(12) **United States Patent**
Farre Guiu et al.

(10) **Patent No.: US 12,387,004 B2**
(45) **Date of Patent: Aug. 12, 2025**

(54) **MACHINE LEARNING MODEL-BASED CONTENT ANONYMIZATION**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 318 days.

(21) Appl. No.: **17/703,686**

(22) Filed: **Mar. 24, 2022**

(65) **Prior Publication Data**

US 2022/0343020 A1 Oct. 27, 2022

Related U.S. Application Data

(60) Provisional application No. 63/178,342, filed on Apr. 22, 2021.

(51) **Int. Cl.**

G06F 21/62	(2013.01)
G06N 3/045	(2023.01)
G06N 3/08	(2023.01)

(52) **U.S. Cl.**
CPC ***G06F 21/6254*** (2013.01); ***G06N 3/045*** (2023.01); ***G06N 3/08*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 21/6254; G06N 3/045; G06N 3/08
USPC 726/28
See application file for complete search history.

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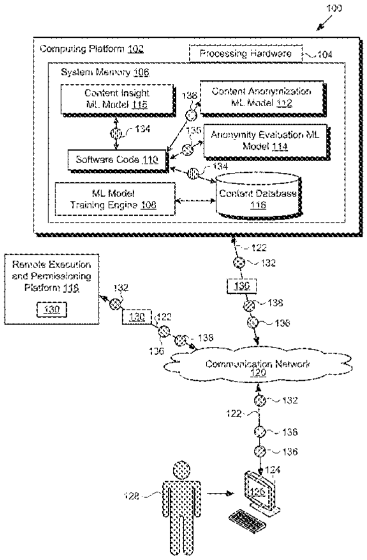
(57) **ABSTRACT**

A system includes a computing platform having processing hardware, and a system memory storing software code and a machine learning (ML) model. The processing hardware is configured to execute the software code to receive from a client, a request for a dataset, the request identifying a content type of the dataset, obtain the dataset having the content type, and select, based on the content type, an anonymization technique for the dataset, the anonymization technique selected so as to render at least one feature included in the dataset recognizable but unidentifiable. The processing hardware is further configured to execute the software code to anonymize, using the ML model and the selected anonymization technique, the at least one feature included in the dataset, and to output to the client, in response to the request, an anonymized dataset including the at least one anonymized feature.

12 Claims, 5 Drawing Sheets


100
Computing Platform 102
Processing Hardware
104
System Memory 106
Content Insight ML Model 115
138
Content Anonymization ML Model 112
134
136
Anonymity Evaluation ML Model 114
Software Code 110
134
ML Model Training Engine 108
Content Database 116
122
132
Remote Execution and Permissioning Platform 118
130
132
130
130
122
138
136
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136
Communication Network 120
132
122
138
136
124
126
128

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Fig. 1

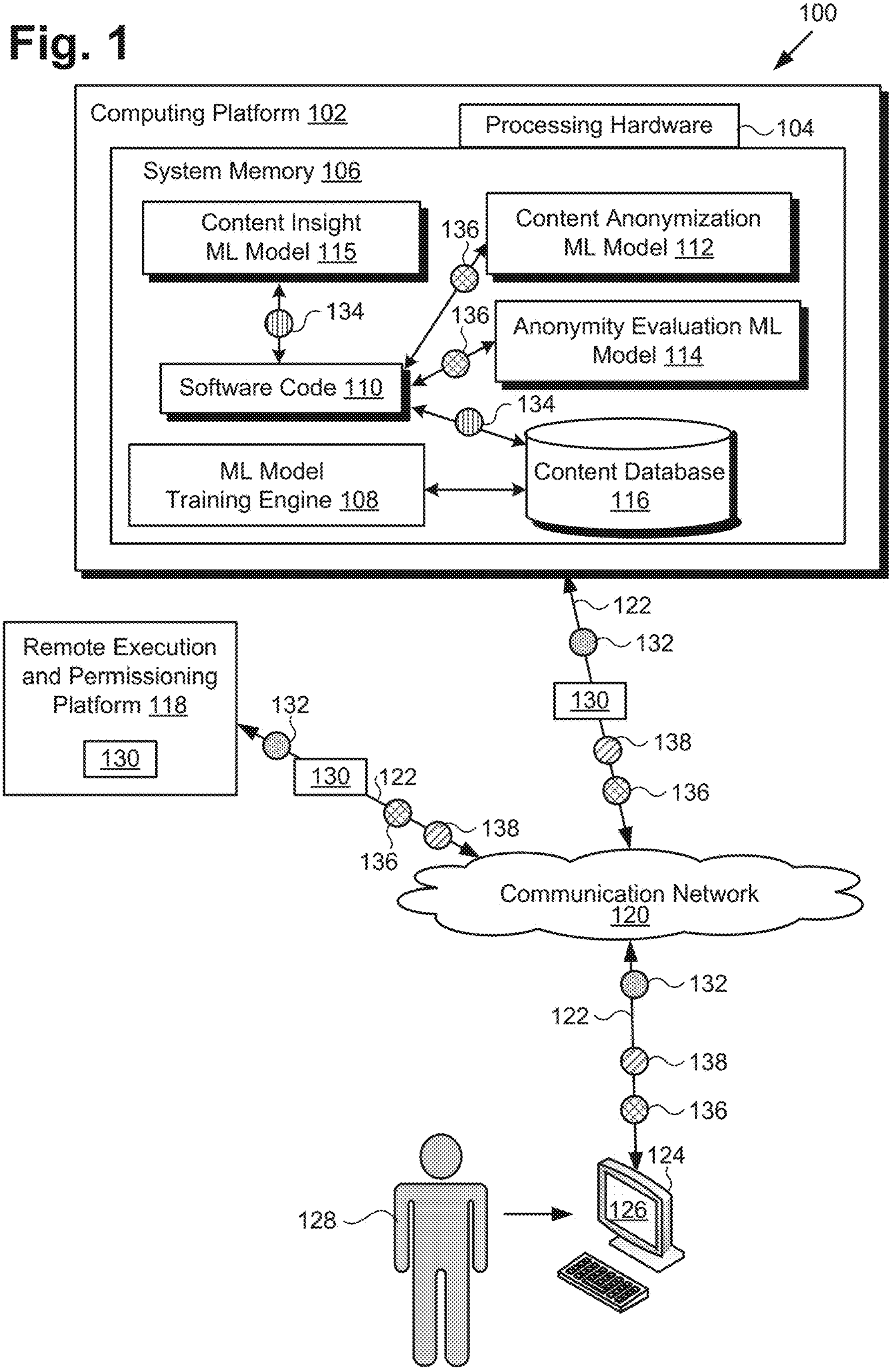
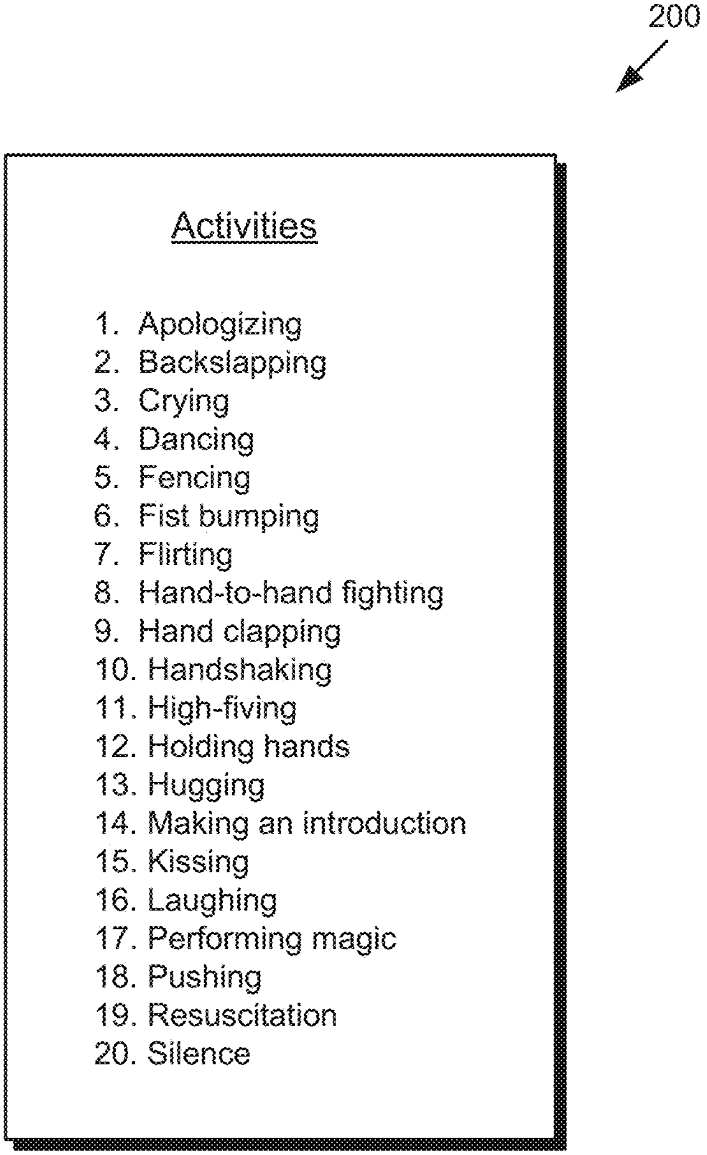

