US 20250260716A1

(19) United States
(12) Patent Application Publication
Zhang et al.

(10) Pub. No.: US 2025/0260716 A1
(43) Pub. Date: Aug. 14, 2025

(54) CLOUD SANDBOX FOR DETECTING MALWARE IN FILES

(71) Applicant: **Netskope, Inc.**, Santa Clara, CA (US)

(72) Inventors: **Xinjun Zhang**, San Jose, CA (US); **Ari Azarafrooz**, Rancho Santa Margarita, CA (US); **Zhenxin Zhan**, Fremont, CA (US); **Ghanashyam Satpathy**, Bangalore (IN); **Hung-Ming Chen**, Kaohsiung City (TW)

(21) Appl. No.: **19/047,436**

(22) Filed: **Feb. 6, 2025**

Related U.S. Application Data

(63) Continuation of application No. 18/437,521, filed on Feb. 9, 2024, now Pat. No. 12,244,637.

Publication Classification

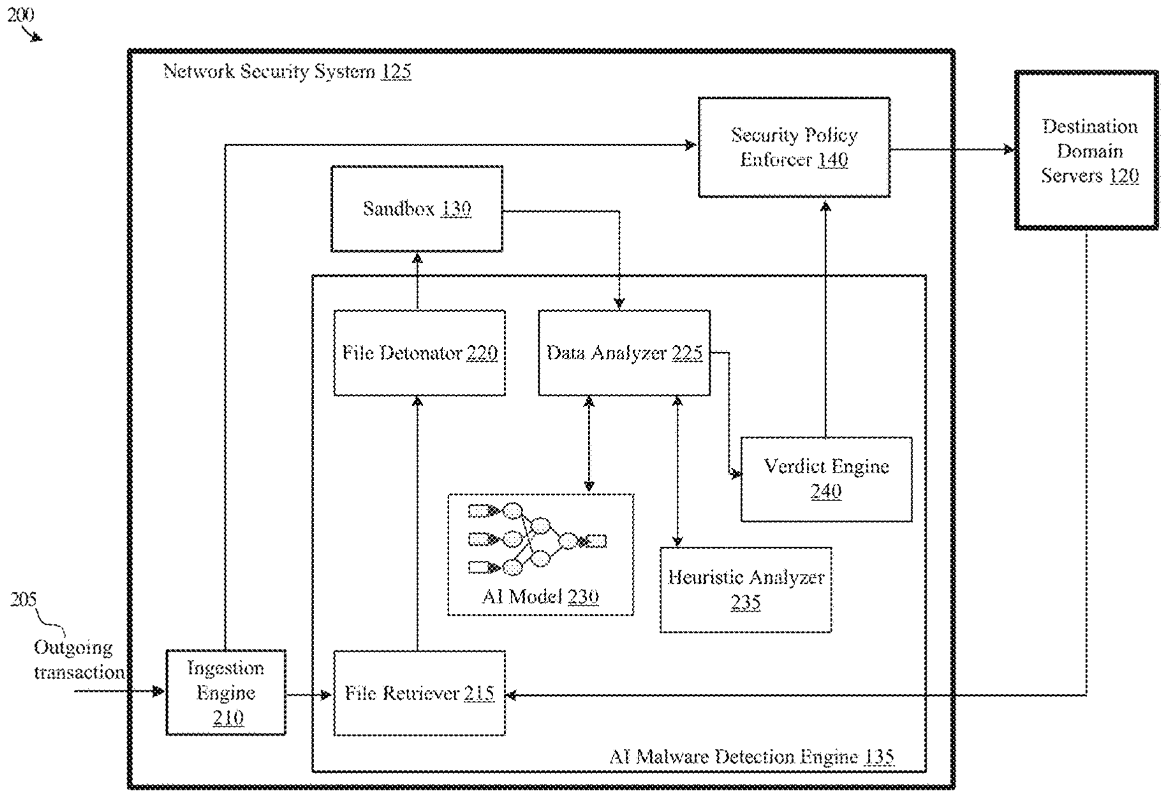
(51) **Int. Cl.**

H04L 9/40	(2022.01)
G06F 21/53	(2013.01)
H04L 41/16	(2022.01)

(52) **U.S. Cl.**
CPC ***H04L 63/1441*** (2013.01); ***G06F 21/53*** (2013.01); ***H04L 41/16*** (2013.01)

(57) **ABSTRACT**

A cloud-based network security system (NSS) is described. The NSS uses a sandbox to safely detonate and extract information about a document and uses machine learning algorithms to analyze the information to predict whether the document contains malicious software. Specifically, during the detonation, static and dynamic information about the document is captured in the sandbox as well as character strings from images in the document. The dynamic information (and sometimes the static information) is input to an AI or machine learning model trained to provide an output indicating a prediction of whether the document contains malware. The character strings are compared with a batch of phishing keywords to generate a heuristic score. A validation engine combines the output from the AI or machine learning model and the heuristic score to classify the document as malicious or clean. Security policies can then be applied based on the classification.



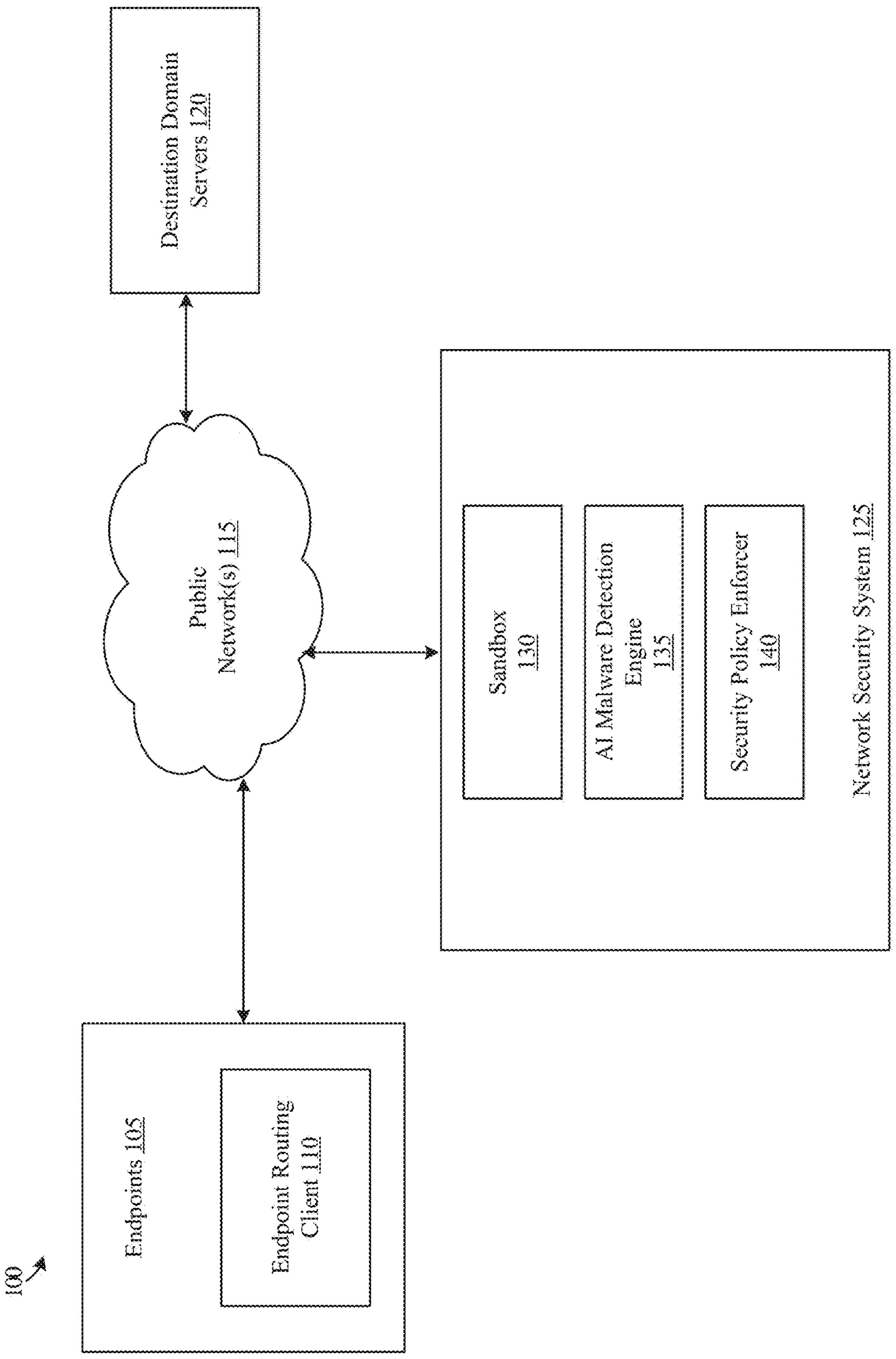

100
Endpoints 105
Endpoint Routing Client 110
Public Network(s) 115
Destination Domain Servers 120
Sandbox 130
AI Malware Detection Engine 135
Security Policy Enforcer 140
Network Security System 125

