damage assessor **130** is shown in FIG. **3**. The processes, methods, software and instructions may be an executable program or portion of an executable program for execution by a processor such as the processor **402** of FIG. **4**. The program may be embodied in software or instructions stored on a non-transitory computer- or machine-readable storage medium such as a CD, a hard drive, a DVD, a Blu-ray disk, a cache, a flash memory, a ROM, a RAM, or any other storage device or storage disk associated with the processor **402** in which information is stored for any duration (e.g., for extended time periods, permanently, for brief instances, for temporarily buffering, and/or for caching of the information). Further, although the example program is described with reference to the flowchart illustrated in FIG. **3**, many other methods of implementing the example damage assessor **130** may alternatively be used. For example, the order of execution of the blocks may be changed, and/or some of the blocks described may be changed, eliminated, or combined. Additionally, or alternatively, any or all of the blocks may be implemented by one or more hardware circuits (e.g., discrete and/or integrated analog and/or digital circuitry, an ASIC, a PLD, an FPGA, an FPLD, a logic circuit, etc.) structured to perform the corresponding operation without executing software or firmware.

The example process of FIG. **3** may be called by the example process of FIG. **2**, and/or be used by the adjuster or agent **112**. The example process begins with the damage assessor **130** determining whether a set of images being processed corresponds to a set of matching images that have been cached (block **302**). If the set of images does not correspond to cached images (block **302**), the damage assessor **130** identifies a set of applicable historical images based on criteria such as make, model, area damaged, etc. (block **304**). The damage assessor **130** compares the captured images **122** with the set of applicable historical images to identify other vehicles having damaged that is similar to that shown in the captured images **122** (block **306**). The damage assessor **130** may cache a list of other vehicles, and their images that were identified (block **308**).

For each identified vehicle, the damage assessor **130** determines whether a part in question was damaged (block **310**). The damage assessor **130** combines the results to determine a likelihood or confidence (e.g., a probability) that the part is damaged in the vehicle being assessed (block **312**). In some examples, the damage assessor **130** queries the manufacturer's data **134**, the insurance data **136**, or the repair data **138** to determine a cost and labor associated with repairing or replacing the part (block **314**). The damage assessor **130** returns the likelihood (e.g., percentage), the cost and the labor (block **316**), and control exits from the example process of FIG. **3**.

Referring now to FIG. **4**, a block diagram of an example computing system **400** to process insurance claims using historic data, in accordance with described embodiments. The example computing system **400** may be used to, for example, implement all or part of the DA server **104**, the virtual adjuster **128**, the damage assessor **130** and/or, more generally, the system **100**.

The computing system **400** includes a processor **402**, a program memory **404**, a RAM **406**, and an input/output (I/O) circuit **408**, all of which are interconnected via an address/data bus **410**. The program memory **404** may store software, and machine- or computer-readable instructions, which may be executed by the processor **402**.

It should be appreciated that although FIG. **4** depicts only one processor **402**, the computing system **400** may include multiple processors **402**. Moreover, different portions of the example claim processing system **100** may be implement by different computing systems such as the computing system **400**. Example processors **402** include a programmable processor, a programmable controller, a graphics processing unit (GPU), a digital signal processor (DSP), an ASIC, a PLD, an FPGA, an FPLD, etc.

The program memory **404** may include memories, for example, one or more RAMs (e.g., a RAM **414**) or one or more program memories (e.g., a ROM **416**), or a cache (not shown) storing one or more corresponding software, and machine- or computer-instructions. For example, the program memory **404** stores software, and machine- or computer-readable instructions, or computer-executable instructions that may be executed by the processor **402** to implement the any of the DA server **104**, the UI **118**, the virtual adjuster **128**, and/or the damage assessor **130** to processing insurance claims using historical data. Modules, systems, etc. instead of and/or in addition to those shown in FIG. **4** may be implemented. The software, machine-readable instructions, or computer-executable instructions may be stored on separate non-transitory computer- or machine-readable storage mediums or disks, or at different physical locations.