100
Computing Platform 102
Processing Hardware
104
System Memory 106
Content Insight ML Model 115
Content Anonymization ML Model 112
136
134
136
Anonymity Evaluation ML Model 114
Software Code 110
134
ML Model Training Engine 108
Content Database 116
122
132
130
138
136
Remote Execution and Permissioning Platform 118
130
132
130
122
136
138
Communication Network 120
132
122
138
136
124
126
128

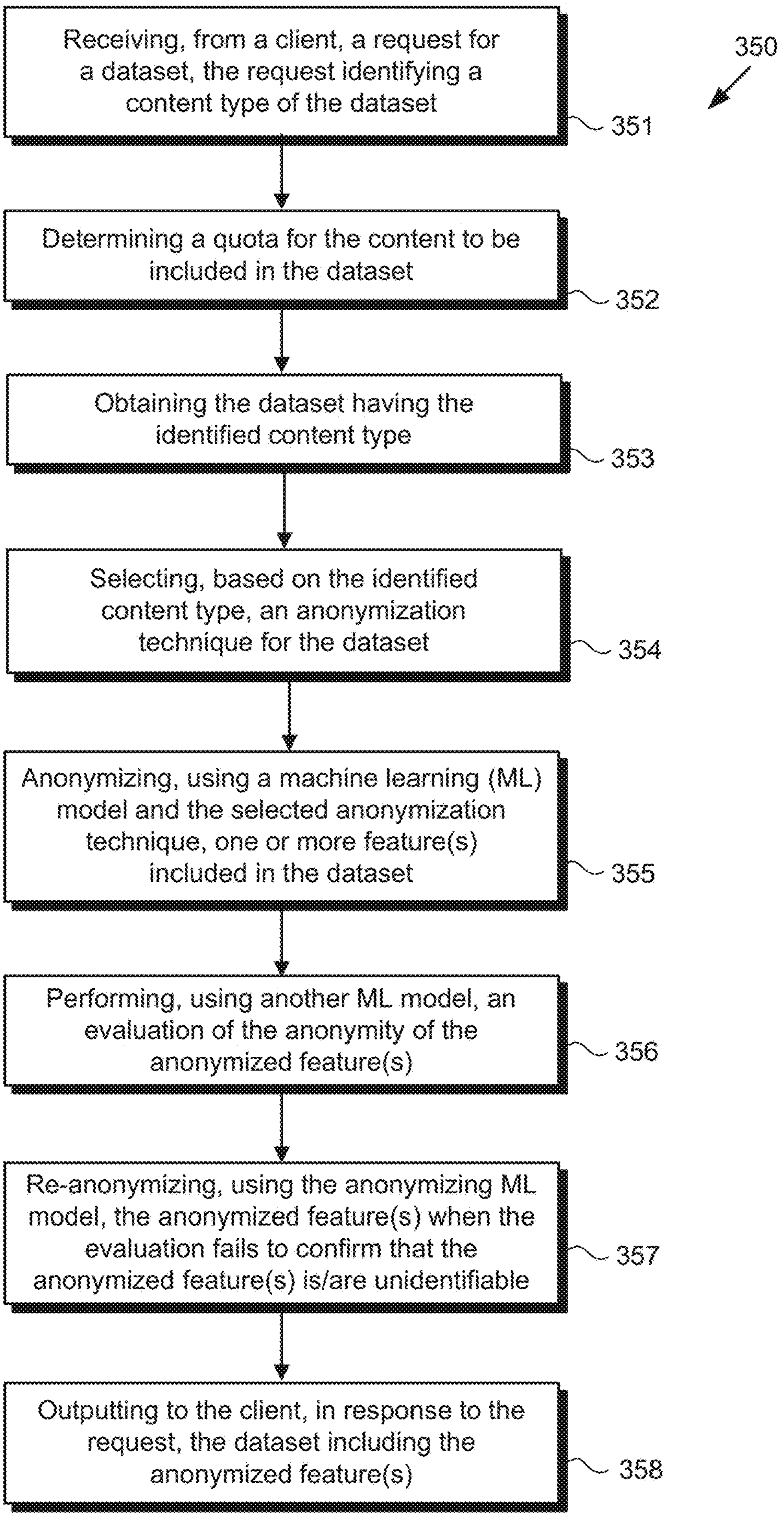
Fig. 2

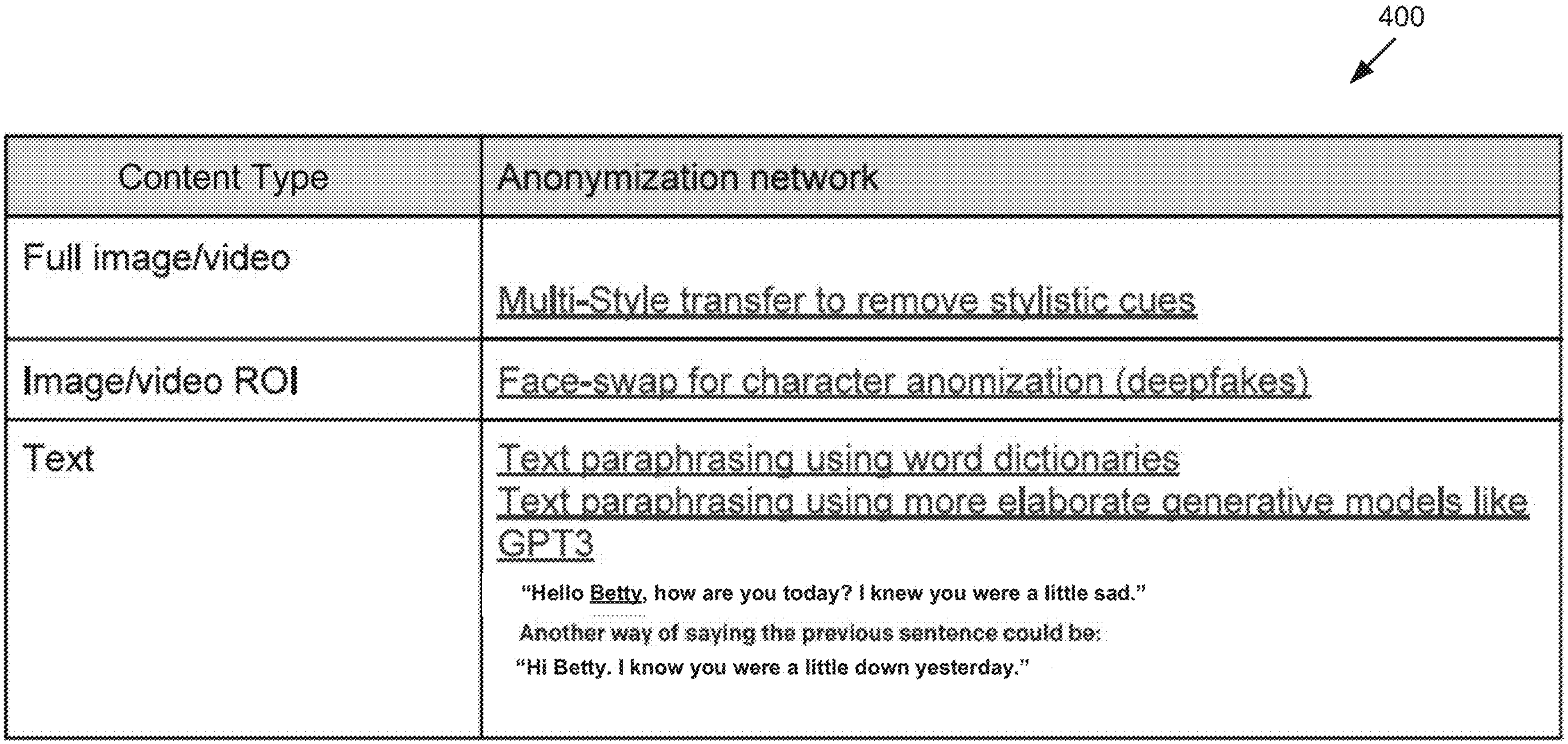


Activities

1. Apologizing
2. Backslapping
3. Crying
4. Dancing
5. Fencing
6. Fist bumping
7. Flirting
8. Hand-to-hand fighting
9. Hand clapping
10. Handshaking
11. High-fiving
12. Holding hands
13. Hugging
14. Making an introduction
15. Kissing
16. Laughing
17. Performing magic
18. Pushing
19. Resuscitation
20. Silence

Fig. 3


350
Receiving, from a client, a request for a dataset, the request identifying a content type of the dataset
351
Determining a quota for the content to be included in the dataset
352
Obtaining the dataset having the identified content type
353
Selecting, based on the identified content type, an anonymization technique for the dataset
354
Anonymizing, using a machine learning (ML) model and the selected anonymization technique, one or more feature(s) included in the dataset
355
Performing, using another ML model, an evaluation of the anonymity of the anonymized feature(s)
356
Re-anonymizing, using the anonymizing ML model, the anonymized feature(s) when the evaluation fails to confirm that the anonymized feature(s) is/are unidentifiable
357
Outputting to the client, in response to the request, the dataset including the anonymized feature(s)
358



Content Type	Anonymization network
Full image/video	Multi-Style transfer to remove stylistic cues
Image/video ROI	Face-swap for character anomization (deepfakes)
Text	Text paraphrasing using word dictionaries Text paraphrasing using more elaborate generative models like GPT3 "Hello Betty, how are you today? I knew you were a little sad." Another way of saying the previous sentence could be: "Hi Betty. I know you were a little down yesterday."