FIG. 1

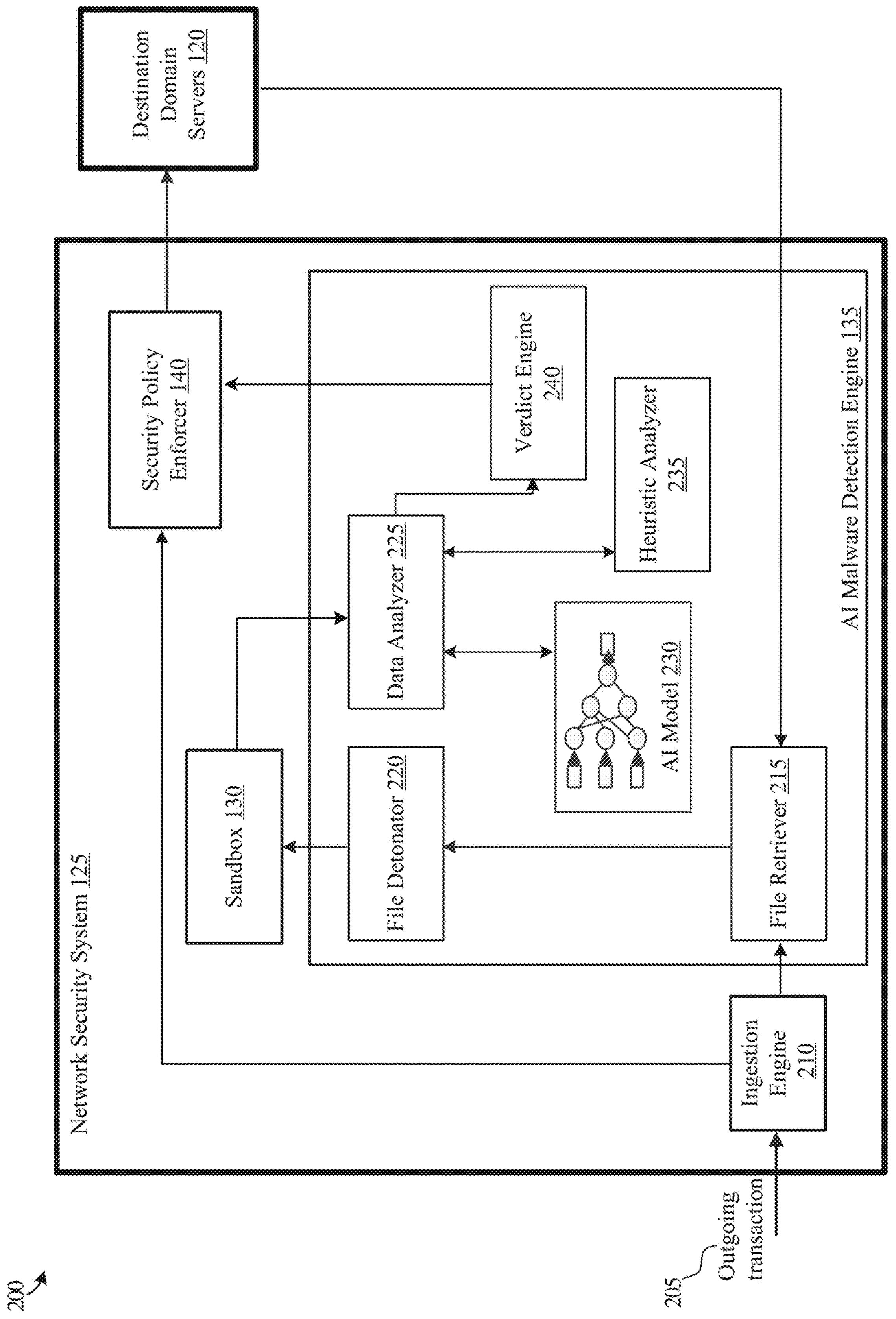

200
205
Outgoing transaction
Network Security System 125
Ingestion Engine 210
AI Malware Detection Engine 135
File Retriever 215
File Detonator 220
Sandbox 130
Data Analyzer 225
AI Model 230
Heuristic Analyzer 235
Verdict Engine 240
Security Policy Enforcer 140
Destination Domain Servers 120

FIG.2

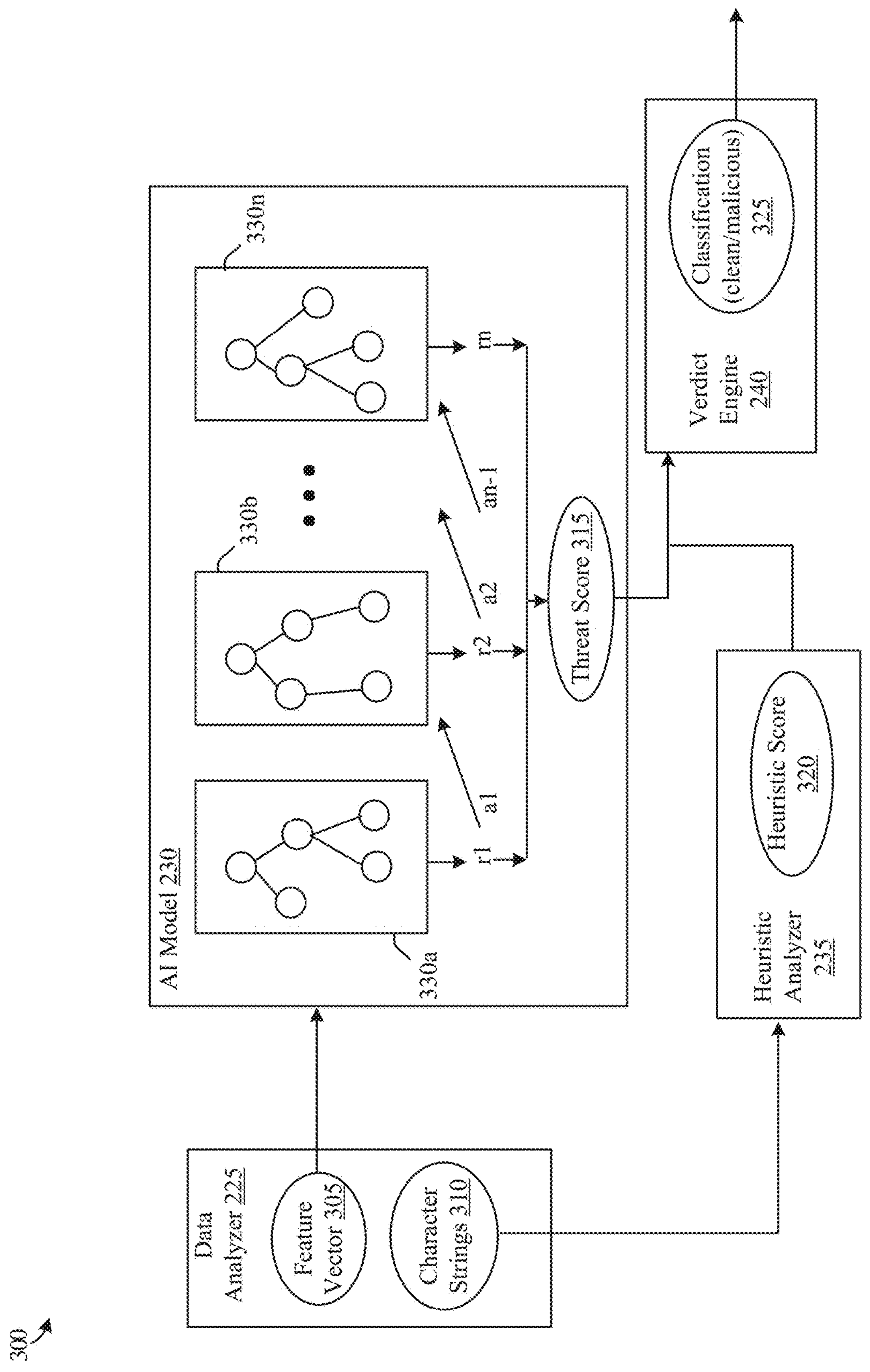

300
Data Analyzer 225
Feature Vector 305
Character Strings 310
AI Model 230
330a
330b
330n
r1
a1
r2
a2
an-1
rn
Threat Score 315
Heuristic Analyzer 235
Heuristic Score 320
Verdict Engine 240
Classification (clean/malicious) 325

FIG.3

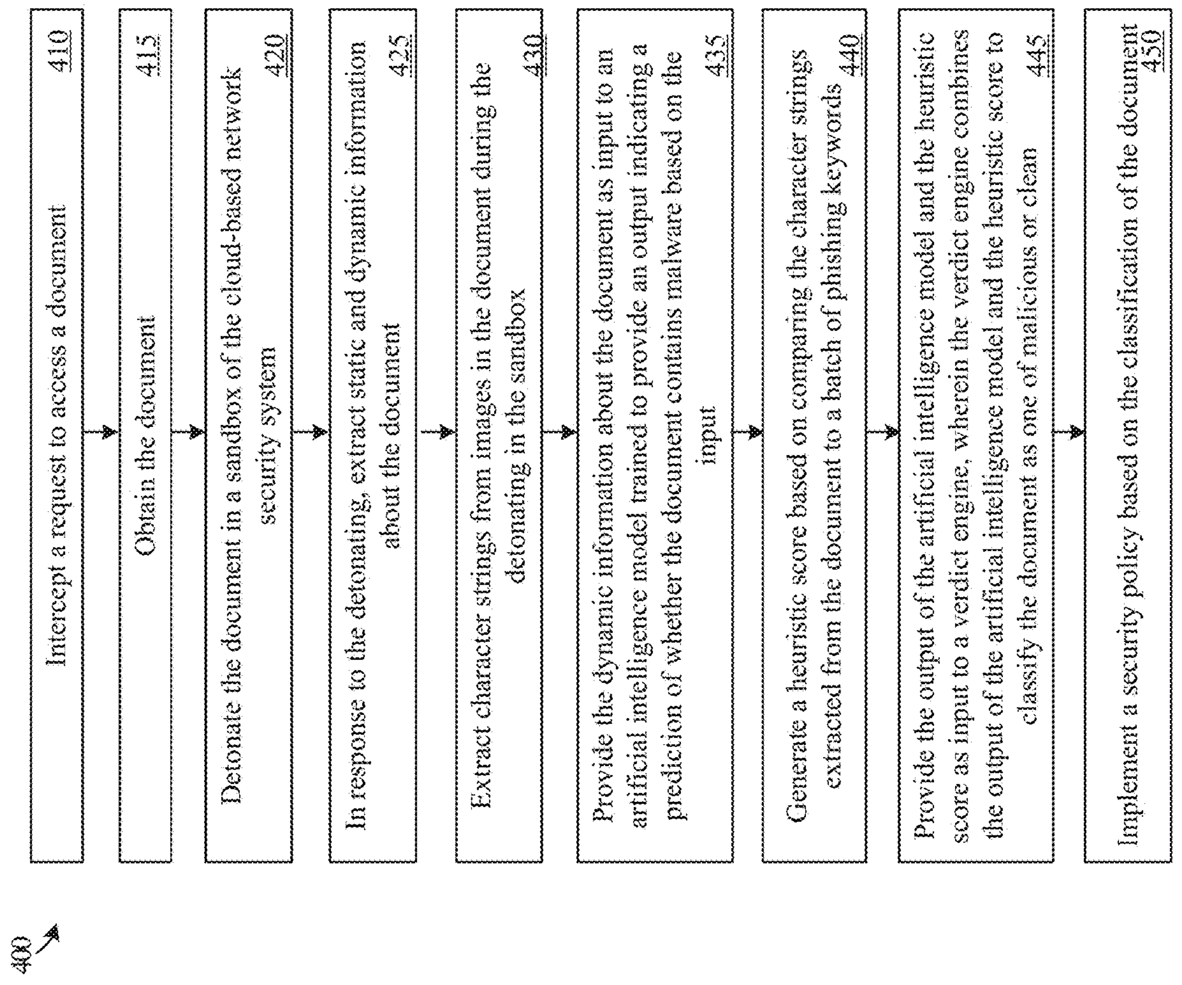

400
Intercept a request to access a document 410
Obtain the document 415
Detonate the document in a sandbox of the cloud-based network security system 420
In response to the detonating, extract static and dynamic information about the document 425
Extract character strings from images in the document during the detonating in the sandbox 430
Provide the dynamic information about the document as input to an artificial intelligence model trained to provide an output indicating a prediction of whether the document contains malware based on the input 435
Generate a heuristic score based on comparing the character strings extracted from the document to a batch of phishing keywords 440
Provide the output of the artificial intelligence model and the heuristic score as input to a verdict engine, wherein the verdict engine combines the output of the artificial intelligence model and the heuristic score to classify the document as one of malicious or clean 445
Implement a security policy based on the classification of the document 450

