US012393338B2

(12) United States Patent
Dar et al.

(10) Patent No.: US 12,393,338 B2
(45) Date of Patent: *Aug. 19, 2025

(54) STORAGE AND METHOD FOR MACHINE LEARNING-BASED DETECTION OF RANSOMWARE ATTACKS ON A STORAGE SYSTEM

(71) Applicant: **Dell Products, L.P.**, Round Rock, TX (US)

(72) Inventors: **Shaul Dar**, Petach Tikva (IL); **Ramakanth Kanagovi**, Bengaluru (IN); **Guhesh Swaminathan**, Tamil Nadu (IN); **Rajan Kumar**, Nawada (IN)

(73) Assignee: **Dell Products L.P.**, Round Rock, TX (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 265 days.

This patent is subject to a terminal disclaimer.

(21) Appl. No.: **18/158,735**

(22) Filed: **Jan. 24, 2023**

(65) **Prior Publication Data**

US 2024/0248604 A1 Jul. 25, 2024

(51) **Int. Cl.**
G06F 21/00 (2013.01)
G06F 3/06 (2006.01)

(52) **U.S. Cl.**
CPC ***G06F 3/061*** (2013.01); ***G06F 3/0655*** (2013.01); ***G06F 3/0679*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 21/568; G06F 21/554
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

10,078,459	B1 *	9/2018	Natanzon	G06F 3/067
10,586,052	B1 *	3/2020	Marelas	G06F 3/0656
2018/0157834	A1 *	6/2018	Continella	G06F 21/568
2018/0293176	A1 *	10/2018	Borlick	G06F 21/55
2021/0216631	A1 *	7/2021	Child	G06F 21/564
2023/0229773	A1 *	7/2023	Madden, Jr.	G06F 21/554 726/23
2024/0005000	A1 *	1/2024	Heath	G06N 20/10
2024/0106856	A1 *	3/2024	Fahim	H04L 63/1425
2024/0289476	A1 *	8/2024	Ueki	G06F 21/554

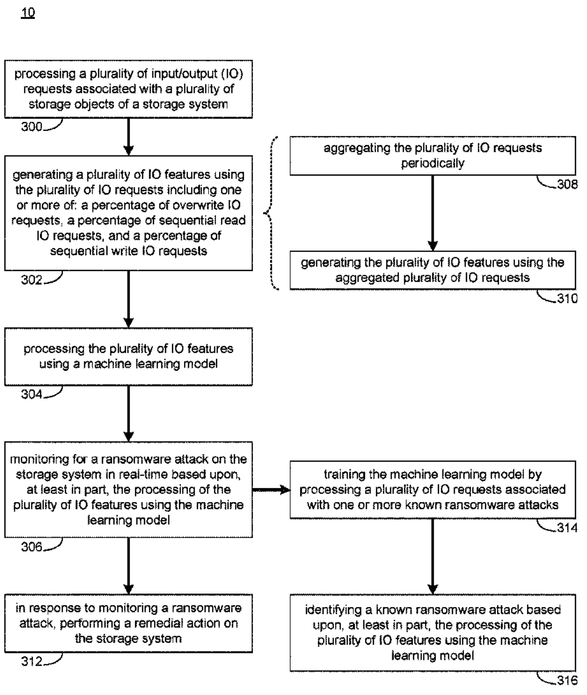
* cited by examiner

Primary Examiner — William A Corum, Jr.
(74) *Attorney, Agent, or Firm* — Brian J. Colandreo; Heath M. Sargeant; Holland & Knight LLP

(57) **ABSTRACT**

A method, computer program product, and computing system for processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. A plurality of IO features may be generated using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. The plurality of IO features may be processed using a machine learning model. A ransomware attack may be monitored for on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

20 Claims, 6 Drawing Sheets


10
processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system
300
generating a plurality of IO features using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests
302
aggregating the plurality of IO requests periodically
308
generating the plurality of IO features using the aggregated plurality of IO requests
310
processing the plurality of IO features using a machine learning model
304
monitoring for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model
306
training the machine learning model by processing a plurality of IO requests associated with one or more known ransomware attacks
314
in response to monitoring a ransomware attack, performing a remedial action on the storage system
312
identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model
316

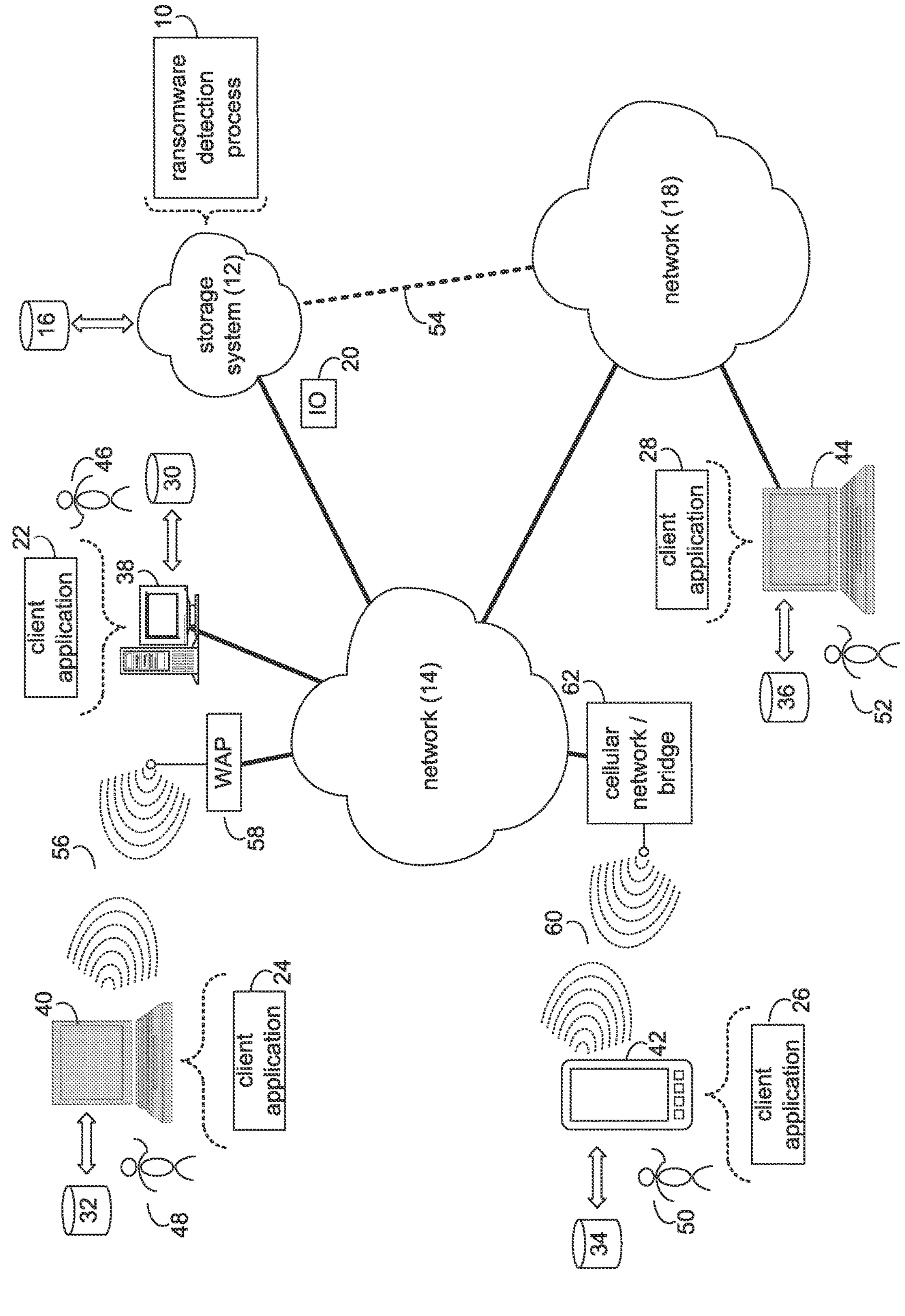

10
ransomware detection process
16
storage system (12)
54
network (18)
20
IO
22
client application
46
30
38
28
client application
44
WAP
56
58
network (14)
62
cellular network / bridge
36
52
40
24
client application
32
48
60
42
26
client application
34
50