Fig. 4

500

Content Type	Additional information provided
Image / video	Darkness, color palette, sharpness compared to other samples
Text / Audio	Types of entities mentioned, sentiment of the sentence
Audio	Presence of music and environmental noise

Fig. 5

MACHINE LEARNING MODEL-BASED CONTENT ANONYMIZATION

RELATED APPLICATIONS

The present application claims the benefit of and priority to a pending Provisional Patent Application Ser. No. 63/178,342, filed Apr. 22, 2021, and titled "Content Anonymization for Accelerated Machine Learning Development," which is hereby incorporated fully by reference into the present application.

BACKGROUND

There are many undertakings that can be advanced more efficiently when performed collaboratively. However, due to any of potentially myriad privacy or confidentiality concerns, it may be undesirable to share data including proprietary or otherwise sensitive information in a collaborative or other semi-public or public environment.

By way of example, collaborative machine learning development endeavors, such as "hackathons" for instance, can advantageously accelerate the process of identifying and optimizing machine learning models for use in a variety of applications, such as activity recognition, location recognition, facial recognition, and object recognition. However, due to the proprietary nature or sensitivity of certain types of content, it may be undesirable to make such content generally available for use in model training.

One conventional approach to satisfying the competing interests of content availability and content security for machine learning development is to utilize a remote execution platform as a privacy shield between model developers and content owners. According to this approach, the remote execution platform can mediate training of a machine learning model using proprietary content, while sequestering that content from the model developer. However, one disadvantage of this approach is that, because the model developer is prevented from accessing the content used for training, it is difficult or impossible to accurately assess the performance of the machine learning model subsequent to training but prior to deployment. Consequently, there is a need in the art for a solution that enables the selective cloaking or anonymization of proprietary or sensitive content included in shared data.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** shows a diagram of an exemplary system for performing machine learning (ML) model-based content anonymization, according to one implementation;

FIG. **2** shows a table listing some exemplary activities that a trainee ML model may be trained to recognize, according to one implementation;

FIG. **3** shows a flowchart describing an exemplary method for performing ML model-based content anonymization, according to one implementation;

FIG. **4** shows a table listing some exemplary techniques suitable for use in anonymizing various types of content, according to one implementation; and

FIG. **5** shows a table providing examples of extra information that may be passed to a development collaborator as a text string accompanying anonymized content, according to one implementation.

DETAILED DESCRIPTION

The following description contains specific information pertaining to implementations in the present disclosure. One skilled in the art will recognize that the present disclosure may be implemented in a manner different from that specifically discussed herein. The drawings in the present application and their accompanying detailed description are directed to merely exemplary implementations. Unless noted otherwise, like or corresponding elements among the figures may be indicated by:like or corresponding reference numerals. Moreover, the drawings and illustrations in the present application are generally not to scale, and are not intended to correspond to actual relative dimensions.

As noted above, collaborative machine learning development endeavors, such as "hackathons" for example, can advantageously accelerate the process of identifying and optimizing machine learning models for use in a variety of applications, such as activity recognition, location recognition, facial recognition, and object recognition, to name a few examples. However, due to the proprietary nature or sensitivity of certain types of content, it may be undesirable to make such content generally available for use in model training. As further noted above, one conventional approach to satisfying the competing interests of content availability and content security for machine learning development is to utilize a remote execution platform as a privacy shield between model developers and content owners. According to this approach, the remote execution platform can mediate training of a machine learning model using proprietary content, while sequestering that content from the model developer. However, one disadvantage of this approach is that, because the model developer is prevented from accessing the content used for training, it is difficult or possible to accurately assess the performance of the machine learning model subsequent to training but prior to deployment.

The present application discloses systems and methods for performing machine learning model-based content anonymization that address and overcome the challenges to effective collaboration described above. It is noted that although the present content anonymizing solution is described below in detail by reference to the exemplary use case of activity recognition in the interests of conceptual clarity, the present novel and inventive principles may be advantageously applied to a wide variety of machine learning predictive processes. Moreover, the content anonymizing solution disclosed herein may advantageously be implemented as an automated process.

It is noted that, as defined in the present application, the terms "automatic," "automated," and "automating" refer to systems and processes that do not require human intervention. Although in some implementations a human system administrator may review the content anonymizing performance of the systems and methods described herein, that human involvement is optional. Thus, the methods described in the present application may be performed under the control of hardware processing components of the disclosed automated systems.

It is further noted that, as defined in the present application, the expression "machine learning model" (hereinafter "ML model") refers to a mathematical model for snaking future predictions based on patterns learned from samples of data or "training data." Various learning algorithms can be used to map correlations between input data and output data. These correlations form the mathematical model that can be used to make future predictions on new input data. Such a predictive model may include one or more logistic regression models, Bayesian models, or neural networks (NNs).

A "deep neural network," in the context of deep learning, may refer to an NN that utilizes multiple hidden layers between input and output layers, which may allow for learning based on features not explicitly defined in raw data. As used in the present application, a feature identified as an NN refers to a deep neural network.

FIG. **1** shows system **100** for performing ML model-based content anonymization, according to one exemplary implementation. As shown in FIG. **1**, system **100** includes computing platform **102** having processing hardware **104** and system memory **106** implemented as a computer-readable non-transitory storage medium. According to the present exemplary implementation, system memory **106** stores software code **110**, ML model training engine **108**, content anonymization ML model **112**, anonymity evaluation ML model **114**, content insight ML model **115**, and content database **116** storing content for use in training ML models, as well as for testing the performance of such models subsequent to training.