FIG. 4

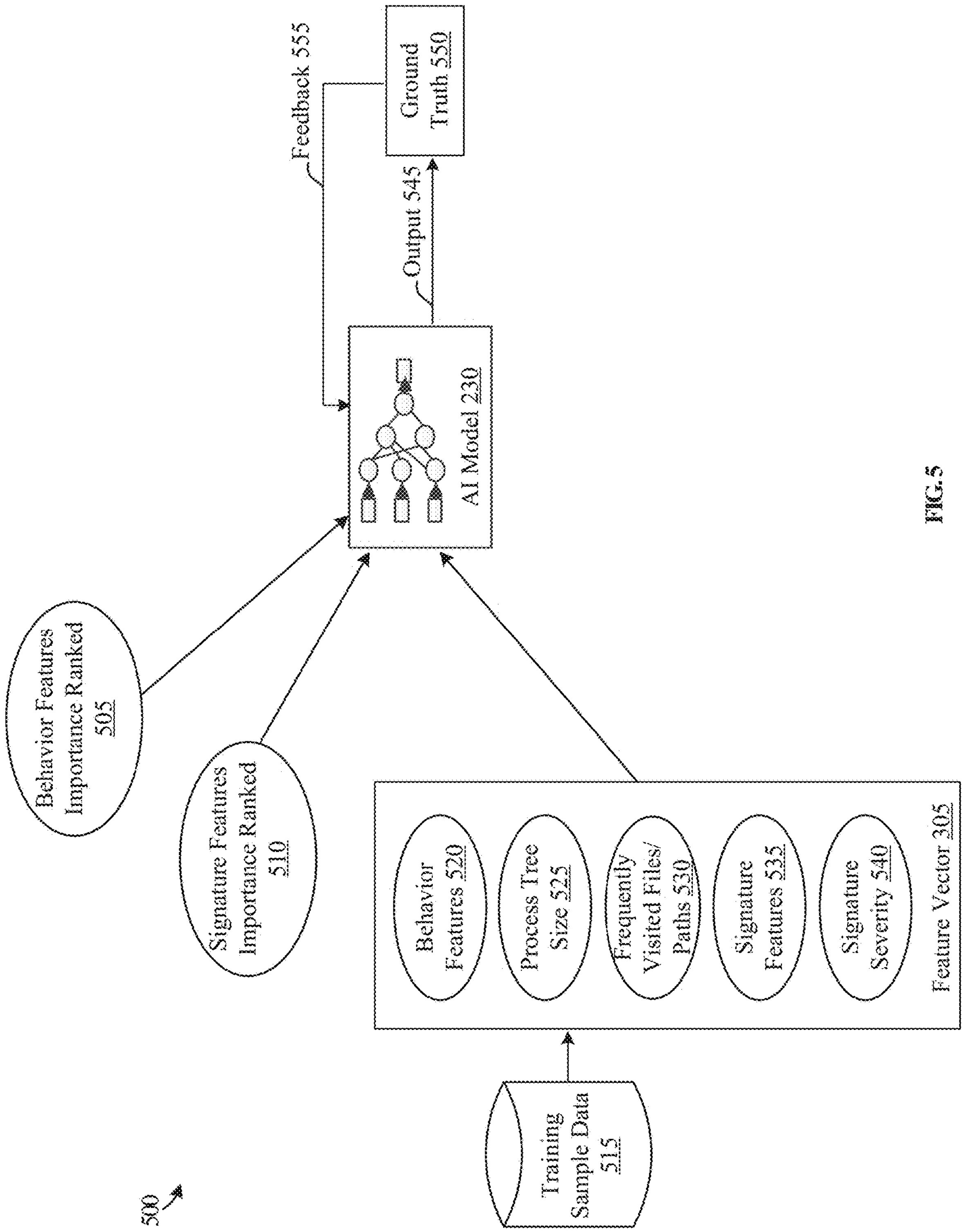

500
Training Sample Data 515
Feature Vector 305
Behavior Features 520
Process Tree Size 525
Frequently Visited Files/ Paths 530
Signature Features 535
Signature Severity 540
Behavior Features Importance Ranked 505
Signature Features Importance Ranked 510
AI Model 230
Output 545
Ground Truth 550
Feedback 555

FIG. 5

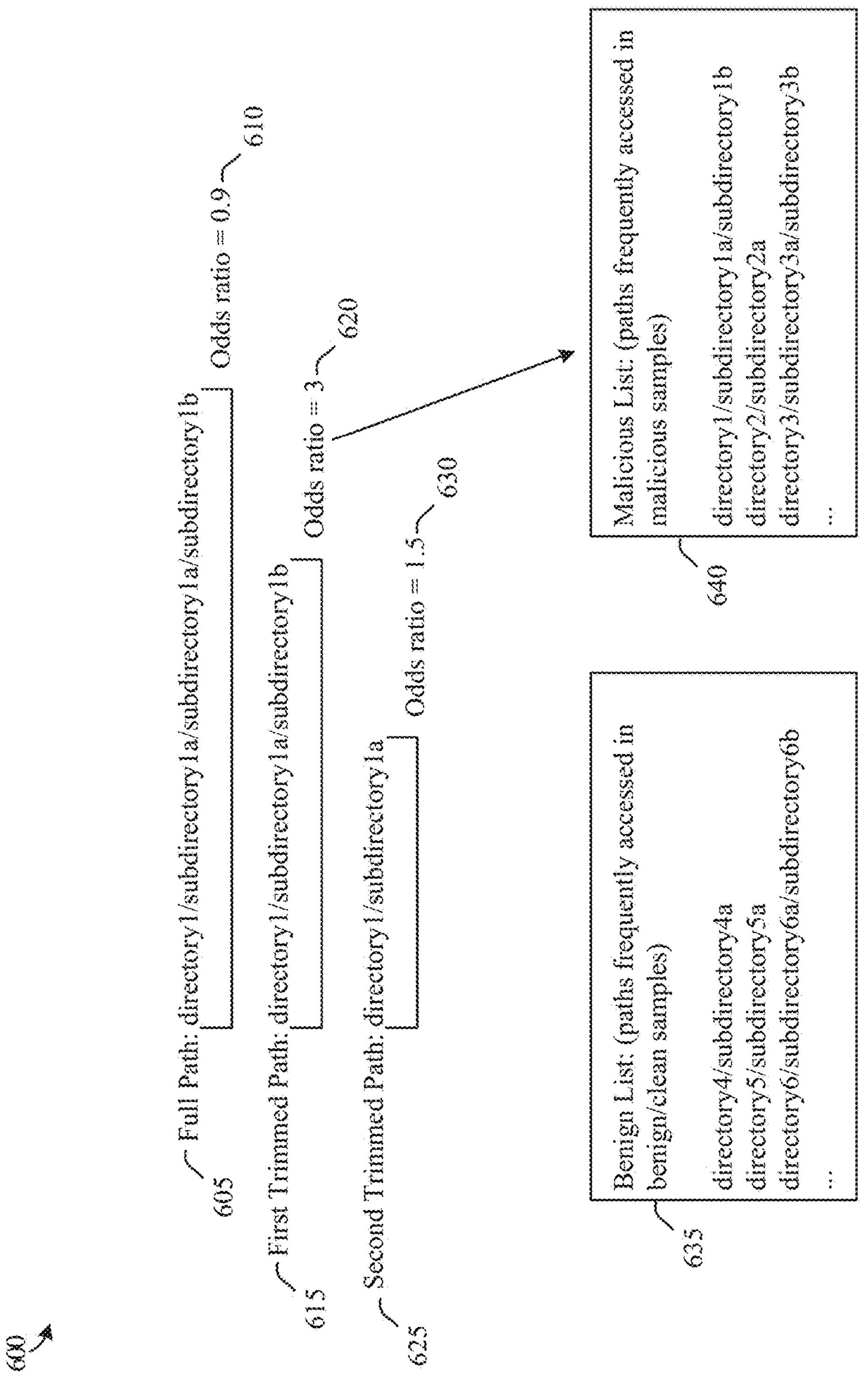

600
605
Full Path: directory1/subdirectory1a/subdirectory1b
Odds ratio = 0.9
610
615
First Trimmed Path: directory1/subdirectory1a/subdirectory1b
Odds ratio = 3
620
625
Second Trimmed Path: directory1/subdirectory1a
Odds ratio = 1.5
630
635
Benign List: (paths frequently accessed in benign/clean samples)
directory4/subdirectory4a
directory5/subdirectory5a
directory6/subdirectory6a/subdirectory6b
...
640
Malicious List: (paths frequently accessed in malicious samples)
directory1/subdirectory1a/subdirectory1b
directory2/subdirectory2a
directory3/subdirectory3a/subdirectory3b
...