FIG. 1

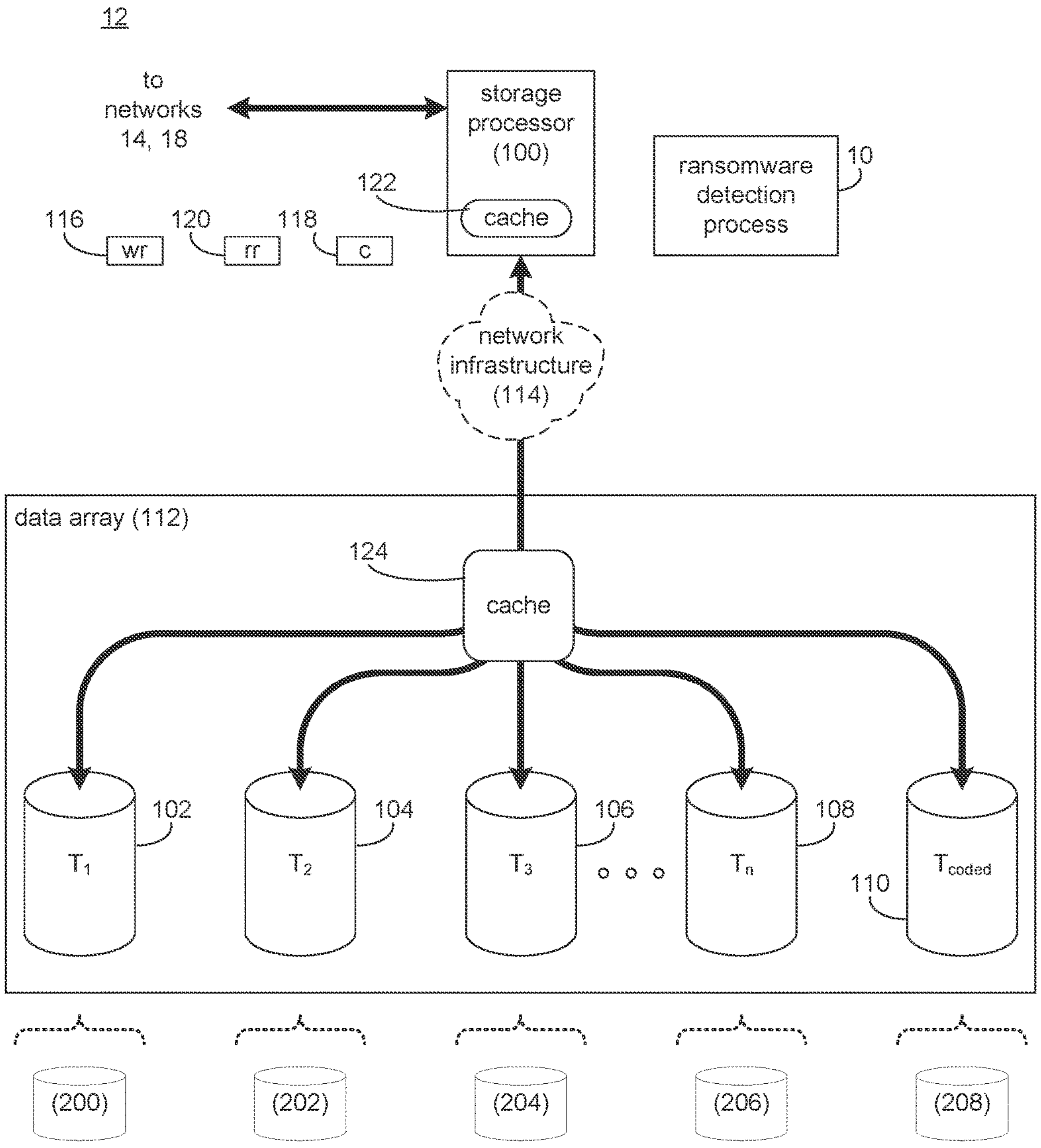

12
to networks 14, 18
storage processor (100)
122
cache
ransomware detection process
10
116
wr
120
rr
118
c
network infrastructure (114)
data array (112)
124
cache
T_1
102
T_2
104
T_3
106
T_n
108
T_{coded}
110
(200)
(202)
(204)
(206)
(208)

FIG. 2

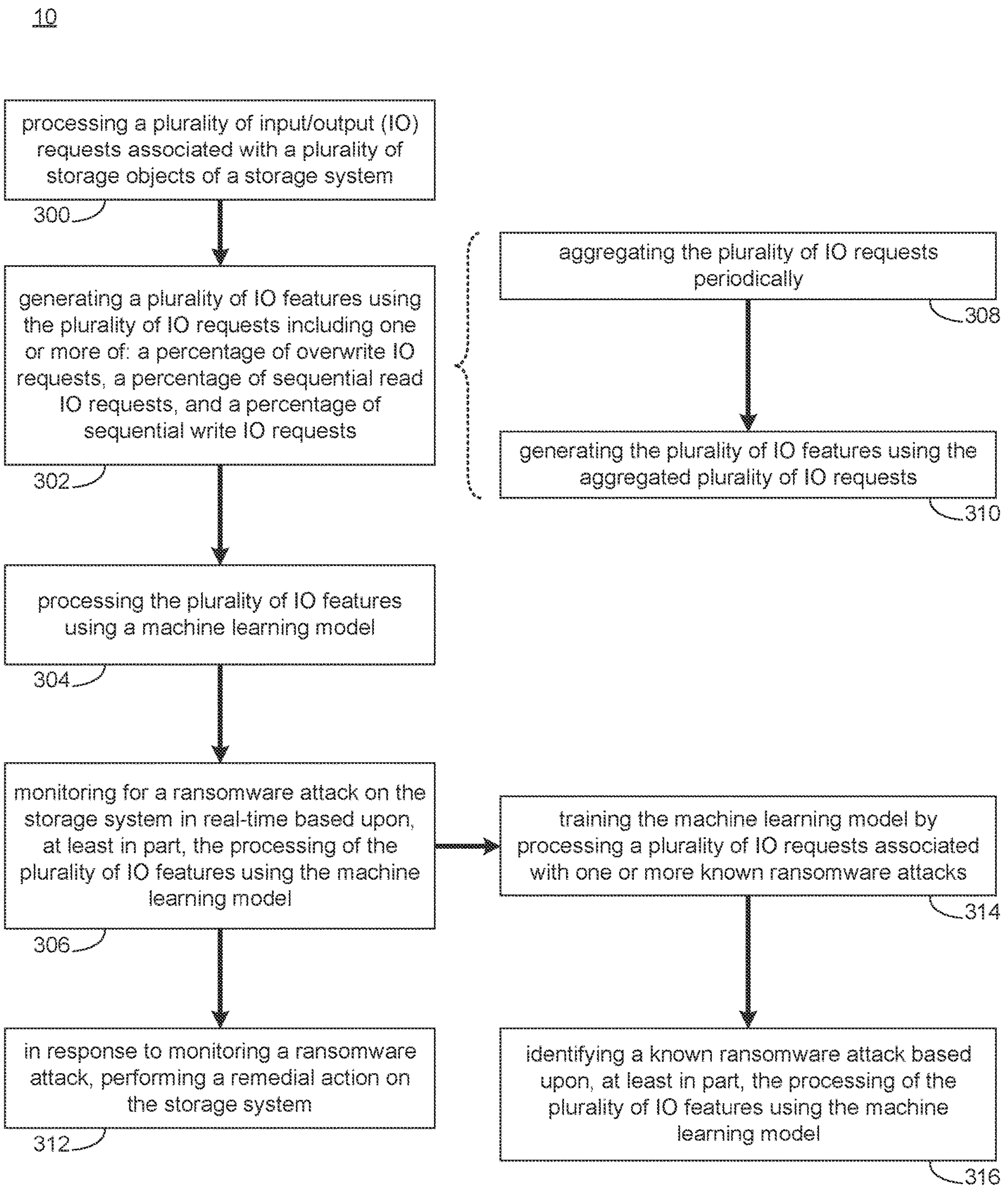

10
processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system
300
generating a plurality of IO features using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests
302
aggregating the plurality of IO requests periodically
308
generating the plurality of IO features using the aggregated plurality of IO requests
310
processing the plurality of IO features using a machine learning model
304
monitoring for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model
306
training the machine learning model by processing a plurality of IO requests associated with one or more known ransomware attacks
314
in response to monitoring a ransomware attack, performing a remedial action on the storage system
312
identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model
316