As further shown in FIG. **1**, system **100** is implemented within a use environment including communication network **120** providing network communication inks **122**, remote execution and permissioning platform **118**, client system **124** including display **126**, and machine learning model development collaborator **128** (hereinafter "client **128**") utilizing client system **124**. Also shown in FIG. **1** are trainee ML model **130**, request **132** for dataset **134**, dataset **136** including one or more anonymized features (hereinafter "anonymized dataset **136**") provided as an output of system **100** in response to request **132**, and optional insights **138** providing clarifying information for the one or more anonymized features included in anonymized dataset **136**. It is noted that anonymized dataset **136** represents dataset **134** after anonymization of one or more features included in dataset **134** has been performed.

Although the present application refers to one or more of software code **110**, ML model training engine **108** content anonymization ML model **112**, anonymity evaluation ML model **114**, content insight ML model **115**, and content database **116** as being stored in system memory **106** for conceptual clarity, more generally, system memory **106** may take the form of any computer-readable non-transitory storage medium. The expression "computer-readable non-transitory storage medium," as defined in the present application, refers to any medium, excluding a carrier wave or other transitory signal that provides instructions to processing hardware **104** of computing platform **102**. Thus, a computer-readable non-transitory storage medium may correspond to various types of media, such as volatile media and non-volatile media, for example. Volatile media may include dynamic memory, such as dynamic random access memory (dynamic RAM), while non-volatile memory lay include optical, magnetic, or electrostatic storage devices. Common forms of computer-readable non-transitory storage media include, for example, optical discs, RAM, programmable read-only memory (PROM), erasable PROM (EPROM), and FLASH memory.

It is further noted that although FIG. **1** depicts software code **110**, ML model training engine **108**, content anonymization ML model **112**, anonymity evaluation ML model **114**, content insight ML model **115**, and content database **116** as being co-located in system memory **106**, that representation is also merely provided as an aid to conceptual clarity. More generally, system **100** may include one or more computing platforms **102**, such as computer servers for example, which may be co-located or may form an interactively linked but distributed system, such as a cloud-based system, for instance. As a result, processing hardware **104** and system memory **106** may correspond to distributed processor and memory resources within system **100**. Consequently, in some implementations, one or more of software code **110**, ML model training engine **108**, content anonymization ML model **112**, anonymity evaluation ML model **114**, content insight ML model **115**, and content database **116** may be stored remotely from one another on the distributed memory resources of system **100**.

Processing hardware **104** may include multiple hardware processing units, such as one or more central processing units, one or more graphics processing units, and one or more tensor processing units, one or more field-programmable gate arrays (FPGAs), custom hardware for machine-learning training or inferencing, and an application programming interface (API) server, for example. By way of definition, as used in the present application, the terms "central processing unit" (CPU), "graphics processing unit" (GPU), and "tensor processing unit" (TPU) have their customary meaning in the art. That is to say, a CPU includes an Arithmetic Logic Unit (ALU) for carrying out the arithmetic and logical operations of computing platform **102**, as well as a Control Unit (CU) for retrieving programs, such as software code **110**, from system memory **106**, while a GPU may be implemented to reduce the processing overhead of the CPU by performing computationally intensive graphics or other processing tasks. A TPU is an application-specific integrated circuit (ASIC) configured specifically for artificial intelligence (AI) processes such as machine learning.

In some implementations, computing platform **102** may correspond to one or more web servers, accessible over communication network **120** in the form of a packet-switched network such as the Internet, for example. Moreover, in some implementations, communication network **120** may be a high-speed network suitable for high performance computing (HPC), for example a 10 GigE network or an Infiniband network. In some implementations, computing platform **102** may correspond to one or more computer servers supporting a private wide area network (WAN), local area network (LAN), or included in another type of limited distribution or private network. As yet another alternative, in some implementations, system **100** may be implemented virtually, such as in a data center. For example, in some implementations, system **100** may be implemented in software, or as virtual machines.

Although client system **124** is shown as a desktop computer in FIG. **1**, that representation is provided merely as an example as well. More generally, client system **124** may be any suitable mobile or stationary computing device or system that includes display **126** and implements data processing capabilities sufficient to provide a user interface, support connections to communication network **120**, and provide the functionality ascribed to client system **124** herein. For example, in other implementations, client system **124** may take the form of a laptop computer, tablet computer, or smartphone, for example.

With respect to display **126** of client system **124**, display **126** may be implemented as a liquid crystal display (LCD), light-emitting diode (LED) display, organic light-emitting diode (OLED) display, quantum dot (QD) display, or any other suitable display screen that perform a physical transformation of signals to light. Furthermore, display **126** may be physically integrated with client system **124** or may be communicatively coupled to but physically separate from client system **124**. For example, where client system **124** is implemented as a smartphone, laptop computer, or tablet computer, display **126** will typically be integrated with client system **124**. By contrast, where client system **124** is implemented as a desktop computer, display **126** may take the form of a monitor separate from client system **124** in the form of a computer tower.

According to the exemplary implementation shown in FIG. **1**, client **128** uses client system **124** and communication network **120** to deliver trainee ML model **130** to remote execution and permissioning platform **118** for training, Remote execution and permissioning platform **118** mediates training of trainee ML model **130** on computing platform **102** of system **100**, using ML model training engine **108** and content obtained from content database **116**, while that content, which may be proprietary or otherwise sensitive, remains inaccessible to client system **124** and client **128**. As shown in FIG. **1**, trainee ML model **130** may be transferred to ML model training engine **108** of system **100** via communication network **120** and network communication links **122**. Trainee ML model **130** may be trained for any of a variety of applications. By way of example, in some implementations, trainee ML model **130** may be trained to perform activity recognition. Table **200**, in FIG. **2**, lists some exemplary activities that trainee ML model **130** may be trained to recognize. It is noted that the activities listed in table **200** are merely provided by way of example. More generally, trainee ML model **130** may be trained to recognize any action, to serve as a predictive model or a generative model, or to perform one or more of a wide variety of inferential problem solving tasks.

The functionality of system **100** and software code **110** will be further described by reference to FIG. **3**. FIG. **3** shows flowchart **350** presenting an exemplary method for performing ML model-based content anonymization, according to one implementation. With respect to the method outlined in FIG. **3**, it is noted that certain details and features have been left out of flowchart **350** in order to not obscure the discussion of the inventive features in the present application.