FIG. 6

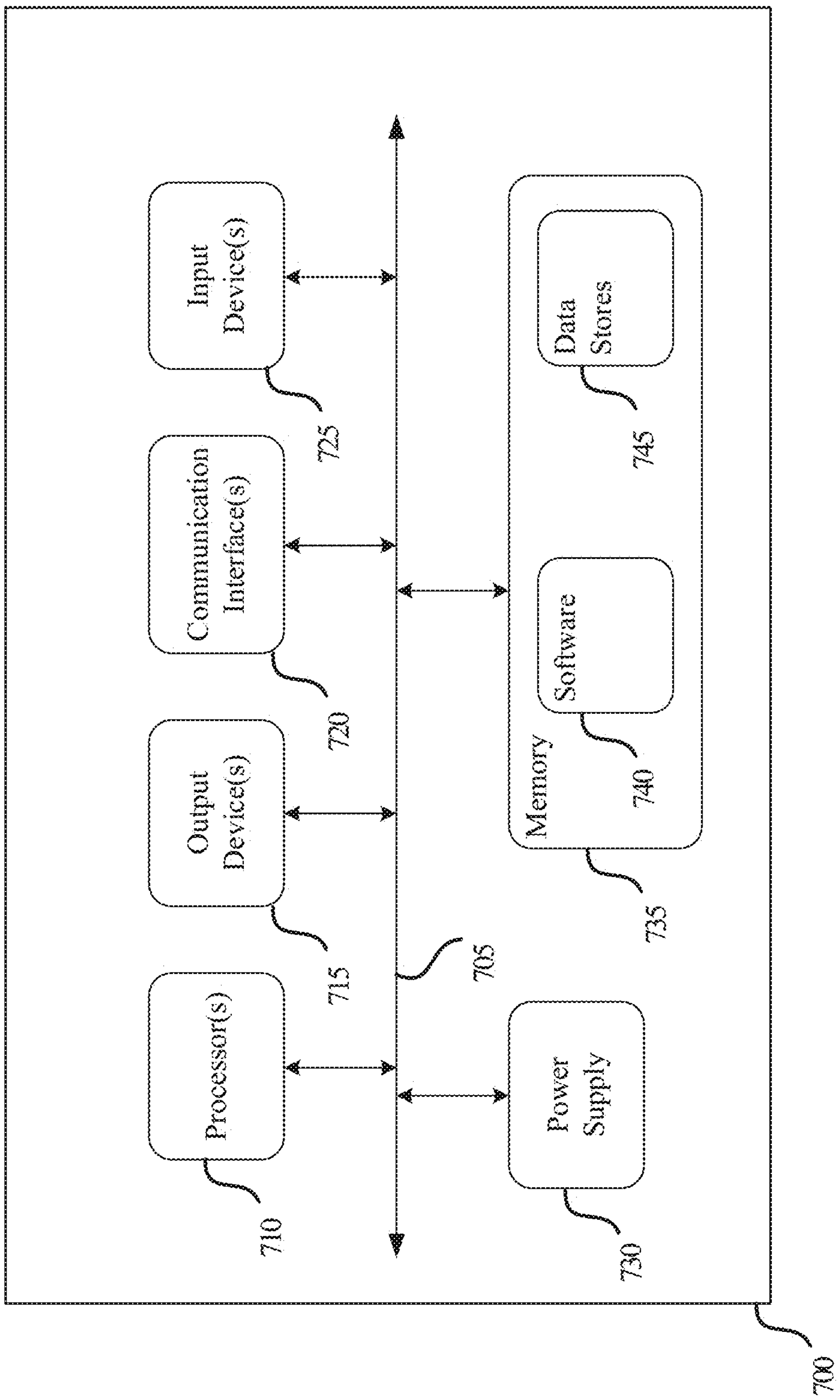

Processor(s)
710
Output Device(s)
715
Communication Interface(s)
720
Input Device(s)
725
705
Power Supply
730
Memory
735
Software
740
Data Stores
745
700

FIG. 7

CLOUD SANDBOX FOR DETECTING MALWARE IN FILES

CROSS REFERENCE TO RELATED APPLICATIONS

[0001] This application is a continuation of U.S. patent application Ser. No. 18/437,521, titled "MACHINE LEARNING POWERED CLOUD SANDBOX FOR MALWARE DETECTION," filed Feb. 9, 2024, the contents of which is hereby incorporated by reference in its entirety for all purposes.

BACKGROUND

[0002] Malicious software (i.e., malware) is used by cybercriminals to harm legitimate people and businesses in many ways including interrupting public services, stealing data (e.g., confidential and secure data such as personally identifying information), and stealing financial resources. Cybercriminals and malware are an ever-present issue for any entity utilizing computing technology. Cybercriminals exploit many technologies including everyday types of office documents (e.g., word processing documents, spreadsheet documents, presentation documents, and the like) to deliver malware. These everyday documents represent a large threat to entities, and a favored choice by cybercriminals, because of their widespread usage. Zero-day malware attacks exploit unknown security flaws and vulnerabilities, so cybercriminals often use these everyday documents to deliver zero-day malware. These malicious files present a substantial risk to organizations because they often initiate the first stage of an attack, triggering execution of the malware.

[0003] Once a user opens or gains access to an infected document, any malware included in the document is executed. The malware in such a document may initiate the attack by installing unwanted malicious software on the user's device, opening access to otherwise secure data locations, and the like. Existing technologies use strategies such as static or signature-based detections, but these strategies often do not detect stealthy malware hidden in this type of everyday office document. Particularly, zero-day malware is difficult to identify and is not detected using only static or signature-based detections because static and signature-based detections use previously known information about malware to detect the malware. By definition, zero-day malware is previously unknown. Additionally, other novel malware, older malware strains that have been modified, or polymorphic malware (i.e., malware that continually changes to evade detection) are not typically detectable using only static or signature-based detections. Accordingly, improvements are needed to ensure that malware hidden in everyday office documents is detected and contained prior to inadvertent execution by the user.

SUMMARY

[0004] To address the limitations described above, a network security system that detonates documents securely in a sandbox is used to analyze the documents and make determinations as to whether the documents are clean or malicious. The system analyzes and extracts static information related to the document (e.g., information about the document itself), dynamic information about the document (e.g., behaviors observed by opening the document) in the sandbox, and character strings from images in the document while accessing the document in the sandbox. The system uses artificial intelligence (AI) models to analyze the dynamic information. The AI models are trained to predict whether the document includes malware. Further, analysis of the character strings provides a heuristic evaluation of whether the document contains malware. A validation engine of the system combines the heuristic evaluation and the output of the AI model to classify the document as malicious or clean. Security policies can then be applied based at least in part on the classification.

[0005] In particular, a system of one or more computers can be configured to perform particular operations or actions by virtue of having software, firmware, hardware, or a combination of them installed on the system that in operation causes or cause the system to perform the actions. One or more computer programs can be configured to perform particular operations or actions by virtue of including instructions that, when executed by data processing apparatus, cause the apparatus to perform the actions. One general aspect includes a computer-implemented method that can be performed by a network security system. The network security system intercepts a request to access a document and, in response, obtains the document. The network security system detonates the document in a sandbox. In response to the detonating, the network security system extracts dynamic information about the document and character strings from images in the document during the detonating in the sandbox. The network security system provides the dynamic information about the document as input to an artificial intelligence model trained to provide an output indicating a prediction of whether the document contains malware based on the input (e.g., the static and dynamic information). The network security system also generates a heuristic score based on comparing the character strings extracted from the document to a batch of phishing keywords. The network security system provides the output of the artificial intelligence model and the heuristic score as input to a verdict engine, where the verdict engine combines the output of the artificial intelligence model and the heuristic score to classify the document as either malicious or clean. Based on the classification, the network security system implements a security policy. Other embodiments of this aspect include corresponding computer systems, apparatus, and computer programs recorded on one or more computer storage devices, each configured to perform the actions of the methods.

[0006] Implementations may include one or more of the following features. Optionally, extracting the dynamic information about the document may include analyzing behavior of the document during detonation in the sandbox and extracting data from the behavior. The dynamic information may include a set of behavior features of the document exhibited during the detonating, a size of a process tree spawned by the detonating, a signature vector having a dimension for each of a number of known software signatures where the value of each dimension indicates whether the document invoked the software signature in the sandbox, and severity scores for each of the software signatures the document invoked. Optionally, the set of behavior features may include frequently visited files, frequently visited paths, pathways explored by processes in the sandbox, or a combination thereof.

[0007] In some embodiments, providing the dynamic information about the document as input may include generating a feature vector representing the dynamic information and providing the feature vector as the input to the artificial intelligence model. In some embodiments, the artificial intelligence model may include a gradient boosting tree algorithm.

[0008] In some embodiments, extracting the character strings from the images in the document may include analyzing the document during detonation in the sandbox with optical character recognition. Optionally, the heuristic score may include a count of the matches identified during the comparing of the character strings to the batch of phishing keywords.

[0009] Optionally, a heuristic rule is triggered based on the heuristic score exceeding a threshold heuristic value and the output of the artificial intelligence model may include a prediction score indicating the prediction. In such embodiments, the verdict engine classifies the document as malicious based on determining if the heuristic rule is triggered and the prediction score exceeds a pre-defined prediction threshold value. Further, the verdict engine in such embodiments classifies the document as clean based on determining if the heuristic rule is not triggered or the prediction score does not exceed the pre-defined prediction threshold value.

[0010] Optionally, the method may further include extracting static information about the document. The static information may be input to the artificial intelligence model with the dynamic information as input, in some embodiments. Implementations of the described techniques may include hardware, a method or process, or computer software on a computer-accessible medium.

BRIEF DESCRIPTION OF THE DRAWINGS

[0011] In the drawings, like reference characters generally refer to like parts throughout the different views. Also, the drawings are not necessarily to scale, with an emphasis instead generally being placed upon illustrating the principles of the technology disclosed. In the following description, various implementations of the technology disclosed are described with reference to the following drawings.

[0012] FIG. **1** illustrates a security environment including a network security system that detects malware, according to some embodiments.

[0013] FIG. **2** illustrates additional details of the network security system of FIG. **1**, according to some embodiments.

[0014] FIG. **3** illustrates a data flow for predicting whether a document is malicious or clean, according to some embodiments.

[0015] FIG. **4** illustrates a method of detecting malware in a document using a sandbox, according to some embodiments.

[0016] FIG. **5** illustrates a training system for training an artificial intelligence model for predicting malware, according to some embodiments.

[0017] FIG. **6** illustrates frequently visited path training data, according to some embodiments.

[0018] FIG. **7** illustrates an exemplary computing system, according to some embodiments.

DETAILED DESCRIPTION

[0019] To more accurately detect malware in documents, more than simply static or signature-based analysis is used. As discussed above, everyday documents including word processing documents (e.g., MICROSOFT WORD®), presentation documents (e.g., MICROSOFT POWERPOINT®), and spreadsheet documents (e.g., MICROSOFT EXCEL®) are often exploited by cybercriminals to attack individuals and enterprises. These cybercriminals embed malware in the documents or otherwise configure the documents to access and initiate execution of malware on the target computers. Identifying the infected documents prior to execution (e.g., opening the document) on the target computers is ideal but difficult. Existing detection often relies on static or signature-based detection, but cybercriminals are constantly evolving their techniques to evade detection. Further, novel malware including zero-day malware, older malware strains that have been modified, or polymorphic malware (i.e., malware that continually changes to evade detection) are not detectable using standard static or signature-based detection methods.

[0020] To increase detection of these types of novel malware and avoid infection to unsuspecting computing devices, the present disclosure includes a cloud-based network security system (NSS) with a document malware detection engine. The document malware detection engine uses a sandbox in which the documents in question are detonated (i.e., opened) and analyzed. Because sandboxes are isolated and secure, detonating the document in the sandbox avoids infection. Nonetheless, the documents can be analyzed to detect many static and dynamic parameters. Additionally, while open in the sandbox, text from images in the document can be analyzed, for example using optical character recognition (OCR) technology. Character strings can be captured based on analysis of the images.

[0021] The document malware detection engine includes an artificial intelligence (AI) model trained to analyze the dynamic characteristics captured about the document while it was open in the sandbox. In some embodiments, the static information/characteristics are also included in the AI model analysis. The AI model is trained to analyze the characteristics and make a prediction as to whether the document includes malware. For example, the AI model may provide a score indicating the probability that the document includes malware.

[0022] The document malware detection engine includes a heuristic analyzer trained to compare the character strings captured from the images in the document against a list of phishing keywords and phrases. The heuristic analyzer can generate a heuristic score, such that a score exceeding a threshold value may be a heuristic trigger, indicating that the document likely contains malware.