FIG. 3

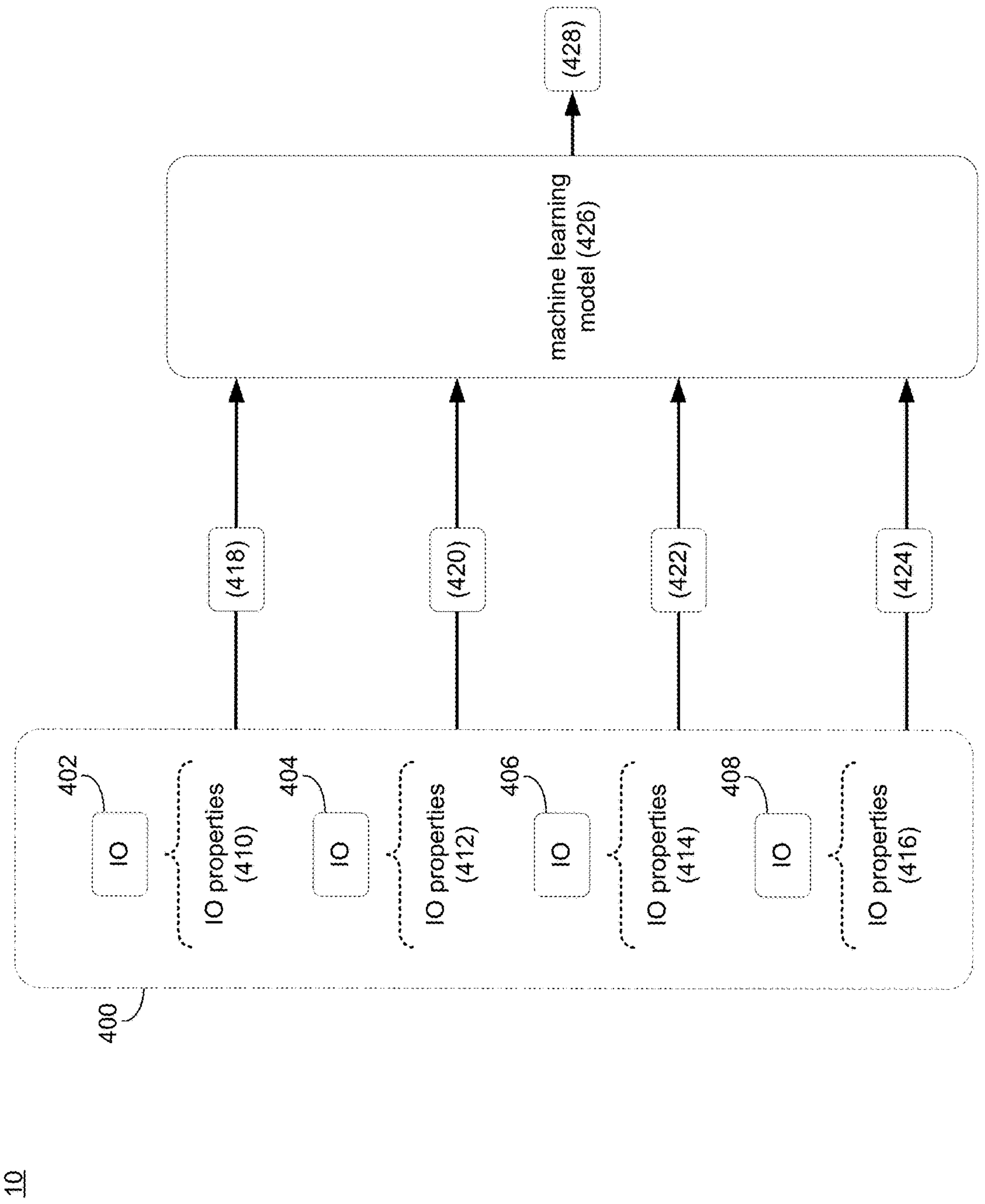

10
400
402
IO
IO properties (410)
404
IO
IO properties (412)
406
IO
IO properties (414)
408
IO
IO properties (416)
(418)
(420)
(422)
(424)
machine learning model (426)
(428)

FIG. 4

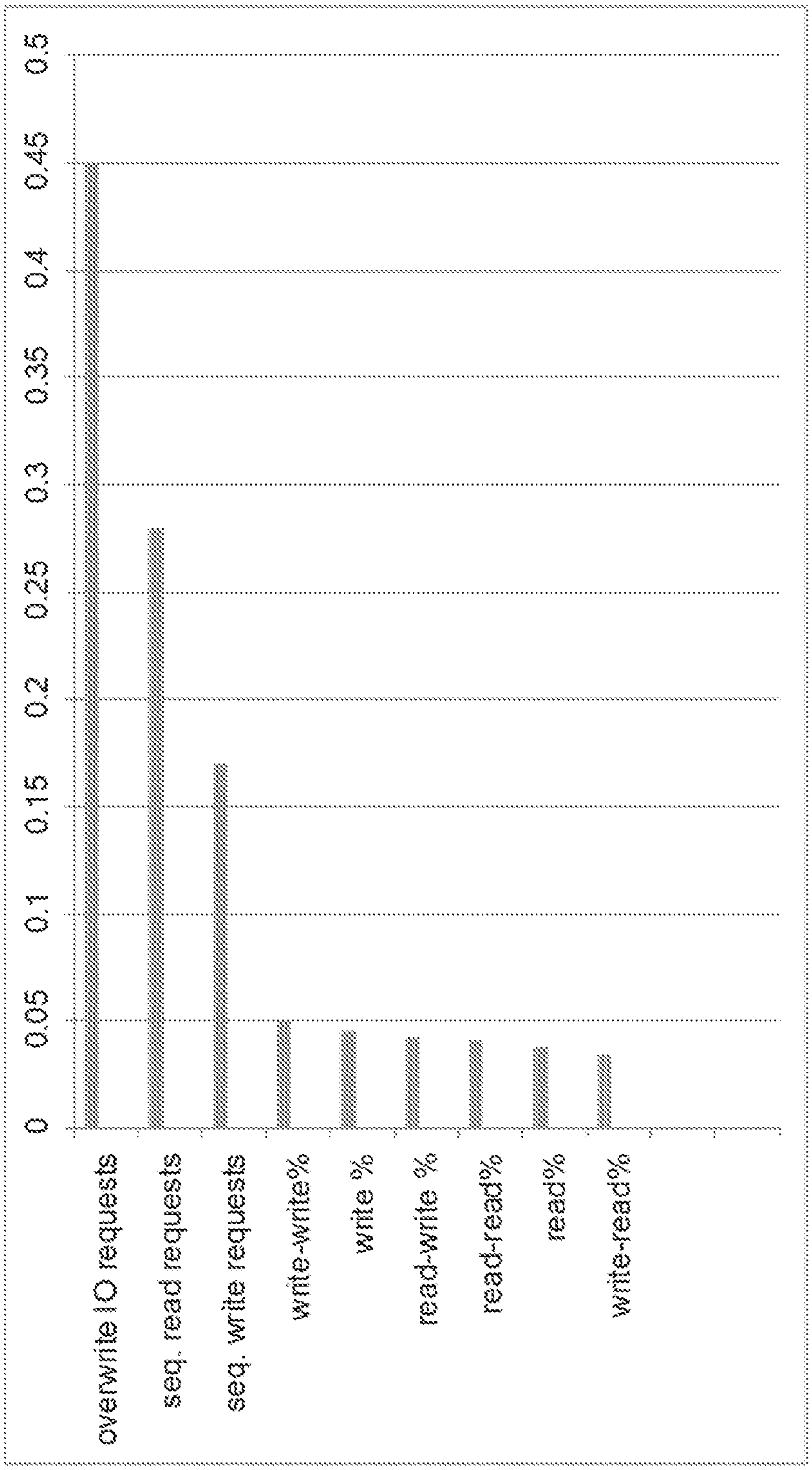

0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
overwrite IO requests
seq. read requests
seq. write requests
write-write%
write %
read-write %
read-read%
read%
write-read%