Referring now to FIG. **3** in combination with FIG. **1**, flowchart **350** includes receiving from client **128**, request **132** for dataset **134**, request **132** identifying the content type of dataset **134** (action **351**). Dataset **134** may include unstructured data, for example. In some implementations, dataset **134** may include one or more of a variety of different content types, such as images, audio samples, and text, for example. Specific examples of images include graphics, digital photographs, or video frames, to name a few. Alternatively, or in addition, dataset **134** may include audio samples including speech, music, or sound effects, for instance. As another alternative, or in addition, dataset **134** may include text, as noted above. Moreover, in some implementations, the type of content identified by request **132** may be or include digital representations of persons, fictional characters, locations, objects, and identifiers such as brands and logos, for example, that populate a virtual reality, augmented reality, or mixed reality environment.

According to the exemplary implementation shown in FIG. **1**, dataset **134** may include validation data for use in assessing the training of trainee ML model **130**. As further shown in FIG. **1**, in some implementations, request **132** may be received from client system **124** utilized by client **128**, via remote execution and permissioning platform **118** and communication network **120**. However, in other implementations, request **132** may be received directly from client system **124** via communication network **120**. In various implementations, request **132** may be received in action **351** by software code **110**, executed by processing hardware **104** of computing platform **102**.

In some implementations, flowchart **350** may include determining a quota for the content to be included in dataset **134** (action **352**). In various use cases it may be advantageous or desirable to limit the amount of data provided by system **100**, based either on the type of content sought by request **132**, the identity of client **128**, or both. For example, system **100** may cap the total amount of data available to any client, or the total amount of data available to an individual client based on the identity of that client. Alternatively, or in addition, system **100** may cap the total amount of data made available based on content type, where more content in the form of audio samples, for instance, is available to a client than content in the form of video frames or other images, or vice versa. Where client **128** makes repeated requests for datasets from system **100**, system **100** may determine a quota for the content to be included in any particular dataset **134** so as prevent client **128** from exceeding the allowable limit.

It is noted that action **352** is optional, and in some implementations may be omitted from the method outlined by flowchart **350**. However, in implementations in which action **352** is performed, the quota for the content to be included in dataset **134** may be determined by software code **110**, executed by processing hardware **104** of computing platform **102**, based on one or both of the content type or an identity of client **128**.

Flowchart **350** further includes obtaining dataset **134** (action **353**). As shown in FIG. **1**, in some implementations, dataset **134** may be obtained from content database **116** of system **100**, in action **353**, by software code **110**, executed by processing hardware **104** of computing platform **102**. Content database **116** may include hundreds, thousands, or tens of thousands of data samples, which may take a variety of forms including images, audio sample, text, and digital representations that populate a virtual reality, augmented reality, or mixed reality environment, as noted above.

Flowchart **350** further includes selecting, based on the content type identified by request **132**, an anonymization technique for dataset **134**, the anonymization technique selected so as to render one or more features included in dataset **134** recognizable but unidentifiable (action **354**). It is noted that, as defined for the purposes of the present application, the term "recognizable" refers to detecting the generic nature of a feature, while the term "identifiable" refers to detecting characteristics of a feature that reveal its particular identity. By way of example, an anonymization technique for an image depicting Lake Tahoe may result in the anonymized image depicting a feature that is recognizable as a body of water but unidentifiable as Lake Tahoe per se.

Referring to FIG. **4**, table **400** in FIG. **4** lists some exemplary techniques suitable for use in anonymizing various types of content. For example, and as shown in FIG. **4**, where full images or video are to be anonymized, a multi-style transfer to remove stylistic cues may be performed, as further described by Reference 1 (https://github.com/zhanghang1989/PyTorch-Multi-Style-Transfer), a copy of which is attached to Provisional Patent Application Ser. No. 63/178,342, and is incorporated herein by reference, as one example of a conventional approach. In addition, or alternatively, acid as further shown in FIG. **4**, where a region of interest (ROI) within an image or video is to be anonymized, face swapping or Gaussian blur techniques may be employed, as further described, respectively, by Reference 2 (https://github.com/hukkelas/DeepPrivacy?utm_source=thenewstack&utm_medium=website&utm_campaign=pl and Reference 3 (NPL: A Study of Face Obfuscation in

ImageNet, by Yang, et al., dated Mar. 14, 2021), copies of which are attached to Provisional Patent Application Ser. No. 63/178,342, and are incorporated herein by reference, as examples of conventional approaches. Moreover and as also shown in FIG. **4**, where text within an image or video is to be anonymized, various text paraphrasing techniques may be used, as further described by Reference 4 (https://www-.paraphrase-online.com) and Reference 5 (https://beta.openai.com), copies of which are attached to Provisional Patent Application Ser. No. 63/178,342, and are incorporated herein by reference, as examples of conventional approaches. It is noted that where audio is to be anonymized, any suitable audio manipulation technique known in the art may be utilized.

Flowchart **350** further includes anonymizing, using content anonymization ML model **112** and the anonymization technique selected in action **354**, at least one feature included in dataset **134** (action **355**). In various implementations, for example, the one or more features anonymized in action **355** may include an activity, location, or a depiction of a person or character. As noted above, the anonymization performed in action **355** is directed to rendering that/those feature(s) recognizable but unidentifiable. By way of example, where dataset **134** includes an image of "Character A" smiling or laughing, the corresponding anonymized image in anonymized dataset **136** may be recognizable as a character who is smiling or laughing, but may be unidentifiable as "Character A."

As another example, where dataset **134** depicts a location including a well-known building or landmark (e.g., the Eiffel Tower), the corresponding anonymized depiction in anonymized dataset **136** may be recognizable as a generic structure in place of the well-known building or landmark. As yet another example, where dataset **134** includes a video of a particular television (TV) series character having dinner in a fictional restaurant identified in the TV series, anonymized dataset **136** may enable recognition that a person is eating while rendering the TV series character, the fictional restaurant that only exists in the TV series, and the actual dialogue of the TV series script being spoken by the character unidentifiable.

It is noted that in some implementations, content anonymization ML model **112** may take the form of one or more trained neural networks (NNs). The anonymization of the feature or features included in dataset **134**, in action **355**, may be performed by software code **110**, executed by processing hardware **104** of computing platform **102**, and using content anonymization ML model **112**, as noted above.