[0023] The document malware detection engine includes a validation engine that ingests the heuristic score and the prediction from the AI model to classify the document as either clean or malicious. Once classified by the validation engine, the NSS may apply security policies to the document based on the classification.

[0024] Advantageously, the disclosed document malware detection engine uses a sandbox to isolate the document during access to avoid infecting any unsuspecting computing systems while still maintaining the ability to analyze the file. While in the sandbox, the document is analyzed to detect static information (e.g., information not requiring the document to be opened), dynamic information (e.g., information generated and captured by opening the document), and other data embedded in images is analyzed. The AI model trained to analyze the dynamic information (and static information in some embodiments) provides a prediction of whether the document includes malware. Alone, this prediction provides satisfactory results. However, in combination with the heuristic trigger based on the data embedded in images, the detection increases by two-fold in testing. The increased rate of detection reduces infected computing systems and saves computing resources as well as human resources in mitigation of infected computing systems.

[0025] FIG. **1** illustrates a security environment **100** used to detect malware in documents. Security environment **100** includes network security system **125** with the features for detecting document malware as described throughout. Security environment **100** includes endpoints **105**, public networks **115**, destination domain servers **120**, and network security system **125**. Security environment **100** may include additional computing systems not shown here for ease of description. For example, more endpoints **105**, more destination domain servers **120**, other computing systems that access public networks **115**, and the like may be included.

[0026] Endpoints **105** comprise user devices including desktops, laptops, mobile devices, and the like. The mobile devices include smartphones, smart watches, and the like. Endpoints **105** may also include internet of things (IoT) devices. Endpoints **105** may include any number of components including those described with respect to computing device **700** of FIG. **7** including processors, output devices, communication interfaces, input devices, memory, and the like, all not depicted here for clarity. Endpoints **105** may be used to access content (e.g., documents, images, and the like) stored in hosted services and other destination domain servers **120** and otherwise interact with servers and other devices connected to public network **115**. Endpoints **105** include endpoint routing client **110**. In some embodiments, endpoint routing client **110** may be a client installed on the endpoint **105**. In other embodiments, endpoint routing client **110** may be implemented using a gateway that traffic from each endpoint **105** passes through for transmission out of a private or sub-network. While a single endpoint **105** is shown for simplicity, any number of endpoints **105** may be included in security environment **100**. Further, multiple endpoints **105** associated each with one of a number of enterprises or clients of network security system **125** may be included. In some embodiments, a number of endpoints **105** associated with an enterprise may connect to a private network (not shown) that uses, for example, a gateway to access public network **115**.

[0027] Endpoint routing client **110** routes network traffic transmitted from its respective endpoint **105** to the network security system **125**. Depending on the type of device for which endpoint routing client **110** is routing traffic, endpoint routing client **110** may use or be a virtual private network (VPN) such as VPN on demand or per-app-VPN that use certificate-based authentication. For example, for some devices having a first operating system, endpoint routing client **110** me be a per-app-VPN may be used or a set of domain-based VPN profiles may be used. For other devices having a second operating system, endpoint routing client **110** me be a cloud director mobile app. Endpoint routing client **110** can also be an agent that is downloaded using e-mail or silently installed using mass deployment tools. As mentioned above, endpoint routing client **110** may be implemented in a gateway through which all traffic from endpoints **105** travels to leave an enterprise network, for example. In any implementation, endpoint routing client **110** routes traffic generated by endpoints **105** to network security system **125**.

[0028] Public network **115** may be any public network including, for example, the Internet. Public network **115** couples endpoints **105**, destination domain servers **120**, and network security system **125** such that any may communicate with any other via public network **115**. While not depicted for simplicity, public network **115** may also couple many other devices for communication including, for example, other servers, other private networks, other user devices, and the like (e.g., any other connected devices). The communication path can be point-to-point over public network **115** and may include communication over private networks (not shown). In some embodiments, endpoint routing client **110**, might be delivered indirectly, for example, via an application store (not shown). Communications can occur using a variety of network technologies, for example, private networks, Virtual Private Network (VPN), multiprotocol label switching (MPLS), local area network (LAN), wide area network (WAN), Public Switched Telephone Network (PSTN), Session Initiation Protocol (SIP), wireless networks, point-to-point networks, star network, token ring network, hub network, Internet, or the like. Communications may use a variety of protocols. Communications can use appropriate application programming interfaces (APIs) and data interchange formats, for example, Representational State Transfer (REST), JavaScript Object Notation (JSON), Extensible Markup Language (XML), Simple Object Access Protocol (SOAP), Java Message Service (JMS), Java Platform Module System, and the like. Additionally, a variety of authorization and authentication techniques, such as username/password, Open Authorization (OAuth), Kerberos, SecureID, digital certificates and more, can be used to secure communications.

[0029] Destination domain servers **120** include any domain servers available on public network **115**. Destination domain servers **120** may include, for example, hosted services such as cloud computing and storage services, financial services, e-commerce services, or any type of applications, websites, or platforms that provide cloud-based storage or web services. At least some destination domain servers **120** may provide or store documents that endpoints **105** access (e.g., store, manipulate, download, upload, open, or the like).

[0030] Network security system **125** may provide network security services to endpoints **105**. Endpoint routing client **110** may route traffic addressed to destination domain servers **120** from the endpoints **105** to network security system **125** to enforce security policies. Based on the security policy enforcement, the traffic may then be routed to the addressed destination domain server **120**, blocked, modified, or the like. While network security system **125** is shown as connected to endpoints **105** via public network **115**, in some embodiments, network security system **125** may be on a private network with endpoints **105** to manage network security on premises. Network security system **125** may implement security management for endpoints **105**. The security management may include protecting endpoints **105** from various security threats including data loss prevention (DLP) and other security vulnerabilities including document malware. For simplicity, the features of network security system **125** related to detecting document malware are shown while other security features are not described in detail. Network security system **125** may be implemented as a cloud-based service and accordingly may be served by one or more server computing systems that provide the cloud-based services that are distributed geographically across data centers, in some embodiments. Network security system **125** may be implemented in any computing system or architecture that can provide the described capabilities without departing from the scope of the present disclosure. Network security system **125** may include, among other security features, sandbox **130**, AI malware detection engine **135**, and security policy enforcer **140**. While a single network security system **125** is depicted for simplicity, any number of network security systems **125** may be implemented in security environment **100** and may include multiple instances of sandbox **130**, AI malware detection engine **135**, and security policy enforcer **140** for handling multiple clients or enterprises on a per/client basis, for example.

[0031] Sandbox **130** is a secure, isolated environment in which a document may be detonated (i.e., opened or launched). Sandbox **130** allows the AI malware detection engine **135** to detonate the document securely such that if it contains malware, the malware is contained and does not harm or infect any client computing systems, including endpoints **105**. The documents may be any office documents including, for example, word processing documents (e.g., MICROSOFT WORD®), spreadsheet documents (e.g., MICROSOFT EXCEL®), presentation documents (e.g., MICROSOFT POWERPOINT®), or the like. Sandbox **130** isolates all running programs and is configured to have tightly controlled resources so that any malware is contained and does not infect the hosting server. While in the sandbox, static information about the document may be extracted. Further, during detonation, dynamic behaviors of the document can be observed and analyzed. For example, data about files and paths visited, static data about the document, processes spawned by detonation of the document, and the like can be safely obtained. Additionally, character strings can be extracted from images in the document safely. For example, optical character recognition (OCR) can be used to extract the character strings. The extracted and obtained data, including the static information and dynamic behavior data as well as the character strings, can be used by AI malware detection engine **135** to classify the document as clean or malicious as described in further detail throughout.

[0032] AI malware detection engine **135** analyzes documents requested by endpoints **105** to determine or predict whether the documents contain malware (i.e., are malicious). AI malware detection engine **135** obtains the requested document from the destination domain server **120** indicated in the access request. Upon obtaining the document, it is detonated in sandbox **130** and its behavior is observed. Static and dynamic data is captured while the document is in and opened in sandbox **130**. In some embodiments, a process in sandbox **130** extracts the desired data and provides it to AI malware detection engine **135**. For example, the process may generate a report containing the relevant static and dynamic data and provide the report to AI malware detection engine **135**. In some embodiments, a data analyzer of AI malware detection engine **135** analyzes the document while it is open in sandbox **130** and extracts the static and dynamic data. In some embodiments, the static data about the document may be obtained outside of sandbox **130** since some static data may be extracted without opening the document. Details of the static and dynamic data that is extracted or obtained is discussed in more detail with respect to FIG. **2**. In addition to the static and dynamic data, character strings are extracted based on analyzing images in the document while the document is open in sandbox **130**. Those character strings are also provided to the data analyzer. Once the character strings and static and dynamic data is retrieved, AI malware detection engine **135** analyzes details about the data to make a prediction of whether the document contains malware or not. For example, upon receiving the static and dynamic behavior data, AI malware detection engine **135** processes the data to extract relevant data for input to an AI model trained to predict whether the document contains malware. Additionally, a heuristic score may be calculated based on the extracted character strings. The character strings may be compared to a batch of phishing keywords and phrases to generate the heuristic score. AI malware detection engine **135** feeds the heuristic score and the output prediction of the AI model to a validation engine. The validation engine uses the heuristic score and the output prediction to classify the document as either malicious or clean. Additional details of AI malware detection engine **135** are described with respect to FIG. **2**.

[0033] Security policy enforcer **140** enforces security policies on all outgoing transactions intercepted by network security system **125** from endpoints **105**. Security policy enforcer **140** may identify security policies to apply to outgoing transactions based on, for example, the user account that the outgoing transaction originates from, the endpoint **105** (i.e., user device) that the outgoing transaction originates from, the destination server addressed, the type of communication protocol used, the type of transaction (e.g., document download, document upload, login transaction, or the like), data included in the traffic (e.g., data in the packet), or any combination. Further, security policies may be applied based on classification of a document access request by AI malware detection engine **135**. For example, if AI malware detection engine **135** classifies a requested document as malicious, security policy enforcer **140** may block the access request. In some embodiments, other security actions may be performed, other security policies may be applied based on the classification, or the like. For example, a notification of the malicious classification may be presented to the user. As another example, if the document is classified as clean, other security policies may be applied. In all cases, security policy enforcer **140** may identify relevant security policies for the outgoing transaction and apply the security policies. The security policies may include document malware specific policies as well as any other security policies implemented by the organization or entity. Accordingly, security policy enforcer **140** may identify and enforce any other security policies (e.g., security policies other than those related to document malware classification). After applying the security policies, the outgoing transaction may be blocked, modified, or transmitted to the destination domain server **120** specified in the outgoing transaction.