Example memories **404**, **414**, **416** include any number or type(s) of volatile or non-volatile non-transitory computer- or machine-readable storage medium or disk, such as a semiconductor memories, magnetically readable memories, optically readable memories, hard disk drive (HDD), an optical storage drive, a solid-state storage device, a solid-state drive (SSD), a read-only memory (ROM), a random-access memory (RAM), a compact disc (CD), a compact disc read-only memory (CD-ROM), a digital versatile disk (DVD), a Blu-ray disk, a cache, a flash memory, or any other storage device or storage disk in which information may be stored for any duration (e.g., permanently, for an extended time period, for a brief instance, for temporarily buffering, for caching of the information, etc.).

As used herein, the term non-transitory computer-readable medium is expressly defined to include any type of computer-readable storage device and/or storage disk and to exclude propagating signals and to exclude transmission media. As used herein, the term non-transitory machine-readable medium is expressly defined to include any type of machine-readable storage device and/or storage disk and to exclude propagating signals and to exclude transmission media.

In some embodiments, the processor **402** may also include, or otherwise be communicatively connected to, a database **412** or other data storage mechanism (one or more hard disk drives, optical storage drives, solid state storage devices, CDs, CD-ROMs, DVDs, Blu-ray disks, etc.). In the illustrated example, the database **412** stores the database **120**.

Although FIG. **4** depicts the I/O circuit **408** as a single block, the I/O circuit **408** may include a number of different types of I/O circuits or components that enable the processor **402** to communicate with peripheral I/O devices. The peripheral I/O devices may be any desired type of I/O device such as a keyboard, a display (a liquid crystal display (LCD), a cathode ray tube (CRT) display, touch, etc.), a navigation device (a mouse, a trackball, a capacitive touch pad, a joystick, etc.), speaker, a microphone, a button, a communication interface, an antenna, etc.

The I/O circuit **408** may include a number of different network transceivers **418** that enable the computing system **400** to communicate with another computer system, such as the computing system **400** that implement other portions of the claim processing system **100** via, e.g., a network (e.g., the communication network such as the Internet **106**). The network transceiver **418** may be a Wi-Fi transceiver, a Bluetooth transceiver, an infrared transceiver, a cellular transceiver, an Ethernet network transceiver, an asynchronous transfer mode (ATM) network transceiver, a digital subscriber line (DSL) modem, a cable modem, etc.

Example methods, apparatus, and articles of manufacture to process insurance claims using historical data are disclosed herein. Further examples and combinations thereof include at least the following.

Example 1 is a method of estimating damage to a vehicle, the method comprising: receiving, using one or more processors, one or more images of damage to a vehicle; identifying, using one or more processors, one or more additional vehicles having damage similar to the damage to the vehicle based on the one or more images; determining, using one or more processors, a likelihood that a part of the vehicle is damaged based on damage associated with the one or more additional vehicles; and determining, using one or more processors, whether to include the part in a repair estimate based on the likelihood.

Example 2 is the method of example 1, further comprising identifying a plurality of vehicles that are similar to the vehicle, wherein the one or more additional vehicles are identified in the plurality of vehicles.

Example 3 is the method of example 2, wherein the plurality of vehicles are identified using machine learning.

Example 4 is the method of example 2 or example 3, wherein the plurality of vehicles are identified based on at least one of make, model, or year.

Example 5 is the method of any of examples 1 to 4, wherein the one or more additional vehicles having damage similar to the damage to the vehicle are identified using machine learning.

Example 6 is the method of any of examples 1 to 5, wherein determining the likelihood includes determining a percentage of the one or more additional vehicles that had the part damaged.

Example 7 is the method of any of examples 1 to 6, further comprising, if the likelihood satisfies a criteria: include the part in the repair estimate; and add a cost associated with repair or replacement of the part to the repair estimate.

Example 8 is the method of example 7, further including determining the cost based on at least one of manufacturer information, dealership information, a labor cost, or parts data.