In some implementations, the method outlined by flowchart **350** may further include performing an evaluation of the anonymity of the one or more features anonymized in action **355** (action **356**). In some implementations, evaluation of the anonymity of the anonymized feature or features included in anonymized dataset **136** may be performed by software code **110**, executed by processing hardware **104** of computing platform **102**, and using anonymity evaluation ML model **114**, which, like content anonymization ML model **112**, may take the form of one or more trained NNs. Thus, in some implementations, content anonymization ML model **112** may include one or more trained NNs, and anonymity evaluation ML model **114** may include one or more other NNs. It is noted that action **356** is optional, and in some implementations may be omitted from the method outlined by flowchart **350**. In implementations in which action **356** is performed, it is performed in order to ensure

that the specific features anonymized in action **355** are recognizable but unidentifiable after the anonymization process.

For example, the one or more features anonymized in action **355** may be run through classifiers, in action **356**, that analyze the features to be anonymized, such as faces, logos, or backgrounds, for instance. Those classifiers can be part of system **100**, i.e., anonymity evaluation ML model **114**, or may be third party resources. The analysis may be repeated for all features anonymized in action **355**.

As a specific example, prior to action **355**, dataset **134** may be run through multiple classifiers, such as image, audio, and text classifiers in a preliminary recognition process to identify features in dataset **134** to be anonymized. For instance, dataset **134** may be run through multiple celebrity recognition or facial recognition classifiers to identify individual faces to be anonymized in action **355**. In addition to identifying specific faces to be anonymized, the confidence values computed for the facial recognitions performed by each classifier can be evaluated. In one implementation, this preliminary process may be performed using anonymity evaluation ML model **114**.

Action **355** may then be performed using content anonymization ML model **112**. Action **356** may then include repeating the preliminary evaluation process on the one or more anonymized features using anonymity evaluation ML model **114**, and comparing the results and confidence values with the results of the preliminary recognition process described above. The anonymization process can be considered successful if the confidence values drop by some predetermined or selectable threshold relative to their pre-anonymization values. If those confidence values fail to satisfy this threshold reduction, the parameters of content anonymization ML model **112** can be adjusted and actions **355** and **356** may be repeated until the confidence value threshold is satisfied, or the one or more features being anonymized become unidentifiable.

In implementations in which the method outlined by flowchart **350** includes action **356** described above, flowchart. **350** may further include re-anonynizing features anonymized its action **355** when the evaluation performed in action fails to confirm that the one or more anonymized features is/are unidentifiable (action **357**). In essence, action **357** includes performing actions **355** and **356** iteratively until the evaluation performed in action **356** confirms that the one or more anonymized features is/are unidentifiable. Action **357** may be performed by software code **110**, executed by processing hardware **104** of computing platform **102**, and using content anonymization ML model **112**, and in some implementations, anonymity evaluation ML model **114** as well.

In some implementations, it may be advantageous or desirable to provide client **128** with additional insights **138** to anonymized dataset **136**, while maintaining the anonymity of specific features included in dataset **134**. Referring to FIG. **5**, table **500** provides examples of extra information (i.e., additional insights) that may be passed to client **128** as a text string accompanying anonymized dataset **136**. Additional insights **138** "clues" may be generated by software code **110**, executed by processing hardware **104**, based on dataset **134** and the output of content insight ML model **115**. Alternatively, or in addition, additional insights **138** may be generated manually, by a human editor.

Additional insights **138** generated using content insight ML model **115** can be added in all use cases or in any use cases in which it is deemed desirable to provide them for example, in cases in which the anonymization process eliminates a feature that may be relevant to request **132** for dataset **134**. For instance, if a type of location is always dark (e.g., a cave) but the anonymization performed in action **355** causes that feature to become colorized while retaining its cave-like structure, it may be advantageous or desirable to provide additional insight **138** stating: "the cave-like structure is dark." Moreover, in some implementations it may be advantageous to generate additional insights **138** in instances when it is necessary to perform action **357**. By way of example, in one implementation, action **355** may obfuscate or otherwise anonymize backgrounds in dataset **134**, but some named entities such as "Famous Character X" may be recognizable from the audio track of dataset **134**. In that situation, action **355** may result in the audio track being cut from dataset **134** and a text string being added to anonymized dataset **136** as an additional insight **138**. For instance, the audio track including the statement "I must find Famous Character X" could be cut from dataset **134** and the following additional insight **138** could be added to anonymized. dataset **136**: "the audio track includes the statement 'I must find John Doe'"

Flowchart **350** further includes outputting to client **128**, in response to request **132**, anonymized dataset **136** including the one or more anonymized features (action **358**). In some implementations, for example, anonymized dataset **136** may be output to remote execution and permissioning platform **118**, via communication network **120**, for use in testing the performance of trainee ML model **130**. However, in other implementations, anonymized dataset **136** may be output to client system **124** utilized by client **128**, via communication network **120**. Action **358** may be performed by software code **110**, executed by processing hardware **104** of computing platform **102**. Moreover, in some implementations, insights **1.38** may be output to remote execution and permissioning platform **118**, to client system **124**, or both, as an accompaniment to anonymized dataset **136**.

As noted above, request **132** may specifically identify or characterize the content desired by client **128**. In such use cases, where a predetermined number of iterations of actions **355** and **356** fail to confirm the anonymity of the anonymized feature or features of dataset **134**, processing hardware **104** may execute software code **110** to obtain alternative content for anonymization and output to remote execution and permissioning platform **118** or client system **124**. This alternative content could be selected by software code **110** based on its being comparable to the content identified by request **132**, but capable of being successfully anonymized using action **355** or **357**.

As further noted above, in various implementations, one or both of actions **356** and **357**, as well as action **352**, are optional. Thus, in some implementations, action **353** may follow directly from action **351**. Moreover, in implementations in which actions **356** and **357** are omitted from the method outlined by flowchart **350**, action **358** may follow directly from action **355**. Alternatively, in implementations in which action **356** is included in the method and the evaluation performed in that action confirms that the one or more features anonymized in action **355** is/are unidentifiable, action **358** may follow directly from action **356**, while action **357** may be omitted. That is to say, in those use cases, anonymized dataset **136** is output to client **128** when the evaluation performed in action **356** confirms that the one or more features anonymized in action **355** is/are unidentifiable.