[0034] In use, endpoint **105** generates an outgoing transaction to a destination domain server **120**. Endpoint routing client **110** routes the outgoing transaction to network security system **125**. Network security system **125** intercepts the outgoing transaction and determines whether the transaction includes a document access request. If not, the outgoing transaction is routed to security policy enforcer **140**. If so, the outgoing transaction is routed to AI malware detection engine **135**. AI malware detection engine **135** analyzes the requested document by detonating it in sandbox **130** and extracting relevant information about the behavior of the document. Based on the analysis, AI malware detection engine **135** classifies the document as clean or malicious and provides the classification with the outgoing transaction to security policy enforcer **140**. Security policy enforcer **140** enforces relevant security policies, some of which may be related to the document classification. Based on enforcement of the relevant security policies, network security system **125** may block the outgoing transaction, modify the outgoing transaction, or transmit the outgoing transaction to the addressed destination domain server **120**.

[0035] FIG. **2** illustrates additional details of network security system **125**. Network security system **125** includes ingestion engine **210**, sandbox **130**, security policy enforcer **140**, and AI malware detection engine **135**. AI malware detection engine **135** includes file retriever **215**, file detonator **220**, data analyzer **225**, AI model **230**, heuristic analyzer **235**, and verdict engine **240**. Network security system **125** may include additional components not shown here for ease of description of the document malware detection feature. Further, while specific components are depicted (e.g., AI malware detection engine **135**, file retriever **215**, file detonator **220**, data analyzer **225**, AI model **230**, heuristic analyzer **235**, and verdict engine **240**) to describe the document malware detection features of network security system **125**, the document malware detection functionality described may be incorporated into more or fewer components, software components, hardware components, firmware components, or a combination without departing from the scope and spirit of the present disclosure.

[0036] Destination domain servers **120**, network security system **125**, sandbox **130**, and security policy enforcer **140** remain as described with respect to FIG. **1**. AI malware detection engine **135** includes file retriever **215**, file detonator **220**, data analyzer **225**, AI model **230**, heuristic analyzer **235**, and verdict engine **240**. While AI malware detection engine **135** depicts the specific components for ease of description, the functionality described for detecting malware in documents may be provided in more or fewer components including distributed components, software components, firmware components, hardware components, or a combination thereof without departing from the spirit and scope of the present disclosure.

[0037] Ingestion engine **210** receives outgoing transaction **205** as it arrives based on being routed from endpoint routing client **110**. As outgoing transactions are routed to network security system **125**, ingestion engine **210** receives each outgoing transaction **205**. Ingestion engine **210** may perform various filtering processes depending on the outgoing transaction **205**. For the purposes of detecting document malware, ingestion engine **210** may determine whether outgoing transaction **205** includes a document access request. For example, ingestion engine **210** may review packet header information to determine the destination domain server **120** to which outgoing transaction **205** is directed. Based, for example, on the destination domain server **120** being a document storage service, ingestion engine **210** may determine outgoing transaction **205** includes a document access request. As another example, ingestion engine **210** may analyze the payload of outgoing transaction **205** to determine outgoing transaction **205** includes a document access request. In any case, upon determining outgoing transaction **205** includes a document access request, ingestion engine **210** sends outgoing transaction **205** to AI malware detection engine **135**. If, however, ingestion engine **210** determines outgoing transaction **205** does not include a document access request, ingestion engine **210** routes outgoing transaction **205** directly to security policy enforcer **140**.

[0038] File retriever **215** is responsible for obtaining a copy of the target document to which the user requested access. File retriever **215** receives outgoing transaction **205** from ingestion engine **210** when ingestion engine **210** routes outgoing transaction **205** to AI malware detection engine **135**. In some embodiments, if ingestion engine **210** determined the file location of the document requested, the file location may be provided separately with outgoing transaction **205** from ingestion engine **210** so that file retriever **215** need not repeat the analysis of outgoing transaction **205**. Otherwise, file retriever **215** analyzes outgoing transaction **205** to determine where the requested document is located. Upon determining the file location, file retriever **215** requests the document from destination domain server **120**. In some embodiments, file retriever **215** generates a request to download the document using user login credentials from the user associated with outgoing transaction **205**. File retriever **215** obtains the document from destination domain server **120** and provides the document to file detonator **220**.

[0039] File detonator **220** is responsible for detonating (i.e., opening) the document in sandbox **130**. File detonator **220** receives the document from file retriever **215**. Upon receipt, file detonator **220** may configure sandbox **130** as needed for accessing the document. Note that many outgoing transactions **205** may be analyzed simultaneously. Accordingly, a specific sandbox **130** is configured to open each document in its own, isolated sandbox **130**. File detonator **220** may, for example, configure settings, parameters, or the types of data to be captured, and in some embodiments the settings, parameters and types of data are configured based on the type of file. Once sandbox **130** is configured, file detonator **220** opens the document in sandbox **130**.

[0040] Data analyzer **225** is responsible for distributing the retrieved data from the document to the relevant components so that AI malware detection engine **135** generates a classification for the document. In some embodiments, data analyzer **225** analyzes the document while it is open in sandbox **130**. Data analyzer **225** may use, for example, optical character recognition (OCR) to analyze the images in the document to extract any character strings or text in the images. Further, data analyzer **225** may obtain other static and dynamic data from the document while it is opened in sandbox **130**. In some embodiments, data analyzer **225** may extract the static data from the document outside of sandbox **130**. In some embodiments, processes within sandbox **130** may obtain the static and dynamic data from the document in sandbox **130** as well as perform the OCR to analyze the images in the document. In such embodiments, sandbox **130** may include a process that generates a report that includes all the extracted, observed, identified, and captured data about the document while in sandbox **130**. In any case, data analyzer **225** obtains the dynamic data from opening (i.e., executing or detonating) the document in sandbox **130**. If processes within sandbox **130** capture the static and dynamic data as well as the character strings from the OCR analysis, the processes may generate a report and send the report or store the report as well as the character strings to a specific destination folder on network security system **125**. Data analyzer **225** can retrieve the report and character strings from the destination folder or otherwise obtain the report and character strings from sandbox **130**.

[0041] Data analyzer **225** may generate a feature vector using the relevant static and dynamic data captured in sandbox **130** to provide to AI model **230**. Static data may include the number of pages in the document, the last saved by name, the author, the title, the creation time, keywords, template information, and the like. Some static data may be identified without opening the document, and static data generally represents information (including current information) about the document. Dynamic information is described further below and represents data that may represent behaviors of the document that are identified upon opening the document. The feature vector generated by data analyzer **225** may include, for example, a dimension including a count of behavior features that were exhibited by the document when opened in sandbox **130**. A selection of features that may be included in the count may include, for example: apistats, dll_loaded, regkey_opened, regkey_read, regkey_written, regkey_deleted, file_loaded, directory_enumerated, file_exists, file_opened, file_deleted, file_moved, file_created, file_failed, file_written, file_copied, file_recreated, file_read, mutex, command_line, guid, wmi_query, directory_created, directory_removed, resolves_host, connects_ip, connects_host, downloads_file, fetches_url. In some embodiments, some features may be determined to have a higher relevance, so those may be weighted by counting for more value in the count, for example. The following table includes further explanation of each of the behavior features listed above.

Behavior Name	Explanation
apistats	Statistics about the API that are called by the document (e.g., by malware in the document)
dll_loaded	Loaded dynamic link library files
regkey_opened	A list of regkey names which were opened by the document (e.g., by malware in the document)
regkey_read	A list of regkey names which were read by the document (e.g., by malware in the document)
regkey_written	A list of regkey names which were written by the document (e.g., by malware in the document)
regkey_deleted	A list of regkey names which were deleted by the document (e.g., by malware in the document)
file_loaded	A list of file paths/names which were loaded by the document (e.g., by malware in the document)
directory_enumerated	A list of file directories whose files or subdirectories were enumerated by the document (e.g., by malware in the document)
file_exists	A list of file paths/names which were checked if existing by the document (e.g., by malware in the document) calling NtCreateFile function
file_opened	A list of file paths/names which were opened by the document (e.g., by malware in the document) calling NtCreateFile function
file_deleted	A list of file paths/names which were deleted by the document (e.g., by malware in the document) calling NtCreateFile function
file_moved	A list of file paths/names which were moved by the document (e.g., by malware in the document) calling NtCreateFile function
file_created	A list of file paths/names which were created by the document (e.g., by malware in the document) calling NtCreateFile function
file_failed	A list of file paths/names which failed to open (e.g., file does not exist) by the document (e.g., by malware in the document) calling NtCreateFile function
file_written	A list of file paths/names which were written by the document (e.g., by malware in the document) calling NtCreateFile function
file_copied	A list of file paths/names which were copied by the document (e.g., by malware in the document) calling NtCreateFile function
file_recreated	A list of file paths/names which were overwritten by the document (e.g., by malware in the document) calling NtCreateFile function
file_read	A list of file paths/names which were successfully read by the document (e.g., by malware in the document) calling NtCreateFile function
mutex	A list of mutex names created by the document (e.g., by malware in the document) calling NtCreateMutant function. Mutual exclusion (mutex) is a program object that prevents multiple threads from accessing the same shared resource simultaneously.
command_line	A list of full names of commands created by the document (e.g., by malware in the document)

-continued

Behavior Name	Explanation
guid	Globally Unique Identifier (GUID). A list of guid which the document (e.g., by malware in the document) created and default-initialized
wmi_query	A list of query commands called by the document (e.g., by malware in the document) using a method to retrieve objects
directory_created	A list of file directories which were created by the document (e.g., by malware in the document)
directory_removed	A list of file directories which were deleted by the document (e.g., by malware in the document)
resolves_host	A list of host names or IP addresses which were resolved by the document (e.g., by malware in the document) using the DnsQuery function. DnsQuery is a generic query interface to the DNS namespace and provides a DNS query resolution interface.
connects_ip	A list of IP addresses which were connected by the document (e.g., by malware in the document)
connects_host	A list of website domain names to which the document (e.g., malware in the document) opens a file transfer protocol (FTP) or hypertext transfer protocol (HTTP) session
downloads_file	A list of files which the document (e.g., malware in the document) downloads bits from connected domains and saves them to a file
fetches_url	A list of uniform resource locators (URLs) either FTP or HTTP which the document (e.g., malware in the document) opens a resource through an internet session

[0042] The feature vector may include a count of the behavior features exhibited by the document, a dimension for each behavior feature indicating whether it was exhibited by the document, or otherwise represent the behavior features exhibited by the document in the feature vector.

[0043] Additionally, data analyzer **225** may include a dimension in the feature vector representing the process tree. For example, a value indicating the size of the process tree may be used as a dimension. The size of the process tree may be determined based on the number of processes and sub-processes that are spawned in response to opening the document. For example, process A may create children processes B and C, and child process C may create a child process D. In this case, the size of the process tree is four (4).