FIG. 5

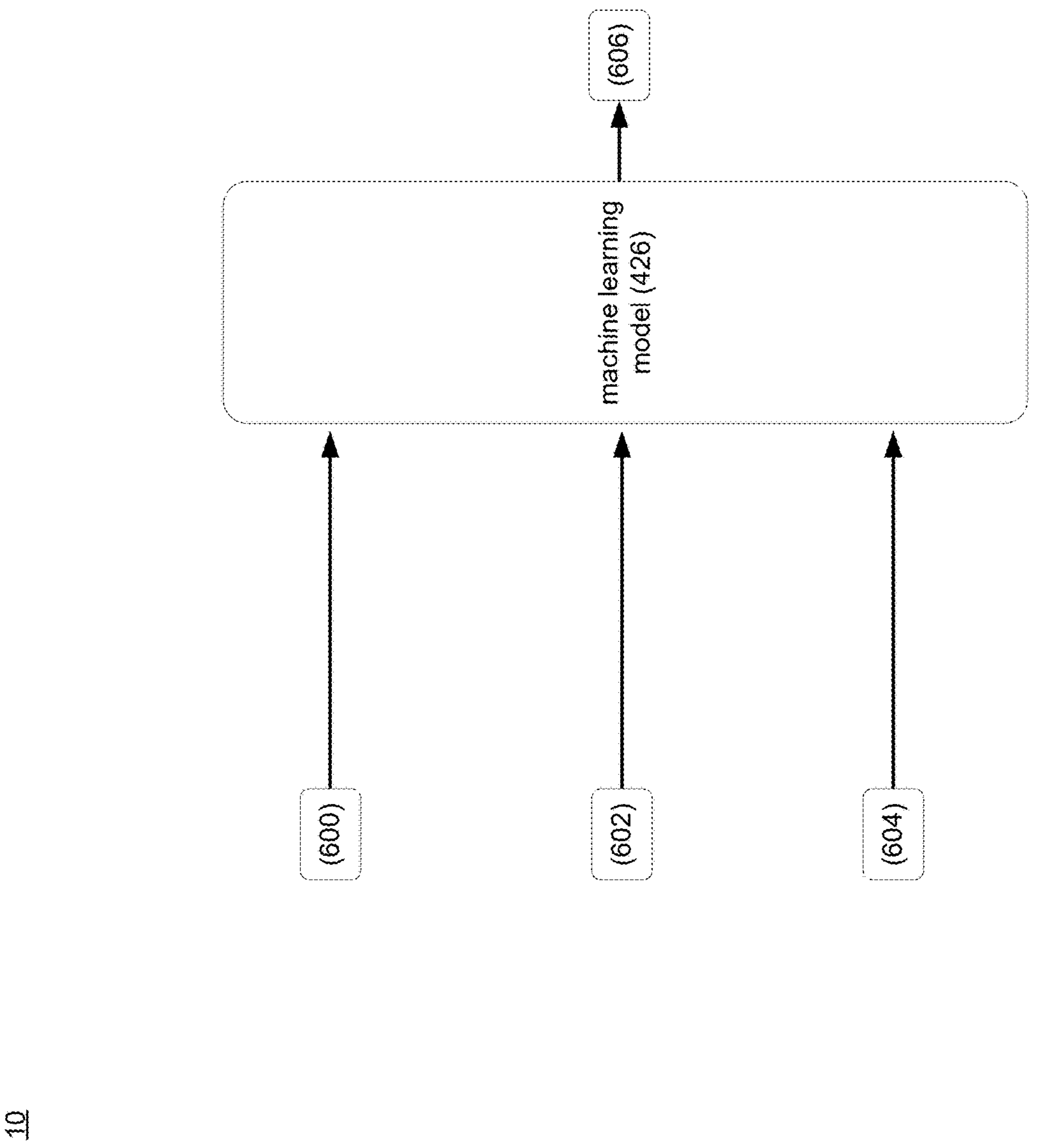


FIG. 6

STORAGE AND METHOD FOR MACHINE LEARNING-BASED DETECTION OF RANSOMWARE ATTACKS ON A STORAGE SYSTEM

BACKGROUND

Ransomware attacks are a primary security threat in today's world and are becoming more and more prevalent. Accurate detection is crucial, since a false negative is a failure to detect an ongoing ransomware attack, while a false positive indicates a false alarm which may cause users of a storage system to halt normal business operations and start a lengthy investigation process. There are different ransomware variants utilizing particular modes of operation (threats, tactics and procedures) which makes detecting a ransomware attack in general (i.e., a binary classification) more challenging, and detection of a specific type of attack (i.e., multi-class classification) even more challenging. Conventional approaches are focused on detection of ransomware attacks on a host, where the attack is occurring (i.e., where the ransomware is being executed). However, in an enterprise setting, the storage is typically separate from the host, using a file or block storage device or storage system. Detection of ransomware attacks on the storage system as opposed to the host poses a unique challenge since the storage system does not have direct access to information about the execution of the ransomware attack.

SUMMARY OF DISCLOSURE

In one example implementation, a computer-implemented method executed on a computing device may include, but is not limited to, processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. A plurality of IO features may be generated using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. The plurality of IO features may be processed using a machine learning model. A ransomware attack may be monitored for on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

One or more of the following example features may be included. The plurality of storage objects may include at least one of a block storage object and a file storage object. The plurality of IO features further include one or more of: a number of IO requests per second (IOPS); a total number of read IO requests; and a total number of write IO requests. Generating the plurality of IO features using the plurality of IO requests may include: aggregating the plurality of IO requests periodically; and generating the plurality of IO features using the aggregated plurality of IO requests. The machine learning model may be trained by processing a plurality of IO requests associated with one or more known ransomware attacks. Monitoring for a ransomware attack on the storage system in real-time may include identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model. In response to monitoring a ransomware attack, a remedial action may be performed on the storage system.

In another example implementation, a computer program product resides on a computer readable medium that has a plurality of instructions stored on it. When executed by a processor, the instructions cause the processor to perform operations that may include, but are not limited to, processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. A plurality of IO features may be generated using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. The plurality of IO features may be processed using a machine learning model. A ransomware attack may be monitored for on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

One or more of the following example features may be included. The plurality of storage objects may include at least one of a block storage object and a file storage object. The plurality of IO features further include one or more of: a number of IO requests per second (IOPS); a total number of read IO requests; and a total number of write IO requests. Generating the plurality of IO features using the plurality of IO requests may include: aggregating the plurality of IO requests periodically; and generating the plurality of IO features using the aggregated plurality of IO requests. The machine learning model may be trained by processing a plurality of IO requests associated with one or more known ransomware attacks. Monitoring for a ransomware attack on the storage system in real-time may include identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model. In response to monitoring a ransomware attack, a remedial action may be performed on the storage system.

In another example implementation, a computing system includes at least one processor and at least one memory architecture coupled with the at least one processor, wherein the at least one processor is configured to processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. A plurality of IO features may be generated using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. The plurality of IO features may be processed using a machine learning model. A ransomware attack may be monitored for on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

One or more of the following example features may be included. The plurality of storage objects may include at least one of a block storage object and a file storage object. The plurality of IO features further include one or more of: a number of IO requests per second (IOPS); a total number of read IO requests; and a total number of write IO requests. Generating the plurality of IO features using the plurality of IO requests may include: aggregating the plurality of IO requests periodically; and generating the plurality of IO features using the aggregated plurality of IO requests. The machine learning model may be trained by processing a plurality of IO requests associated with one or more known ransomware attacks. Monitoring for a ransomware attack on the storage system in real-time may include identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model. In response to monitoring a ransomware attack, a remedial action may be performed on the storage system.

The details of one or more example implementations are set forth in the accompanying drawings and the description

below. Other possible example features and/or possible example advantages will become apparent from the description, the drawings, and the claims. Some implementations may not have those possible example features and/or possible example advantages, and such possible example features and/or possible example advantages may not necessarily be required of some implementations.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is an example diagrammatic view of a storage system and a ransomware detection process coupled to a distributed computing network according to one or more example implementations of the disclosure;

FIG. **2** is an example diagrammatic view of the storage system of FIG. **1** according to one or more example implementations of the disclosure;

FIG. **3** is an example flowchart of ransomware detection process according to one or more example implementations of the disclosure;

FIG. **4** is an example diagrammatic view of the ransomware detection process according to one or more example implementations of the disclosure;

FIG. **5** is a chart depicting various IO features and their relative importance in detecting a ransomware attack; and

FIG. **6** is an example diagrammatic view of the training of a machine learning model according to one or more example implementations of the disclosure.

Like reference symbols in the various drawings indicate like elements.

DETAILED DESCRIPTION

System Overview

Referring to FIG. **1**, there is shown ransomware detection process **10** that may reside on and may be executed by storage system **12**, which may be connected to network **14** (e.g., the Internet or a local area network). Examples of storage system **12** may include, but are not limited to: a Network Attached Storage (NAS) system, a Storage Area Network (SAN), a personal computer with a memory system, a server computer with a memory system, and a cloud-based device with a memory system.

As is known in the art, a SAN may include one or more of a personal computer, a server computer, a series of server computers, a mini computer, a mainframe computer, a RAID device and a NAS system. The various components of storage system **12** may execute one or more operating systems, examples of which may include but are not limited to: Microsoft® Windows®; Mac® OS X®; Red Hat® Linux®, Windows® Mobile, Chrome OS, Blackberry OS, Fire OS, or a custom operating system. (Microsoft and Windows are registered trademarks of Microsoft Corporation in the United States, other countries or both; Mac and OS X are registered trademarks of Apple Inc. in the United States, other countries or both; Red Hat is a registered trademark of Red Hat Corporation in the United States, other countries or both; and Linux is a registered trademark of Linus Torvalds in the United States, other countries or both).

The instruction sets and subroutines of ransomware detection process **10**, which may be stored on storage device **16** included within storage system **12**, may be executed by one or more processors (not shown) and one or more memory architectures (not shown) included within storage system **12**. Storage device **16** may include but is not limited to: a hard disk drive; a tape drive; an optical drive; a RAID device; a

random access memory (RAM); a read-only memory (ROM); and all forms of flash memory storage devices. Additionally/alternatively, some portions of the instruction sets and subroutines of ransomware detection process **10** may be stored on storage devices (and/or executed by processors and memory architectures) that are external to storage system **12**.

Network **14** may be connected to one or more secondary networks (e.g., network **18**), examples of which may include but are not limited to: a local area network; a wide area network; or an intranet, for example.

Various IO requests (e.g. IO request **20**) may be sent from client applications **22**, **24**, **26**, **28** to storage system **12**. Examples of IO request **20** may include but are not limited to data write requests (e.g., a request that content be written to storage system **12**) and data read requests (e.g., a request that content be read from storage system **12**).

The instruction sets and subroutines of client applications **22**, **24**, **26**, **28**, which may be stored on storage devices **30**, **32**, **34**, **36** (respectively) coupled to client electronic devices **38**, **40**, **42**, **44** (respectively), may be executed by one or more processors (not shown) and one or more memory architectures (not shown) incorporated into client electronic devices **38**, **40**, **42**, **44** (respectively). Storage devices **30**, **32**, **34**, **36** may include but are not limited to: hard disk drives; tape drives; optical drives; RAID devices; random access memories (RAM); read-only memories (ROM), and all forms of flash memory storage devices. Examples of client electronic devices **38**, **40**, **42**, **44** may include, but are not limited to, personal computer **38**, laptop computer **40**, smartphone **42**, notebook computer **44**, a server (not shown), a data-enabled, cellular telephone (not shown), and a dedicated network device (not shown).

Users **46**, **48**, **50**, **52** may access storage system **12** directly through network **14** or through secondary network **18**. Further, storage system **12** may be connected to network **14** through secondary network **18**, as illustrated with link line **54**.