With respect to the method outlined by flowchart **350**, it is also noted that actions **351**, **353**, **354**, **355**, and **358**, or actions **351**, **352**, **353**, **354**, **355** (hereinafter "actions **351-355**") and **358**, or actions **351**, **353**, **354**, **355**, **356**, and **358**, or actions **351-355**, **356**, and **358**, or actions **351**, **353**, **354**, **355**, **356**, **357**, and **358**, or actions **351-355**, **356**, **357**, and **358**, may be performed in an automated process from which human involvement may be omitted.

Thus, the present application discloses systems and methods for performing machine learning model-based content anonymization that address and overcome the drawbacks and deficiencies in the conventional art. From the above description it is manifest that various techniques can be used for implementing the concepts described in the present application without departing from the scope of those concepts. Moreover, while the concepts have been described with specific reference to certain implementations, a person of ordinary skill in the art would recognize that changes can be made in form and detail without departing from the scope of those concepts. As such, the described implementations are to be considered in all respects as illustrative and not restrictive. It, should also be understood that, the present application is not limited to the particular implementations described herein, but many rearrangements, modifications, and substitutions are possible without departing from the scope of the present disclosure.

What is claimed is:

1. A system comprising:

a processing hardware; and

a system memory storing a software code, a first trained neural network (NN) and a second trained NN;

the processing hardware configured to execute the software code to:

receive from a client, a request for a dataset, the request identifying a content type of the dataset, the dataset including an image;

obtain the dataset having the content type;

select, based on the content type, an anonymization technique for the dataset, the anonymization technique selected so as to render at least one feature included in the dataset recognizable but unidentifiable;

anonymize, using the first trained NN and the selected anonymization technique, the at least one feature included in the image, such that a generic nature of the at least one feature included in the image is maintained by anonymizing, but an identifiable nature of the at least one feature included in the image is removed by anonymizing, wherein the at least one feature included in the image and anonymized is indicative of at least one of a location where the image is captured or an activity being performed, wherein the activity includes one of dancing, fencing, first bumping, hand-to-hand fighting, hand clapping, handshaking, hand-fiving, holding hands, hugging, performing magic, or pushing;

evaluate, using the second trained NN, an anonymity of the at least one anonymized feature;

re-anonymize, using the first trained NN, the at least one anonymized feature when evaluating the anonymity of the at least one anonymized feature fails to confirm that the at least one anonymized feature is unidentifiable, until when evaluating the anonymity of the at least one anonymized feature indicates that a confidence value of the at least one anonymized feature being unidentifiable satisfies a predetermined threshold; and

output to the client, in response to the request, an anonymized dataset including the image having the at least one anonymized feature.

2. The system of claim **1**, wherein the at least one feature included in the image and anonymized is indicative of the location where the image is captured.

3. The system of claim **1**, wherein prior to obtaining the dataset having the content type, the processing hardware is further configured to execute the software code to:

determine that quota for content having the content type does not exceed an allowable limit; and

in response to determining, including the content in the dataset having the content type.

4. The system of claim **1**, wherein the image is in a video frame.

5. The system of claim **1**, wherein the at least one feature included in the image further comprises a depiction of a person or a character, and the at least one feature and anonymized is indicative of the location where the image is captured and includes one of a building, a landmark or a restaurant.

6. The system of claim **1**, wherein the content type comprises digital representations that populate a virtual reality, augmented reality, or mixed reality environment.

7. A method for use by a system including a processing hardware, and a system memory storing a software code, a first trained neural network (NN) and a second trained NN, the method comprising:

receiving from a client, by the software code executed by the processing hardware, a request for a dataset, the request identifying a content type of the dataset, the dataset including an image;

determining, by the software code executed by the processing hardware, quota for content having the content type does not exceed an allowable limit;

obtaining, by the software code executed by the processing hardware, the dataset having the content type and including the content;

selecting, by the software code executed by the processing hardware, based on the content type, an anonymization technique for the dataset, the anonymization technique selected so as to render at least one feature included in the dataset recognizable but unidentifiable;

anonymizing, by the software code executed by the processing hardware and using the first trained NN and the selected anonymization technique, the at least one feature included in the image, such that a generic nature of the at least one feature included in the image is maintained by anonymizing, but an identifiable nature of the at least one feature included in the image is removed by anonymizing, wherein the at least one feature included in the image and anonymized is indicative of at least one of a location where the image is captured or an activity being performed, wherein the activity includes one of dancing, fencing, first bumping, hand-to-hand fighting, hand clapping, handshaking, hand-fiving, holding hands, hugging, performing magic, or pushing;

evaluate, by the software code executed by the processing hardware and using the second trained NN, an anonymity of the at least one anonymized feature;

re-anonymize, by the software code executed by the processing hardware and using the first trained NN, the at least one anonymized feature when evaluating the anonymity of the at least one anonymized feature fails to confirm that the at least one anonymized feature is unidentifiable, until when evaluating the anonymity of the at least one anonymized feature indicates that a confidence value of the at least one anonymized feature being unidentifiable satisfies a predetermined threshold; and

outputting to the client, by the software code executed by the processing hardware in response to the request, an anonymized dataset including the image having the at least one anonymized feature.

8. The method of claim **7**, wherein the at least one feature included in the image and anonymized is indicative of the location where the image is captured.

9. The method of claim **7**, wherein prior to obtaining the dataset having the content type, the method further comprises:

determining, by the software code executed by the processing hardware, that quota for content having the content type does not exceed an allowable limit; and

in response to determining, including, by the software code executed by the processing hardware, the content in the dataset having the content type.

10. The method of claim **7**, wherein the image is in a video frame.

11. The method of claim **7**, wherein the at least one feature included in the image further comprises a depiction of a person or a character, and the at least one feature and anonymized is indicative of the location where the image is captured and includes one of a building, a landmark or a restaurant.

12. The method of claim **7**, wherein the content type comprises digital representations that populate a virtual reality, augmented reality, or mixed reality environment.

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