[0044] Data analyzer **225** may include one or more dimensions representing frequently visited files and paths of the document. For example, malicious documents may access (e.g., load, read, open delete, or the like) some directories or files which are less frequently accessed by benign documents. To fully analyze this behavior, the dynamic data may include particular information about frequently visited files and paths. The training associated with this dimension of the feature vector is described in more detail with respect to FIG. **6**. For example, previously identified files and paths associated with malware may be identified and previously identified files and paths associated with benign documents may be identified. Behavior features associated with those particular files and paths may further be identified. One or more dimensions of the feature vector may provide information regarding those behaviors and features exhibited by the document and associated with the previously identified files and paths. For example, if a first directory path is previously identified as associated with malware, particularly with respect to a subset of the behavior features (described above), they may be used to train AI model **230**. On detonation of a file associated with outgoing transaction **205**, the dynamic data obtained by data analyzer **225** may be used to determine, for example, a count of the behavior features associated with the relevant path that were exhibited by the document. In some embodiments, that count may be provided as a dimension of the feature vector. In other embodiments, the information can be provided in other ways as dimensions in the feature vector. Accordingly, particular information about document behavior associated with known frequently visited paths and files for malware and benign documents can be extracted and provided as a dimension in the feature vector.

[0045] Data analyzer **225** further includes signature related features associated with the document that are captured during detonation of the document in sandbox **130**. For example, a one-hot vector having a dimension for each of a number of known signatures may be included in the feature vector. Each dimension may have a value of zero (0) or one (1) indicating whether or not the specific signature was invoked by the document detonation in sandbox **130**. Each known signature may have a known severity score. In some embodiments, the severity scores for each invoked signature can be summed to provide a total severity score as a dimension in the feature vector.

[0046] After analyzing the data from sandbox **130**, data analyzer **225** generates the feature vector as discussed above and submits it to AI model **230**. AI model **230** is trained (as discussed in more detail with respect to FIGS. **5** and **6**) to predict whether the document contains malware or not. For example, AI model **230** may provide a threat score such that the higher the threat score, the more likely the document includes malware. AI model **230** provides the threat score back to data analyzer **225**.

[0047] As previously discussed, data analyzer **225** may also obtain character strings, for example using OCR, from images in the document while it was open in sandbox **130**. Data analyzer **225** provides the character strings to heuristic analyzer **235**. Heuristic analyzer **235** may analyze the character strings by, for example, comparing the character strings to a batch of known phishing keywords and/or phrases to identify matches. In some embodiments, partial matches may be included. In some embodiments, a count of the matches may be used to generate a heuristic score. In some embodiments, partial matches are used and may be weighted to account for a smaller portion of the score than a complete or exact match. Heuristic analyzer **235** may return a heuristic score in some embodiments. In other embodiments, heuristic analyzer **235** may determine whether to indicate a heuristic trigger based on a heuristic rule, for example, the heuristic score exceeding a threshold value. In other words, the heuristic rule may be triggered if sufficient matches to known phishing keywords and phrases are identified in images within the document. The result (e.g., a heuristic trigger, a heuristic score, a true or false indicator, or the like) from heuristic analyzer **235** is returned to data analyzer **225**. Data analyzer **225** provides the heuristic analyzer **235** result and the output from AI model **230** to verdict engine **240**.

[0048] Verdict engine **240** is responsible for classifying the document as clean or malicious. For example, upon receipt of the heuristic score and the threat score from AI model **230**, verdict engine **240** may combine the two values to classify the document. In some embodiments, based on the threat score exceeding a threshold threat value and the heuristic score exceeding a threshold heuristic value, verdict engine **240** classifies the document as malicious. In some embodiments, upon receiving a prediction from AI model **230** that the document includes malware and the heuristic trigger having been triggered, verdict engine **240** classifies the document as malicious. In other words, when both AI model **230** indicates malware and heuristic analyzer **235** indicates malware, verdict engine **240** may classify the document as malicious. Similarly, if verdict engine **240** receives a threat value from AI model **230** that is below a threshold threat value and a heuristic score that is below a threshold heuristic value, verdict engine **240** may classify the document as clean. Further, if either AI model **230** or heuristic analyzer **235** indicates no malware (e.g., one or the other returns a score falling below the respective threshold value), verdict engine **240** may classify the document as clean. In other words, unless both AI model **230** and heuristic analyzer **235** indicate malware in the document, the document is classified by verdict engine **240** as clean. After classification, verdict engine **240** provides outgoing transaction **205** and the classification to security policy enforcer **140**.

[0049] Security policy enforcer **140** enforces security policies on outgoing transaction **205** based at least in part on the classification from verdict engine **240**. For example, if the document is classified as malicious, outgoing transaction **205** may be blocked, a notification may be sent to the user, the document may be quarantined, a notification may be sent to administrators, or the like. Further, any combination of security policies may be applied. If the document is classified as clean, security policies may be applied including forwarding outgoing transaction **205** to the destination domain server **120**, limiting the user's ability to share, modify, or delete the document based on user privileges, or the like.

[0050] FIG. **3** illustrates a data flow **300** of data in portions of the AI malware detection engine **135**. To begin, as described with respect to FIG. **2**, data analyzer **225** uses the data extracted during document detonation in sandbox **130** to generate a feature vector **305**. Data analyzer **225** inputs the feature vector **305** to AI model **230**. Feature vector **305** may be a five hundred and twelve (512) dimension feature vector in some embodiments, though any number of dimensions may be used. The dimensions correspond to dimensions determined to generate a most accurate prediction of whether the document includes malware based on testing and training. For example, the behavior features described in the table above that are exhibited by the document may be included in feature vector **305**. For example, a count of the behavior features exhibited by the document may be included as a dimension of feature vector **305**. In some embodiments, a dimension for each behavior feature may be included in feature vector **305** such that each behavior feature is either indicated as exhibited or not exhibited by the value of the dimension (e.g., zero (0) for not exhibited and one (1) for exhibited). Another dimension may include the size of the process tree spawned by the document in sandbox **130**. Further dimensions may include frequently visited paths or files information. For example, as described in more detail with respect to FIGS. **5** and **6**, AI model **230** may be trained based on previously identified frequently visited paths or files information. This training may identify and use a first selection of frequently visited files and paths for malicious documents and a second selection of frequently visited files and paths for clean documents. Further, a first set of the behavior features exhibited relevant to the frequently visited files and paths of malicious files are identified, and a second set of the behavior features exhibited relevant to the frequently visited files and paths of clean files are identified and used during training. During use, a count of the first set of behavior features exhibited by the document with respect to the known frequently visited files and paths of malicious files may be included as a dimension. Also, a count of the second set of behavior features exhibited by the document with respect to the known frequently visited files and paths of clean files may be included as a dimension. Other dimensions may include indications of signatures invoked by the document. For example, a listing of specific signatures may be relevant. There are many known signatures, and a subset of the known signatures may be used, or all known signatures may be used. In some embodiments, a one-hot vector having a dimension for each relevant signature may be generated in which the one-hot vector includes a zero for each dimension corresponding to a signature that was not invoked by the document and a one for each dimension corresponding to a signature that was invoked by the document. The one-hot vector can be included in feature vector **305**. For example, each dimension of the one-hot vector may correspond to a dimension in feature vector **305**. Another dimension may indicate the severity of the invoked signatures. Each signature is associated with a severity score. The sum of the severity scores for each invoked signature may be calculated, and a dimension of feature vector **305** may be the sum of the severity scores. Further details of feature vector **305** including the dimensions and how they are selected to train AI model **230** are discussed with respect to FIGS. **2**, **5**, and **6**.

[0051] AI model **230** may be or use a gradient boosting tree algorithm (e.g., eXtreme Gradient Boosting (XGBoost)). AI model **230** may include trees **330***a*, **330***b*, and **330***n* (collectively referred to as trees **330**) indicating that there may be any number of trees **330**. In some embodiments, AI model **230** includes one hundred forty (140) decision trees having a maximum depth of sixteen (16). AI model **230** uses trees **330** to generate threat score **315**. The details of how gradient boosting tree algorithms work are not described in detail here as they are known in the art. However, further details of how AI model **230** is trained specifically to generate threat score **315** are described with respect to FIGS. **5** and **6**.

[0052] Data analyzer **225** further obtains character strings **310**. Character strings **310** may represent data extracted from the document while it was open in sandbox **130**. For example, optical character recognition may be used to analyze images in the document to extract text from the images. Other character strings may be extracted from the document as well including from metadata or plain text in the document. The selection of character strings **310** are sent by data analyzer **225** to heuristic analyzer **235**.

[0053] Heuristic analyzer **235** may include a batch of known phishing keywords, phrases, or a combination thereof. Heuristic analyzer **235** may compare each of the character strings **310** to the batch of known phishing keywords and phrases. Each match may be counted to generate a score. For example, each match may increase the score by one (1). In some embodiments, partial matches may be included. In some embodiments, partial matches may count for less in the score than exact matches. In some embodiments, the score may be used as heuristic score **320**. In other embodiments, the score may be used to determine whether it exceeds a threshold heuristic value. If the score exceeds the threshold heuristic value, it may be considered a heuristic trigger, and heuristic score **320** may indicate a binary value (e.g., zero (0) for no heuristic trigger and one (1) for the heuristic trigger). In either case, heuristic score **320** is generated by heuristic analyzer **235**.

[0054] Threat score **315** generated by AI model **230** and heuristic score **320** generated by heuristic analyzer **235** are provided to verdict engine **240**. In some embodiments, AI model **230** sends threat score **315** and heuristic analyzer **235** sends heuristic score **320** directly to verdict engine **240**. In some embodiments, AI model **230** sends threat score **315** and heuristic analyzer **235** sends heuristic score **320** back to data analyzer **225**, and data analyzer **225** sends both to verdict engine **240**. In either case, verdict engine **240** receives threat score **315** and heuristic score **320**. Verdict engine **240** combines threat score **315** and heuristic score **320** to generate classification **325**, classifying the document as either clean or malicious. Verdict engine **240** may be an AI classifier that takes the threat score **315** and the heuristic score **320** as input and outputs a classification. Verdict engine **240** may, in some embodiments, be a simpler algorithm that determines whether there is a heuristic trigger. The heuristic trigger may either be determined by heuristic analyzer **235** and indicated by heuristic score **320** being a positive value (e.g., one (1)), indicating the heuristic trigger, or verdict engine **240** may determine whether the heuristic trigger is positive by comparing the heuristic score **320** to a threshold heuristic value. In either case, a rule may be used to determine whether the heuristic trigger happened with respect to the document. Further, verdict engine **240** may compare threat score **315** against a threshold threat value such that when the threat score **315** exceeds the threshold threat value it indicates that the document includes malware. Verdict engine **240** may classify the document as malicious when the heuristic trigger happens and the threat score **315** indicates the document includes malware (e.g., threat score **315** exceeds the threshold threat value). Otherwise, verdict engine **240** may classify the document as clean. In other words, both heuristic analyzer **235** and AI model **230** may need to indicate the document includes malware for verdict engine **240** to classify the document as malicious. In other embodiments, verdict engine may classify the document as clean when both AI model **230** and heuristic analyzer **235** indicate the document does not include malware and otherwise classify the document as malicious. In yet other embodiments, when threat score **315** falls within an intermediate range, heuristic score **320** may determine the classification (e.g., when the heuristic trigger does not happen, the document is classified as clean and when the heuristic trigger does happen, the document is classified as malicious). In such embodiments when threat score **315** falls below the intermediate range the document is classified as clean and when threat score **315** falls above the intermediate range the document is classified as malicious. As can be seen, verdict engine **240** may combine threat score **315** and heuristic score **320** in any way to classify the document as clean or malicious.