The various client electronic devices may be directly or indirectly coupled to network **14** (or network **18**). For example, personal computer **38** is shown directly coupled to network **14** via a hardwired network connection. Further, notebook computer **44** is shown directly coupled to network **18** via a hardwired network connection. Laptop computer **40** is shown wirelessly coupled to network **14** via wireless communication channel **56** established between laptop computer **40** and wireless access point (e.g., WAP) **58**, which is shown directly coupled to network **14**. WAP **58** may be, for example, an IEEE 802.11a, 802.11b, 802.11g, 802.11n, Wi-Fi, and/or Bluetooth device that is capable of establishing wireless communication channel **56** between laptop computer **40** and WAP **58**. Smartphone **42** is shown wirelessly coupled to network **14** via wireless communication channel **60** established between smartphone **42** and cellular network/bridge **62**, which is shown directly coupled to network **14**.

Client electronic devices **38**, **40**, **42**, **44** may each execute an operating system, examples of which may include but are not limited to Microsoft® Windows®; Mac® OS X®; Red Hat® Linux®, Windows® Mobile, Chrome OS, Blackberry OS, Fire OS, or a custom operating system. (Microsoft and Windows are registered trademarks of Microsoft Corporation in the United States, other countries or both; Mac and OS X are registered trademarks of Apple Inc. in the United States, other countries or both; Red Hat is a registered trademark of Red Hat Corporation in the United States, other countries or both; and Linux is a registered trademark of Linus Torvalds in the United States, other countries or both).

In some implementations, as will be discussed below in greater detail, a ransomware detection process, such as ransomware detection process **10** of FIG. **1**, may include but is not limited to, processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. A plurality of IO features may be generated using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. The plurality of IO features may be processed using a machine learning model. A ransomware attack may be monitored for on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

For example purposes only, storage system **12** will be described as being a network-based storage system that includes a plurality of electro-mechanical backend storage devices. However, this is for example purposes only and is not intended to be a limitation of this disclosure, as other configurations are possible and are considered to be within the scope of this disclosure.

The Storage System

Referring also to FIG. **2**, storage system **12** may include storage processor **100** and a plurality of storage targets T 1-n (e.g., storage targets **102**, **104**, **106**, **108**). Storage targets **102**, **104**, **106**, **108** may be configured to provide various levels of performance and/or high availability. For example, one or more of storage targets **102**, **104**, **106**, **108** may be configured as a RAID 0 array, in which data is striped across storage targets. By striping data across a plurality of storage targets, improved performance may be realized. However, RAID 0 arrays do not provide a level of high availability. Accordingly, one or more of storage targets **102**, **104**, **106**, **108** may be configured as a RAID 1 array, in which data is mirrored between storage targets. By mirroring data between storage targets, a level of high availability is achieved as multiple copies of the data are stored within storage system **12**.

While storage targets **102**, **104**, **106**, **108** are discussed above as being configured in a RAID 0 or RAID 1 array, this is for example purposes only and is not intended to be a limitation of this disclosure, as other configurations are possible. For example, storage targets **102**, **104**, **106**, **108** may be configured as a RAID 3, RAID 4, RAID 5 or RAID 6 array.

While in this particular example, storage system **12** is shown to include four storage targets (e.g. storage targets **102**, **104**, **106**, **108**), this is for example purposes only and is not intended to be a limitation of this disclosure. Specifically, the actual number of storage targets may be increased or decreased depending upon e.g., the level of redundancy/performance/capacity required.

Storage system **12** may also include one or more coded targets **110**. As is known in the art, a coded target may be used to store coded data that may allow for the regeneration of data lost/corrupted on one or more of storage targets **102**, **104**, **106**, **108**. An example of such a coded target may include but is not limited to a hard disk drive that is used to store parity data within a RAID array.

While in this particular example, storage system **12** is shown to include one coded target (e.g., coded target **110**), this is for example purposes only and is not intended to be a limitation of this disclosure. Specifically, the actual number of coded targets may be increased or decreased depending upon e.g. the level of redundancy/performance/capacity required.

Examples of storage targets **102**, **104**, **106**, **108** and coded target **110** may include one or more electro-mechanical hard disk drives and/or solid-state/flash devices, wherein a combination of storage targets **102**, **104**, **106**, **108** and coded target **110** and processing/control systems (not shown) may form data array **112**.

The manner in which storage system **12** is implemented may vary depending upon e.g. the level of redundancy/performance/capacity required. For example, storage system **12** may be a RAID device in which storage processor **100** is a RAID controller card and storage targets **102**, **104**, **106**, **108** and/or coded target **110** are individual "hot-swappable" hard disk drives. Another example of such a RAID device may include but is not limited to an NAS device. Alternatively, storage system **12** may be configured as a SAN, in which storage processor **100** may be e.g., a server computer and each of storage targets **102**, **104**, **106**, **108** and/or coded target **110** may be a RAID device and/or computer-based hard disk drives. Further still, one or more of storage targets **102**, **104**, **106**, **108** and/or coded target **110** may be a SAN.

In the event that storage system **12** is configured as a SAN, the various components of storage system **12** (e.g. storage processor **100**, storage targets **102**, **104**, **106**, **108**, and coded target **110**) may be coupled using network infrastructure **114**, examples of which may include but are not limited to an Ethernet (e.g., Layer 2 or Layer 3) network, a fiber channel network, an InfiniBand network, or any other circuit switched/packet switched network.

Storage system **12** may execute all or a portion of ransomware detection process **10**. The instruction sets and subroutines of ransomware detection process **10**, which may be stored on a storage device (e.g., storage device **16**) coupled to storage processor **100**, may be executed by one or more processors (not shown) and one or more memory architectures (not shown) included within storage processor **100**. Storage device **16** may include but is not limited to: a hard disk drive; a tape drive; an optical drive; a RAID device; a random access memory (RAM); a read-only memory (ROM); and all forms of flash memory storage devices. As discussed above, some portions of the instruction sets and subroutines of ransomware detection process **10** may be stored on storage devices (and/or executed by processors and memory architectures) that are external to storage system **12**.

As discussed above, various IO requests (e.g. IO request **20**) may be generated. For example, these IO requests may be sent from client applications **22**, **24**, **26**, **28** to storage system **12**. Additionally/alternatively and when storage processor **100** is configured as an application server, these IO requests may be internally generated within storage processor **100**. Examples of IO request **20** may include but are not limited to data write request **116** (e.g., a request that content **118** be written to storage system **12**) and data read request **120** (i.e. a request that content **118** be read from storage system **12**).

During operation of storage processor **100**, content **118** to be written to storage system **12** may be processed by storage processor **100**. Additionally/alternatively and when storage processor **100** is configured as an application server, content **118** to be written to storage system **12** may be internally generated by storage processor **100**.

Storage processor **100** may include frontend cache memory system **122**. Examples of frontend cache memory system **122** may include but are not limited to a volatile, solid-state, cache memory system (e.g., a dynamic RAM cache memory system) and/or a non-volatile, solid-state, cache memory system (e.g., a flash-based, cache memory system).

Storage processor **100** may initially store content **118** within frontend cache memory system **122**. Depending upon the manner in which frontend cache memory system **122** is configured, storage processor **100** may immediately write content **118** to data array **112** (if frontend cache memory system **122** is configured as a write-through cache) or may subsequently write content **118** to data array **112** (if frontend cache memory system **122** is configured as a write-back cache).

Data array **112** may include backend cache memory system **124**. Examples of backend cache memory system **124** may include but are not limited to a volatile, solid-state, cache memory system (e.g., a dynamic RAM cache memory system) and/or a non-volatile, solid-state, cache memory system (e.g., a flash-based, cache memory system). During operation of data array **112**, content **118** to be written to data array **112** may be received from storage processor **100**. Data array **112** may initially store content **118** within backend cache memory system **124** prior to being stored on e.g. one or more of storage targets **102**, **104**, **106**, **108**, and coded target **110**.

As discussed above, the instruction sets and subroutines of ransomware detection process **10**, which may be stored on storage device **16** included within storage system **12**, may be executed by one or more processors (not shown) and one or more memory architectures (not shown) included within storage system **12**. Accordingly, in addition to being executed on storage processor **100**, some or all of the instruction sets and subroutines of ransomware detection process **10** may be executed by one or more processors (not shown) and one or more memory architectures (not shown) included within data array **112**.

Further and as discussed above, during the operation of data array **112**, content (e.g., content **118**) to be written to data array **112** may be received from storage processor **100** and initially stored within backend cache memory system **124** prior to being stored on e.g. one or more of storage targets **102**, **104**, **106**, **108**, **110**. Accordingly, during use of data array **112**, backend cache memory system **124** may be populated (e.g., warmed) and, therefore, subsequent read requests may be satisfied by backend cache memory system **124** (e.g., if the content requested in the read request is present within backend cache memory system **124**), thus avoiding the need to obtain the content from storage targets **102**, **104**, **106**, **108**, **110** (which would typically be slower).