Example 9 is the method of any of examples 1 to 8, further comprising: receiving a query from a claim adjuster regarding an additional part; and in response to the query, determining, using the one or more processors, an additional likelihood that the additional part of the vehicle is damaged based on damage associated with the one or more additional vehicles, and determining, using the one or more processors, whether to include the additional part in the repair estimate based on the additional likelihood.

Example 10 is a non-transitory machine-readable storage medium storing instructions that, when executed, cause a processor to at least: receive one or more images of damage to a vehicle; identify one or more additional vehicles having damage similar to the damage to the vehicle based on the one or more images; determine a likelihood that a part of the vehicle is damaged based on damage associated with the one or more additional vehicles; and determine whether to include the part in a repair estimate based on the likelihood.

Example 11 is the non-transitory machine-readable storage medium of example 10, wherein the instructions, when executed, cause the processor to identify a plurality of vehicles that are similar to the vehicle, wherein the one or more additional vehicles are identified in the plurality of vehicles.

Example 12 is the non-transitory machine-readable storage medium of example 11, wherein the instructions, when executed, cause the processor to identify the plurality of vehicles based on at least one of a make, a model, or a year.

Example 13 is the non-transitory machine-readable storage medium of any of examples 10 to 12, wherein the instructions, when executed, cause the processor to use machine learning to identify the one or more additional vehicles.

Example 14 is the non-transitory machine-readable storage medium of any of examples 10 to 13, wherein the instructions, when executed, cause the processor to determine the likelihood by determining a percentage of the one or more additional vehicles that had the part damaged.

Example 15 is the non-transitory machine-readable storage medium of any of examples 10 to 14, wherein the instructions, when executed, cause the processor to, if the likelihood satisfies a criteria: include the part in the repair estimate; and add a cost associated with repair or replacement of the part to the repair estimate.

Example 16 is a claim adjuster comprising: a processor and a non-transitory machine-readable storage medium storing instructions that, when executed, cause the processor to at least: receive one or more images of damage to a vehicle; identify one or more additional vehicles having damage similar to the damage to the vehicle based on the one or more images; determine a likelihood that a part of the vehicle is damaged based on damage associated with the one or more additional vehicles; and determine whether to include the part in a repair estimate based on the likelihood.

Example 17 is the claim adjuster of example 16, wherein the instructions, when executed, cause the processor to identify a plurality of vehicles that are similar to the vehicle, wherein the one or more additional vehicles are identified in the plurality of vehicles.

Example 18 is the claim adjuster of example 16 or example 17, wherein the instructions, when executed, cause the processor to determine the likelihood by determining a percentage of the one or more additional vehicles that had the part damaged.

Example 19 is the claim adjuster of any of examples 16 to 18, wherein the instructions, when executed, cause the processor to, if the likelihood satisfies a criteria: include the part in the repair estimate; and add a cost associated with repair or replacement of the part to the repair estimate.

Example 20 is the claim adjuster of any of examples 16 to 19, wherein the instructions, when executed, cause the processor to determine the cost based on at least one of manufacturer information, dealership information, a labor cost, or parts data.

Use of "a" or "an" are employed to describe elements and components of the embodiments herein. This is done merely for convenience and to give a general sense of the description. This description, and the claims that follow, should be read to include one or at least one and the singular also includes the plural unless it is obvious that it is meant otherwise. A device or structure that is "configured" in a certain way is configured in at least that way, but may also be configured in ways that are not listed.

Further, as used herein, the expressions "in communication," "coupled" and "connected," including variations thereof, encompasses direct communication and/or indirect communication through one or more intermediary components, and does not require direct mechanical or physical (e.g., wired) communication and/or constant communication, but rather additionally includes selective communication at periodic intervals, scheduled intervals, aperiodic intervals, and/or one-time events. The embodiments are not limited in this context.

Further still, unless expressly stated to the contrary, "or" refers to an inclusive or and not to an exclusive or. For example, "A, B or C" refers to any combination or subset of A, B, C such as (1) A alone, (2) B alone, (3) C alone, (4) A with B, (5) A with C, (6) B with C, and (7) A with B and with C. As used herein, the phrase "at least one of A and B" is intended to refer to any combination or subset of A and B such as (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. Similarly, the phrase "at least one of A or B" is intended to refer to any combination or subset of A and B such as (1) at least one A, (2) at least one B, and (3) at least one A and at least one B.

Moreover, in the foregoing specification, specific embodiments have been described. However, one of ordinary skill in the art appreciates that various modifications and changes can be made in view of aspects of this disclosure without departing from the scope of the invention as set forth in the claims below. Accordingly, the specification and figures are to be regarded in an illustrative rather than a restrictive sense, and all such modifications made in view of aspects of this disclosure are intended to be included within the scope of present teachings.

Additionally, the benefits, advantages, solutions to problems, and any element(s) that may cause any benefit, advantage, or solution to occur or become more pronounced are not to be construed as a critical, required, or essential features or elements of any or all the claims.

Furthermore, although certain example methods, apparatus and articles of manufacture have been disclosed herein, the scope of coverage of this patent is not limited thereto. On the contrary, this patent covers all methods, apparatus and articles of manufacture fairly falling within the scope of the claims of this patent.

Finally, any references, including publications, patent applications, and patents cited herein are hereby incorporated in their entirety by reference to the same extent as if each reference were individually and specifically indicated to be incorporated by reference and were set forth in its entirety herein.

Unless a claim element is defined by reciting the word "means" and a function without the recital of any structure, it is not intended that the scope of any claim element be interpreted based on the application of 35 U.S.C. § 112, sixth paragraph.

Although certain example methods, apparatus and articles of manufacture have been disclosed herein, the scope of coverage of this patent is not limited thereto. On the contrary, this patent covers all methods, apparatus and articles of manufacture fairly falling within the scope of the claims of this patent.

What is claimed is:

1. A method of estimating damage to a vehicle, the method comprising:

receiving, by one or more processors, one or more images illustrating damage to an area of a particular vehicle, wherein the one or more images are:
received, via a network, from an electronic device separate from the one or more processors, and
digital images captured by an imaging sensor of the electronic device;
selecting, by the one or more processors, based on a vehicle type of the particular vehicle, and from a plurality of machine learning algorithms trained using respective sets of digital images illustrating damaged vehicles of a same vehicle type, a first machine learning algorithm configured to identify similarities between digital images illustrating damaged vehicles of the vehicle type;
identifying, by the one or more processors, using the first machine learning algorithm, a plurality of stored images that are matching in appearance with an image of the one or more images, each image of the plurality of stored images illustrating a damaged vehicle of the vehicle type;
identifying, by the one or more processors, based on previously-processed insurance claims associated with damaged vehicles illustrated in the plurality of stored images, a subset of the plurality of stored images, wherein:
each image of the subset illustrates a vehicle having damage to a same vehicle component,
the same vehicle component is identified as damaged by the insurance claims, and
the same vehicle component is obscured from view in the received one or more images illustrating damage to the area of the particular vehicle;
determining, by the one or more processors, a proportion indicating a likelihood that the same vehicle component of the particular vehicle is damaged, wherein determining the proportion comprises:
determining a first quantity that indicates a total number of individual vehicles illustrated in the subset of the plurality of stored images, and
determining a second quantity that indicates a total number of individual vehicles illustrated in the plurality of stored images;
determining, by the one or more processors, that the proportion is greater than a threshold value;
determining, by the one or more processors and based on the proportion being greater than the threshold value, a repair estimate including a cost associated with repair or replacement of the component;
generating, by the one or more processors, a user interface indicating the repair estimate;
providing, by the one or more processors, the user interface such that the repair estimate is output via the user interface;
determining, by the one or more processors, that the repair estimate is within a threshold amount of an actual cost of repair; and
based on determining that the repair estimate is within the threshold amount of the actual cost of repair, augmenting, by the one or more processors, a set of training data to include:
the received one or more images illustrating damage to the area of the particular vehicle, and
the repair estimate, wherein
the augmented set of training data is configured to train a second machine learning algorithm, different from the first machine learning algorithm, to generate a repair estimate.