The Ransomware Detection Process

Referring also to the examples of FIGS. **3**-**6** and in some implementations, ransomware detection process **10** may process **300** a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. A plurality of IO features may be generated **302** using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. The plurality of IO features may be processed **304** using a machine learning model. A ransomware attack may be monitored **306** for on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

As will be discussed in greater detail below, implementations of the present disclosure may allow for real-time or

near real-time monitoring and detection of ransomware attacks on a storage system. Ransomware attacks are a primary security threat in today's world and are becoming more and more prevalent. Accurate detection is crucial, since a false negative is a failure to detect an ongoing ransomware attack, while a false positive indicates a false alarm which may cause users of a storage system to halt normal business operations and start a lengthy investigation process. Early detection is important, as it provides the opportunity to automatically or manually (e.g., by alerting a user) block the ransomware attack before it has caused most of its damage, and to recover from the attack using valid copies of the compromised data, such as snapshots or replicas. There are different ransomware variants utilizing particular modes of operation (threats, tactics and procedures) which makes detecting a ransomware attack in general (i.e., a binary classification) more challenging, and detection of a specific type of attack (i.e., multi-class classification) even more challenging. Conventional approaches are focused on detection of ransomware attacks on a host, where the attack is occurring (i.e., where the ransomware is being executed). However, in an enterprise setting, the storage is typically separate from the host, using a file or block storage device or storage system. Detection of ransomware attacks on the storage system as opposed to the host poses a unique challenge since the storage system does not have direct access to information about the execution of the ransomware attack.

Conventional approaches detect ransomware attack by postmortem analysis, hours or days after an attack occurs. The practical benefit of such an approach is limited since it is too late for the user or customer to take steps to block or mitigate the attack, and the damage is already done. As will be discussed in greater detail below, implementations of the present disclosure analyze the stream of input/output (IO) operations issued from the host to the storage system (i.e., dynamic analysis), and also the resulting changes in the data that is stored (i.e., static analysis). For example, ransomware detection process **10** uses a supervised machine learning classification model to detect ransomware attacks on storage systems as they are occurring, with high accuracy. As such, implementations of the present disclosure: 1) analyze IO workloads running against the storage device in real time or near-real time; 2) generate innovative IO features for machine learning using both aggregate counters and the relationships between individual IO requests; 3) generate a machine learning classification model that can differentiate between a ransomware workload and a benign workload, with high accuracy for particular behavioral machine learning features related to the execution of ransomware malware; 4) extends the machine learning model to handle multi-class classification (i.e., detection of specific ransomware attack variants); 5) enhance the machine learning model to mitigate the risk of model overfitting because of the imbalance between the benign class and the (one or more) ransomware attack class(es). In some implementations, ransomware detection process **10** is applicable for both file and block storage devices.

In some implementations, ransomware detection process **10** processes **300** a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system. For example and referring again to FIG. **2**, during the operation of a storage system (e.g., storage system **12**), IO operations may be generated for processing data on various storage objects (e.g., storage objects **200**, **202**, **204**, **206**, **208**). Storage objects (e.g., storage objects **200**, **202**, **204**, **206**, **208**) may generally include any container or storage unit configured to store data within a storage system (e.g., storage system **12**). For example, a storage object may be any one of the following: a volume (aka Logical Unit Number (LUN)), a file, or parts thereof that may be defined e.g. by offsets or address ranges (e.g., sub-LUNs, disk extents, and/or slices). In some implementations, the plurality of storage objects include a block storage object and/or a file storage object. A block storage object is a block or chunk of storage that can be accessed by various operating systems. In some implementations, a file storage object is a folder or subset of a hierarchical data structure accessible by a particular path within the hierarchical data structure. As will be discussed in greater detail below, ransomware detection process **10** is able to detect a ransomware attack by generating IO features for block storage objects and/or file storage objects.

Referring also to FIG. **4**, a plurality of IO requests (e.g., plurality of IO requests **400**) may include e.g., four IO requests associated with various storage objects and/or the same storage object. IO request **402** may include a request to perform a read IO operation on a first storage object (e.g., storage object **200**); IO request **404** may include a request to perform a write IO operation on storage object **200**; IO request **406** may include a request to perform a read IO operation on storage object **200**; and IO request **408** may include a request to perform an operation on storage object **200**. While four separate IO requests for a single storage object have been described, it will be appreciated that this is for example purposes only and that any number of IO requests may be received for any number of storage objects within the present disclosure.

In some implementations, ransomware detection process **10** generates a plurality of IO features using the plurality of IO requests. An IO feature is a representation of a plurality of IO properties associated with a particular storage object over a period of time. In some implementations, an IO feature is used by a machine learning model to identify trends indicative of a ransomware attack involving the storage object. Examples of IO features include a number of IO requests per second (IOPS); a total number of read IO requests; a total number of write IO requests; a percentage of overwrite IO requests; a percentage of sequential read IO requests; a percentage of sequential write IO requests; an average length of read IO requests; an average length of write IO requests; a standard deviation in read IO request length; a standard deviation in write IO request length; an average arrival rate of any IO request; an average arrival rate for read IO requests; an average arrival rate for write IO requests; an average difference in logical block address (LBA) between IO requests; an average difference in LBA between consecutive read IO requests; an average difference in logical block address (LBA) between consecutive write IO requests; etc.

In some implementations, ransomware detection process **10** generates **302** a plurality of IO features using the plurality of IO requests including one or more of: a percentage of overwrite IO requests, a percentage of sequential read IO requests, and a percentage of sequential write IO requests. For example, an overwrite IO request is the combination of as read IO request or operation followed by a write IO request or operation with the same logical address (e.g., LBA) and length. In this manner, the subsequent write operation overwrites the address range that was read, with no intervening IO operations on that address range. A sequential read IO request is identified by a second read IO operation of a pair of read operations such that the second read IO operations begins were the first read IO operation ended, (i.e., the LBA of second read IO operation equals the sum of the LBA of the first read IO operation plus the number of bytes read). A sequential write IO request is identified by a second write IO operation of a pair of write operations such that the second write IO operations begins were the first write IO operation ended, (i.e., the LBA of second write IO operation equals the sum of the LBA of the first write IO operation plus the number of bytes written).

In some implementations, there may be no intervening IO requests between the sequential IO operations. For example, suppose ransomware detection process **10** receives IO request **402** concerning a particular LBA range (e.g., either a read request or a write request) and IO request **404** concerns the next LBA range is received directly after IO request **402** such that no intervening IO requests are processed between IO requests **402** and **404**. In another example, sequential IO requests may include a threshold amount of intervening IO requests and/or time between sequential IO requests. For instance, ransomware detection process **10** may receive a user-defined threshold for a number of intervening IO requests to define sequential IO requests. The threshold may be a default value (e.g., up to three intervening IO requests and/or three intervening IO requests that concern the same or a different LBA range). As such, it will be appreciated that various thresholds (e.g., number of IO requests, time between IO requests, range of LBAs, etc.) may be defined and used to identify sequential IO requests within the scope of the present disclosure.

As noted above, while IO features may be used by a machine learning model to identify trends indicative of a ransomware attack involving the storage object, the IO features of overwrite IO requests, sequential read IO requests, and sequential write IO requests are the most effective at accurately identifying trends indicative of a ransomware attack. For instance, in a ransomware attack, IO requests may be issued by ransomware malware to copy target data from the storage system and replace the target data with inaccessible or an encrypted version of data, until the victim pays a ransom fee to the attacker. As these ransomware processes include overwriting data, sequential reading data, and sequentially writing data in the manner described above, ransomware detection process **10** may generate **302** IO features concerning these suspect types of features from the plurality of IO requests.

For example and referring also to FIG. **5**, the relative "importance" or weighting of several IO features are shown in detecting ransomware attacks (e.g., percentage of overwrite IO requests; percentage of sequential read IO requests; percentage of sequential write IO requests; percentage of write IO requests followed by write IO requests; percentage of write IO requests; percentage of read IO requests followed by write IO requests; percentage of read IO requests followed by read IO requests; percentage of read IO requests; and percentage of write IO requests followed by read IO requests). As shown in FIG. **5**, percentage of overwrite IO requests represent the most important indicator of a ransomware attack, followed by percentage of sequential read IO requests, and then percentage of sequential write IO requests. As each of these three IO features perform significantly better than other IO features, ransomware detection process **10** generates **302** a plurality of IO features including one or more of these IO features in order to more effectively detect potential ransomware attacks on the storage system.

In some implementations, ransomware detection process **10** generates **302** the plurality of IO features by extracting salient data elements (e.g., one or more IO properties) such as volume ID, timestamp, IO command type (e.g. read, write, unmap, etc.), logical block address (LBA) (i.e., an offset in the data path's thin address space), length, pattern (e.g., sequential, random, caterpillar, IO-stride), etc. from the plurality of IO requests. In this manner, ransomware detection process **10** may extract various IO properties associated with the plurality of IO requests. Referring again to FIG. **4** and in some implementations, ransomware detection process **10** may extract one or more IO properties from plurality of IO requests **400**. For example, ransomware detection process **10** may extract IO properties **418** from IO request **402**; IO properties **420** from IO request **404**; IO properties **422** from IO request **406**; and IO properties **424** from IO request **408**.