2. The method of claim **1**, wherein the vehicle type is indicative of at least one of make, model, or year.

3. The method of claim **1**, wherein the cost is based on at least one of manufacturer information, a labor cost, or repair data of the same vehicle component.

4. The method of claim **1**, further comprising:
receiving a query from a claim adjuster regarding an additional component;
in response to the query, determining, by the one or more processors, a likelihood that the additional component of the particular vehicle is damaged based on damage associated with individual vehicles illustrated in the subset of the plurality of stored images;
determining, by the one or more processors, that the likelihood is greater than the threshold value; and
determining, by the one or more processors and based on the likelihood being greater than the threshold value, an additional cost associated with repair or replacement of the additional component to be included in the repair estimate.

5. A non-transitory machine-readable storage medium storing instructions that, when executed, cause a processor to at least:
receive, via a network and from an electronic device separate from the processor, one or more images illustrating damage to an area of a particular vehicle, wherein the one or more images are captured by a digital camera of the electronic device;
select, based on a vehicle type of the particular vehicle, from a plurality of machine learning algorithms trained using respective sets of digital images illustrating damaged vehicles of a same vehicle type, a first machine learning algorithm configured to identify similarities between digital images illustrating damaged vehicles of the vehicle type;
identify, using the first machine learning algorithm, a plurality of stored images that are matching in appearance with an image of the one or more images, each image of the plurality of stored images illustrating a damaged vehicle of the vehicle type;
identify, based on previously-processed insurance claims associated with damaged vehicles illustrated in the plurality of stored images, a subset of the plurality of stored images, wherein:
each image of the subset illustrates a vehicle having damage to a same vehicle component,
the same vehicle component is identified as damaged by the insurance claims, and
the same vehicle component is obscured from view in the received one or more images illustrating damage to the area of the particular vehicle;
determine a proportion indicating a likelihood that the same vehicle component of the particular vehicle is damaged, wherein determining the proportion comprises:
determining a first quantity that indicates a total number of individual vehicles illustrated in the subset of the plurality of stored images, and
determining a second quantity that indicates a total number of individual vehicles illustrated in the plurality of stored images;
determine that the proportion is greater than a threshold value;

determine, based on the proportion being greater than the threshold value, a repair estimate including a cost associated with repair or replacement of the component;

generate a user interface indicating the repair estimate;

provide the user interface such that the repair estimate is output via the user interface;

determine that the repair estimate is within a threshold amount of an actual cost of repair; and

based on determining that the repair estimate is within the threshold amount of the actual cost of repair, augmenting a set of training data to include:

the received one or more images illustrating damage to the area of the particular vehicle, and

the repair estimate, wherein

the augmented set of training data is configured to train a second machine learning algorithm, different from the first machine learning algorithm, to generate a repair estimate.

6. A claim adjuster, comprising:

a processor; and

a non-transitory machine-readable storage medium storing instructions that, when executed, cause the processor to at least:

receive, via a network and from an electronic device separate from the processor, one or more images illustrating damage to an area of a particular vehicle, wherein the one or more images are captured by a digital camera associated with the electronic device;

select, based on a vehicle type of the particular vehicle, from a plurality of machine learning algorithms trained using respective sets of digital images illustrating damaged vehicles of a same vehicle type, a first machine learning algorithm configured to identify similarities between digital images illustrating damaged vehicles of the vehicle type;

identify, using the first machine learning algorithm, a plurality of stored images that are matching in appearance with an image of the one or more images, each image of the plurality of stored images illustrating a damaged vehicle of the vehicle type and having damage to the area;

identify, based on previously-processed insurance claims associated with damaged vehicles illustrated in the plurality of stored images, a subset of the plurality of stored images, wherein;