In some implementations, generating **302** the plurality of IO features using the plurality of IO requests includes aggregating **308** the plurality of IO requests periodically, and generating **310** the plurality of IO features using the aggregated plurality of IO requests. For example, ransomware detection process **10** may aggregate the one or more IO properties periodically to optimize for memory/storage requirements and/or CPU costs. Additionally, ransomware detection process **10** may use a sampling approach where IO properties for every "n"th IO request are extracted. In some implementations, the number of IO requests between extracting the one or more IO properties may be user-defined, a default number of IO requests, and/or defined automatically by ransomware detection process **10**. In this manner, ransomware detection process **10** may limit the amount of processing of IO requests to generate IO features by sampling and aggregating **308** a limited set of all of the IO requests received at the storage system. Referring again to FIG. **4** and in some implementations, ransomware detection process **10** may aggregate **308** IO properties **410** from IO request **402**; IO properties **412** from IO request **404**; IO properties **414** from IO request **406**; and IO properties **416** from IO request **408** and generate **310** a plurality of IO features (e.g., IO features **418**, **420**, **422**, **424**).

In some implementations, ransomware detection process **10** processes **304** the plurality of IO features using a machine learning model. A machine learning model may generally include an algorithm or combination of algorithms that has been trained to recognize certain types of patterns. For example, machine learning approaches may be generally divided into three categories, depending on the nature of the signal available: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning may include presenting a computing device with example inputs and their desired outputs, given by a "teacher", where the goal is to learn a general rule that maps inputs to outputs. With unsupervised learning, no labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning). Reinforcement learning may generally include a computing device interacting in a dynamic environment in which it must perform a certain goal (such as driving a vehicle or playing a game against an opponent). As it navigates its problem space, the machine learning model is provided feedback that is analogous to rewards, which it tries to maximize. While three examples of machine learning approaches have been provided, it will be appreciated that other machine learning approaches are possible within the scope of the present disclosure. Ransomware detection process **10** may use any machine learning model or other machine learning algorithm to classify a plurality of IO features associated with a storage object as being indicative of a ransomware attack. In one example, a random-forest machine learning model may be used due to its generality, simplicity, tunability, and ability to cope with over-fitting. However, it will be appreciated that various machine learning models may be used within the scope of the present disclosure to process **304** the plurality of IO features. Referring again to FIG. **4** and in some implementations, ransomware detection process **10** may process **304** the plurality of IO features (e.g., IO features **418**, **420**, **422**, **424**) using a machine learning model (e.g., machine learning model **426**).

In some implementations, ransomware detection process **10** monitors **306** for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model. A ransomware attack is an attack involving a type of malicious software that threatens to publish or blocks access to data or a computer system, usually by encrypting it, until the victim pays a ransom fee to the attacker. In many cases, the ransom demand comes with a deadline. If the victim does not pay in time, the data is gone forever or the ransom increases. As discussed above, ransomware attacks are becoming more and more frequent. Studies estimate that there is a ransomware attack every eleven seconds. Nevertheless, considering the vast number of IO requests that are being executed on storage systems around the world every second, a ransomware attack is a statistically rare event. The class imbalance between ransomware attacks and benign workloads likely exceeds 1:1,000,000. As such, this raises the concern of model overfitting. To reduce this risk, various machine learning techniques such as resampling (oversampling the small class, under-sampling the large class), SMOTE (i.e., a machine learning technique that solves problems that occur when using an imbalanced data set), etc. may be used by ransomware detection process **10** within the scope of the present disclosure.

As discussed above, conventional approaches to ransomware detection is accomplished by postmortem analysis, hours or days after an attack occurs. The practical benefit of such an approach is limited since it is too late for the user or customer to take steps to block or mitigate the attack, and the damage is already done. By contrast, ransomware detection process **10** analyzes the stream of input/output (IO) operations issued from the host to the storage system (i.e., dynamic analysis), and also the resulting changes in the data that is stored (i.e., static analysis) to generate IO features. Ransomware detection process **10** uses a supervised machine learning classification model to detect ransomware attacks on storage systems as they are occurring, with high accuracy. In this manner, "real-time" or "near real-time" monitoring means monitoring and detecting ransomware attacks as they are occurring and within the time for processing the plurality of IO requests, generating the plurality of IO features, and processing the plurality of IO features using the machine learning model. In one example, ransomware detection process **10** aggregates and generates the plurality of IO features every e.g., five minutes. In this example, ransomware detection process **10** is able to monitor for ransomware attacks in real-time or near real-time based on the timing associated with generating the plurality of IO features during a ransomware attack.

As shown in FIG. **4**, ransomware detection process **10** monitors **306** for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features (e.g., IO features **418**, **420**, **422**, **424**) using the machine learning model (e.g., machine learning model **426**). In some implementations, monitoring **306** for a ransomware attack on the storage system in real-time includes using the plurality of IO features (e.g., IO features **418**, **420**, **422**, **424**) to generate a ransomware attack probability score (e.g., ransomware attack probability score **428**). In some implementations, ransomware attack probability score **428** is a score ranging from zero to one indicating a probability that a ransomware attack is occurring involving the storage object. In some implementations, ransomware detection process **10** uses ransomware attack probability score **428** to distinguish normal IO request workloads from potential ransomware attacks.

In some implementations and in response to monitoring **306** a ransomware attack, ransomware detection process **10** performs **312** a remedial action on the storage system. For example, ransomware detection process **10** may include one or more thresholds for evaluating ransomware attack probability scores. In some implementations, the threshold(s) for particular ransomware attacks may be predefined, user-defined, and/or automatically defined using ransomware detection process **10**. For example, ransomware detection process **10** may define a threshold between a false negative and a false positive (i.e., binary classification). In one example, the default threshold may be 0.5. In some implementations, ransomware detection process **10** may tune the threshold up or down for particular situations (e.g., increasing the threshold for those less willing to have a false positive or decreasing the threshold for those preferring to be alerted about all potential ransomware attacks).

Ransomware detection process **10** may perform **312** a remedial action on the storage system when the ransomware attack probability score exceeds the threshold(s). For example, the remedial action may include generating an alert (e.g., for a storage system administrator, for one or more hosts/users of the storage system, etc.); suspending one or more IO requests on the storage object and/or the storage system; logging the plurality of IO features for training the machine learning model; etc. In some implementations, ransomware detection process **10** may process a plurality of IO requests and aggregate in-memory counters relevant to the plurality of IO features used by a machine learning model. At every fixed time interval (e.g., 5 minutes), ransomware detection process **10** aggregates the memory counters and calculates the relevant features. In some implementations, ransomware detection process **10** can also trigger the generation of the plurality of IO features if the storage system is running out of room in the memory area dedicated for the counters.

Periodically (e.g., every 15 minutes) the latest machine learning model may be invoked to calculate the risk of ransomware attacks for all the storage objects in the storage system, or only for the relevant ones. For example, ransomware detection process **10** may focus on storage objects that had significant IO activity and specifically write IO requests, over the recent time interval. In some implementations, when the predicted risk is higher than the default, or a threshold set for a particular storage system, an alert may be issued, with all the relevant details, including the statistics of the IO patterns that triggered the alert. In some implementations, the storage system may report (e.g., to various computing devices, monitoring systems, etc.) instances of ransomware alert firing, along with detailed ransomware data, and/or feedback, indicating whether the alert was deemed correct (i.e., a true positive) or not (i.e., a false positive). Ransomware detection process **10** may also send a similar report if a user reports on a ransomware attack on the storage system that was not alerted (i.e., a false negative). In some implementations, these reports may be used tune the machine learning model to improve its accuracy.

In some implementations, ransomware detection process **10** trains **314** the machine learning model by processing a plurality of IO requests associated with one or more known ransomware attacks. For example, ransomware detection process **10** may obtain traces of well-known or new ransomware attack variants. In one example, ransomware detection process **10** may execute a known ransomware attack in a secure environment, typically known as a "dirty lab". During the execution, ransomware detection process **10** can run a utility that captures a trace of the IO requests labeled with the specific ransomware attack variant. In another example, ransomware attack traces may be obtained from reliable open source or closed source malware repositories. These traces can be added to a training set used in building or updating the machine learning model. In some implementations, model training can be done in a centralized location such as the cloud. In this example, a machine learning model can be trained periodically (e.g., weekly) or when new ransomware attack variants become available, and IO traces of their execution are obtained. Trained or updated machine learning models may be distributed by ransomware detection process **10** to all relevant storage systems. Referring also to FIG. **6**, ransomware detection process **10** may train **314** a machine learning model (e.g., machine learning model **426**) by processing training data (e.g., training data formed from IO features **600**, **602**, **604**) associated with a known ransomware attack to generate a threshold or other classification basis (e.g., ransomware attack classification **606**) for the known ransomware attack. In some implementations, ransomware detection process **10** may train **314** the machine learning model (e.g., machine learning model **426**) to recognize IO features associated with particular known ransomware attacks such that machine learning model **426** provides a ransomware attack probability score and a ransomware attack classification (e.g., ransomware attack classification **606**) indicating which ransomware attack is being observed from the plurality of IO features.