each image of the subset illustrates a vehicle having damage to a same vehicle component,

the same vehicle component is identified as damaged by the insurance claims, and

the same vehicle component is obscured from view in the received one or more images illustrating damage to the area of the particular vehicle;

determine a proportion indicating a likelihood that the same vehicle component of the particular vehicle is damaged, wherein determining the proportion comprises:

determining a first quantity that indicates a total number of individual vehicles illustrated in the subset of the plurality of stored images, and

determining a second quantity that indicates a total number of individual vehicles illustrated in the plurality of stored images;

determine that the proportion is greater than a threshold value;

determine, based on the proportion being greater than the threshold value, a repair estimate including a cost associated with repair or replacement of the component;

generate a user interface indicating the repair estimate;

provide the user interface such that the repair estimate is output via the user interface;

determine that the repair estimate is within a threshold amount of an actual cost of repair; and

based on determining that the repair estimate is within the threshold amount of the actual cost of repair, augment a set of training data to include:

the received one or more images illustrating damage to the area of the particular vehicle, and

the repair estimate, wherein

the augmented set of training data is configured to train a second machine learning algorithm, different from the first machine learning algorithm, to generate a repair estimate.

7. The claim adjuster of claim **6**, wherein determining the proportion comprises determining a percentage based on the first quantity and the second quantity.

8. The claim adjuster of claim **6**, wherein the instructions, when executed, cause the processor to determine the cost based on at least one of manufacturer information, dealership information, a labor cost, or parts data.

9. The method of claim **1**, further comprising:

selecting, by the one or more processors and based on the area of the vehicle, the second machine learning algorithm; and

determining, by the one or more processors, the repair estimate by providing the one or more images as input to the second machine learning algorithm.

10. The method of claim **9**, further comprising:

receiving, by the one or more processors, an actual repair cost of the vehicle; and

refining, by the one or more processors and based on a difference between the actual repair cost and the repair estimate, the second machine learning algorithm.

11. The method of claim **1**, further comprising:

determining, by the one or more processors, that the one or more images does not satisfy a set of criteria;

displaying, by the one or more processors, on a display the electronic device, a request for additional images; and

receiving, by the one or more processors, from the electronic device, and in response to the request, one or more additional images captured from a prescribed set of positions and angles.

12. The non-transitory machine-readable storage medium of claim **5**, wherein the cost is based on at least one of manufacturer information or repair data of the component.

13. The non-transitory machine-readable storage medium of claim **5**, wherein the repair estimate is determined by the second machine learning algorithm.

14. The claim adjuster of claim **6**, wherein the electronic device comprises one of a smartphone, a tablet computer, a drone, or a device communicatively coupled to a drone.

15. The method of claim **1**, wherein the electronic device is a first electronic device, and providing the user interface comprises: providing the user interface to a second electronic device, separate from the first electronic device and via a network, such that the user interface, including the repair estimate, is output by a display of the second electronic device.

16. The claim adjuster of claim **6**, wherein the electronic device is a first electronic device, and the instructions, when executed, cause the processor to provide the user interface to a second electronic device, separate from the first electronic device.

17. The method of claim **1**, further comprising:

determining, by the one or more processors, that the one or more images satisfy a set of criteria for providing as inputs to the first machine learning algorithm.

18. The method of claim **1**, further comprising:

training, by the one or more processors and based on the augmented set of training data, the second machine learning algorithm; and

determining, by the one or more processors and using the trained second machine learning algorithm, a repair estimate associated with a set of images illustrating damage to an additional vehicle.

19. The non-transitory machine-readable storage medium of claim **5**, the instructions, when executed, further cause the processor to:

train, using the augmented set of training data, the second machine learning algorithm; and

determine, using the trained second machine learning algorithm, a repair estimate associated with a set of images illustrating damage to an additional vehicle.

20. The claim adjuster of claim **6**, wherein the instructions, when executed, cause the processor to train, using the augmented set of training data, the second machine learning algorithm.

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