In some implementations, monitoring for a ransomware attack on the storage system in real-time includes identifying **316** a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model. For example, when training **314** the machine learning model, ransomware detection process **10** may use training data specific to a particular ransomware attack type to identify a known ransomware attack at runtime. As discussed above and in some implementations, ransomware detection process **10** may process **304** the plurality of IO features using the machine learning model to generate a ransomware attack classification indicating a particular ransomware attack is being observed. The ransomware attack classification may include a probability score associated with one or more ransomware attacks. In this manner, ransomware detection process **10** may provide the likelihood that a storage object is being subjected to a known ransomware attack in real-time or near real-time by generating a probability score associated with the known ransomware attack.

General

As will be appreciated by one skilled in the art, the present disclosure may be embodied as a method, a system, or a computer program product. Accordingly, the present disclosure may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a “circuit,” “module” or “system.” Furthermore, the present disclosure may take the form of a computer program product on a computer-usable storage medium having computer-usable program code embodied in the medium.

Any suitable computer usable or computer readable medium may be utilized. The computer-usable or computer-readable medium may be, for example but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, device, or propagation medium. More specific examples (a non-exhaustive list) of the computer-readable medium may include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a transmission media such as those supporting the Internet or an intranet, or a magnetic storage device. The computer-usable or computer-readable medium may also be paper or another suitable medium upon which the program is printed, as the program can be electronically captured, via, for instance, optical scanning of the paper or other medium, then compiled, interpreted, or otherwise processed in a suitable manner, if necessary, and then stored in a computer memory. In the context of this document, a computer-usable or computer-readable medium may be any medium that can contain, store, communicate, propagate, or transport the program for use by or in connection with the instruction execution system, apparatus, or device. The computer-usable medium may include a propagated data signal with the computer-usable program code embodied therewith, either in baseband or as part of a carrier wave. The computer usable program code may be transmitted using any appropriate medium, including but not limited to the Internet, wireline, optical fiber cable, RF, etc.

Computer program code for carrying out operations of the present disclosure may be written in an object oriented programming language such as Java, Smalltalk, C++ or the like. However, the computer program code for carrying out operations of the present disclosure may also be written in conventional procedural programming languages, such as the “C” programming language or similar programming languages. The program code may execute entirely on the user’s computer, partly on the user’s computer, as a stand-alone software package, partly on the user’s computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer may be connected to the user’s computer through a local area network/a wide area network/the Internet (e.g., network **14**).

The present disclosure is described with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems) and computer program products according to implementations of the disclosure. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, may be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer/special purpose computer/other programmable data processing apparatus, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

These computer program instructions may also be stored in a computer-readable memory that may direct a computer or other programmable data processing apparatus to function in a particular manner, such that the instructions stored in the computer-readable memory produce an article of manufacture including instruction means which implement the function/act specified in the flowchart and/or block diagram block or blocks.

The computer program instructions may also be loaded onto a computer or other programmable data processing apparatus to cause a series of operational steps to be performed on the computer or other programmable apparatus to produce a computer implemented process such that the instructions which execute on the computer or other programmable apparatus provide steps for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

The flowcharts and block diagrams in the figures may illustrate the architecture, functionality, and operation of possible implementations of systems, methods and computer program products according to various implementations of the present disclosure. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of code, which comprises one or more executable instructions for implementing the specified logical function(s). It should also be noted that, in some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustrations, and combinations of blocks in the block diagrams and/or flowchart illustrations, may be implemented by special purpose hardware-based systems that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions.

The terminology used herein is for the purpose of describing particular implementations only and is not intended to be limiting of the disclosure. As used herein, the singular forms “a”, “an” and “the” are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will be further understood that the terms “comprises” and/or “comprising,” when used in this specification, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof.

The corresponding structures, materials, acts, and equivalents of all means or step plus function elements in the claims below are intended to include any structure, material, or act for performing the function in combination with other claimed elements as specifically claimed. The description of the present disclosure has been presented for purposes of illustration and description, but is not intended to be exhaustive or limited to the disclosure in the form disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the disclosure. The embodiment was chosen and described in order to best explain the principles of the disclosure and the practical application, and to enable others of ordinary skill in the art to understand the disclosure for various implementations with various modifications as are suited to the particular use contemplated.

A number of implementations have been described. Having thus described the disclosure of the present application in detail and by reference to implementations thereof, it will be apparent that modifications and variations are possible without departing from the scope of the disclosure defined in the appended claims.

What is claimed is:

1. A computer-implemented method, executed on a computing device, comprising:
   - processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system;
   - generating a plurality of IO features using the plurality of IO requests including a combination of:
     - a percentage of overwrite IO requests, wherein an overwrite IO request is a read IO request followed by a write IO request with the same logical address and length,
     - a percentage of sequential read IO requests, wherein a sequential read IQ request is a read IO request concerning an adjacent portion of memory as read from an immediately previous read IO request, and
     - a percentage of sequential write IO requests, wherein a sequential write IO request is a write IO request concerning an adjacent portion of memory as written to by an immediately previous write IO request;
   - processing the plurality of IO features using a machine learning model; and
   - monitoring for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

2. The computer-implemented method of claim **1**, wherein the plurality of storage objects include at least one of a block storage object and a file storage object.

3. The computer-implemented method of claim **1**, wherein the plurality of IO features further include one or more of:
   - a number of IO requests per second (IOPS);
   - a total number of read IO requests; and
   - a total number of write IO requests.

4. The computer-implemented method of claim **1**, wherein generating the plurality of IO features using the plurality of IO requests includes:
   - aggregating the plurality of IO requests periodically; and
   - generating the plurality of IO features using the aggregated plurality of IO requests.

5. The computer-implemented method of claim **1**, further comprising:
   - training the machine learning model by processing a plurality of IO requests associated with one or more known ransomware attacks.

6. The computer-implemented method of claim **5**, wherein monitoring for a ransomware attack on the storage system in real-time includes identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

7. The computer-implemented method of claim **1**, further comprising:
   - in response to monitoring a ransomware attack, performing a remedial action on the storage system.

8. A computer program product residing on a non-transitory computer readable medium having a plurality of

instructions stored thereon which, when executed by a processor, cause the processor to perform operations comprising:
   - processing a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system;
   - generating a plurality of IO features using the plurality of IO requests including a combination of:
     - a percentage of overwrite IO requests, wherein an overwrite IO request is a read IO request followed by a write IO request with the same logical address and length,
     - a percentage of sequential read IO requests, wherein a sequential read IQ request is a read IO request concerning an adjacent portion of memory as read from an immediately previous read IO request, and
     - a percentage of sequential write IO requests, wherein a sequential write IQ request is a write IO request concerning an adjacent portion of memory as written to by an immediately previous write IO request;
   - processing the plurality of IO features using a machine learning model; and
   - monitoring for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

9. The computer program product of claim **8**, wherein the plurality of storage objects include at least one of a block storage object and a file storage object.

10. The computer program product of claim **8**, wherein the plurality of IO features further include one or more of:
   - a number of IO requests per second (IOPS);
   - a total number of read IO requests; and
   - a total number of write IO requests.

11. The computer program product of claim **8**, wherein generating the plurality of IO features using the plurality of IO requests includes:
   - aggregating the plurality of IO requests periodically; and
   - generating the plurality of IO features using the aggregated plurality of IO requests.

12. The computer program product of claim **8**, wherein the operations further comprise:
   - training the machine learning model by processing a plurality of IO requests associated with one or more known ransomware attacks.

13. The computer program product of claim **12**, wherein monitoring for a ransomware attack on the storage system in real-time includes identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

14. The computer program product of claim **8**, wherein the operations further comprise:
   - in response to monitoring a ransomware attack, performing a remedial action on the storage system.

15. A computing system comprising:
   - a memory; and
   - a processor configured to process a plurality of input/output (IO) requests associated with a plurality of storage objects of a storage system, wherein the processor is further configured to generate a plurality of IO features using the plurality of IO requests including a combination of a percentage of overwrite IO requests, wherein an overwrite IO request is a read IO request followed by a write IO request with the same logical address and length, a percentage of sequential read IO requests, wherein a sequential read IO request is a read IO request concerning an adjacent portion of memory

as read from an immediately previous read IO request, and a percentage of sequential write IO requests, wherein a sequential write IO request is a write IO request concerning an adjacent portion of memory as written to by an immediately previous write IO request, wherein the processor is further configured to process the plurality of IO features using a machine learning model, and wherein the processor is further configured to monitor for a ransomware attack on the storage system in real-time based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

16. The computing system of claim **15**, wherein the plurality of storage objects include at least one of a block storage object and a file storage object.

17. The computing system of claim **15**, wherein the plurality of IO features further include one or more of:

a number of IO requests per second (IOPS);

a total number of read IO requests; and

a total number of write IO requests.

18. The computing system of claim **15**, wherein generating the plurality of IO features using the plurality of IO requests includes:

aggregating the plurality of IO requests periodically; and

generating the plurality of IO features using the aggregated plurality of IO requests.

19. The computing system of claim **15**, wherein the processor is further configured to:

training the machine learning model by processing a plurality of IO requests associated with one or more known ransomware attacks.

20. The computing system of claim **19**, wherein monitoring for a ransomware attack on the storage system in real-time includes identifying a known ransomware attack based upon, at least in part, the processing of the plurality of IO features using the machine learning model.

* * * * *