[0055] Upon completing analysis, verdict engine **240** generates classification **325** and sends it to security policy enforcer **140** for security policy enforcement of the outgoing transaction **205**.

[0056] FIG. **4** illustrates method **400** for securing outgoing transactions requesting document access using network security system **125** as described above. Method **400** may be performed by network security system **125** in a cloud-based implementation or an on-premises implementation. While specific steps are shown, network security system **125** may include additional functionality, and more or fewer steps than shown in method **400** may be performed. Method **400** begins with step **410** where a request to access a document is intercepted. For example, network security system **125** may intercept outgoing transaction **205**. Ingest engine **210** may analyze outgoing transaction **205** and determine that outgoing transaction **205** requests access to a document from a destination domain server **120**.

[0057] At step **415**, the document is obtained. For example, file retriever **215** may retrieve the file from the addressed destination domain server **120**. In some embodiments, the user credentials used for outgoing transaction **205** may be used to obtain the file.

[0058] At step **420**, the document is detonated (i.e., opened) in a sandbox of the network security system. For example, file detonator **220** may open the file in sandbox **130**.

[0059] At step **425**, in response to detonating the document, dynamic information about the document is extracted. Static information may also be extracted. For example, processes running in sandbox **130** may extract behavior feature data, signature data, process data, and the like. The processes may generate a report providing the relevant information. In some embodiments, data analyzer **225** may obtain the report such that data analyzer **225** retrieves all the data for analyzing whether the document includes malware. Data analyzer **225** can then extract the relevant data from the report. In some embodiments, data analyzer **225** probes sandbox **130** while the document is opened and extracts and obtains the information directly including the static and dynamic data.

[0060] At step **430**, character strings from images in the document are extracted while the document is open in the sandbox. For example, OCR technology may be used to extract character strings from images in the document. In some embodiments, a process within sandbox **130** is configured to launch the OCR technology and provide the information in a report (e.g., the same report providing the static and dynamic data or a different report).

[0061] At step **435**, the dynamic information about the document is provided as input to an artificial intelligence model trained to provide an output indicating a prediction of whether the document contains malware based on the input. For example, data analyzer **225** generates feature vector **305** and provides it as input to AI model **230**. AI model **230** is trained to generate threat score **315** as output. In some embodiments, the static information is also provided as a portion of the input to the artificial intelligence model.

[0062] At step **440**, a heuristic score is generated based on comparing the character strings extracted from images in the document to a batch of phishing keywords. For example, data analyzer **225** sends character strings **310** to heuristic analyzer **235** to compare character strings **310** to a batch of phishing keywords and phrases (collectively phishing keywords). Heuristic analyzer **235** generates heuristic score **320**. Heuristic score may be a count of the matches, a weighted count of the matches and partial matches, a number indicating a heuristic trigger is triggered or not (e.g., the count of matches exceeds a threshold heuristic value), or any value that indicates a likelihood that the document includes malware based on the comparison of character strings **310** to the batch of phishing keywords.

[0063] At step **445**, the output of the artificial intelligence model and the heuristic score are input to a verdict engine that combines the output and the heuristic score to classify the document as either clean or malicious. For example, threat score **315** and heuristic score **320** are input to verdict engine **240**, which uses them to generate classification **325**.

[0064] At step **450**, a security policy is implemented based on the classification of the document. For example, security policy enforcer **140** may implement one or more security policies on outgoing transaction **205** based on whether verdict engine **240** provided classification **325** indicating the document was clean or malicious. If, for example, the document is classified as clean, security policy enforcer **140** may implement different security policies than if the document is classified as malicious. As one example, if classified as malicious, security policy enforcer **140** may block transmission of outgoing transaction **205**. However, if classified as clean, security policy enforcer **140** may apply further security policies to outgoing transaction.

[0065] FIG. **5** illustrates a simplified training model **500** depicting training data provided to AI model **230** for training and the feedback loop. To begin, behavior features may be importance ranked and the information for importance ranked behavior features **505** may be embedded in AI model **230**. Similarly, signature features (i.e., signatures) may be importance ranked, and importance ranked signature features **510** may be embedded in AI model **230**.

[0066] After initial setup, including identifying frequently visited files and paths that are discussed in more detail with respect to FIG. **6**, training sample data **515** is used to further train AI model **230**. The training samples include documents, some of which include malware. For each training sample, feature vector **305** is generated based on opening (i.e., accessing or detonating) the document in sandbox **130**. Feature vector **305** was discussed with respect to FIG. **3**. To expand on this discussion, each feature vector **305** includes behavior features **520**, process tree size **525**, frequently visited files and paths **530**, signature features **535**, and signature severity **540**.

[0067] Behavior features **520** may include any or all of the behavior features discussed in the table above with respect to FIG. **2**. Other behavior features may also be included in some embodiments. The behavior features **520** may be included in feature vector **305** by using a single dimension to indicate a count of the behavior features that are exhibited by the document when detonated. In some embodiments, a dimension for each behavior feature is included, and the corresponding dimension includes a value that indicates whether the behavior feature was exhibited by the document when detonated.

[0068] Process tree size **525** may be a dimension of feature vector **305** that indicates an integer value of the size of the process tree spawned by detonating the document. The process tree size may indicate malware if, for example, a large process tree is spawned.

[0069] Frequently visited files and paths **530** may be identified and included as one or more dimensions of feature vector **305**. Specifically, known frequently visited files and paths of malicious files that may exhibit particular behavior features with respect to those known paths and files are used to generate a count for a one dimension of feature vector **305**. In other words, when a document exhibits a behavior feature known to be often exhibited in a known path (e.g., file_created in path: directory1/subdirectory2/subdirectory3), the count increases by one. Similarly, known frequently visited files and paths of benign files that exhibit particular behavior features with respect to those known paths and files are used to generate a count for another dimension of feature vector **305**. Those dimensions make up the frequently visited files and paths **530** data included in feature vector **305**. Additional details about how the frequently visited files and paths are identified for inclusion is described with respect to FIG. **6**.

[0070] Signature features **535** includes data regarding signatures that are invoked by detonation of the document. Each signature may be associated with a corresponding dimension of feature vector **305**. When the signature is invoked, the dimension indicates the invocation (e.g., has a value of one (1)), and when the signature is not invoked, the dimension indicates no invocation (e.g., has a value of zero (0)). The list of signatures included may be based on known signatures that are published and known for network security.

[0071] Signature severity **540** may include the severity information for the signatures invoked by the document. For example, each signature that is tracked in signature features **535** includes a severity score. A dimension of feature vector **305** may include a sum of the signature severity scores for the signatures invoked by the document.

[0072] Once feature vector **305** is generated for a given training data sample from training sample data **515**, it is input to AI model **230**. AI model **230** generates output **545** (e.g., threat score **315**). The training system compares output **545** against the ground truth **550** for the given training sample. For example, each training sample may be labeled as malicious or clean. When output **545** indicates that the training sample is malicious, but the ground truth **550** indicates the document is clean, the AI model **230** is wrong, and that information is provided as feedback **555** to AI model **230**. Similarly, when AI model **230** is correct, feedback **555** indicates the correct classification. AI model **230** is trained until it reaches an acceptable level of accuracy. Once trained, it is deployed to use in a production environment.

[0073] FIG. **6** illustrates one sample **600** of identifying and using frequently visited paths and files (e.g., frequently visited files and paths **530**) for training and in production. The paths for malicious and clean files are identified by looking at a large set of documents and analyzing the frequently visited paths and files for known clean and known malicious documents. The theory is that malicious documents are more likely to access (e.g., load, read, open delete, or the like) some directories and files which are less frequently accessed by benign files. However, trimmed subdirectories provides a more robust analysis because it avoids failing to see the frequently visited paths when the full path is unique to one or a few samples of malware.

[0074] Once a set of paths are identified as visited by benign and malicious samples, the paths are analyzed. The sample **600** shown in FIG. **6** illustrates the process. First, the full path **605** is analyzed, and an odds ratio **610** is calculated. Then, the first trimmed path **615** is identified by removing the last subdirectory (i.e., subdirectory1b). The odds ratio **620** is calculated for the first trimmed path **615**. The second trimmed path **625** is similarly generated and the odds ratio **630** calculated. This is done for each full path and trimmed path identified for analysis.

[0075] Each trimmed path is scored with an odds ratio as shown in FIG. **6**. The odds ratio is the odds of seeing a trimmed path visited by a malicious file divided by the odds the trimmed path is visited by a benign file. If the score exceeds a threshold value (e.g., 2), it is included in the malicious list **640**. If the score falls below another threshold value (e.g., 0.5) it is included in the benign list **635**. In this way, the meaningful paths are identified. As shown in sample **600**, first trimmed path **615** has an odds ratio **620** with a value of three (3). Accordingly, first trimmed path **615** is included in malicious list **640**.

[0076] The odds ratio is calculated by dividing odds1 by odds2 (i.e., odds ratio=odds1/odds2). Further, a value M0 is calculated indicating the total number of malicious samples that visited a specific trimmed path (e.g., the first trimmed path **615**). A second value M1 is calculated indicating the number of malicious samples that did not visit the specific trimmed path. Another value B0 is calculated indicating the total number of benign samples that visited the trimmed path, and a value B1 is calculated indicating the total number of benign samples that did not visit the trimmed path. Odds1 is calculated as M0 divided by M1 (i.e., odds1=M0/M1), and Odds2 is calculated as B0 divided by B1 (i.e., odds2=B0/B1).

[0077] In addition to generating the malicious list **640** and the benign list **635** indicating trimmed paths and files frequently visited by the malicious and benign documents, a list of behavior features for each frequently visited path in the malicious list **640** can be identified, and a list of behavior features for each frequently visited path in the benign list **635** can be identified. For example, behavior features including file_exists, file_created, file_failed, file_written, file_recreated, file_read, and file_opened may be included in the behavior features relevant to the frequently visited paths and files in benign list **635**. Behavior features including directory_enumerated, file_exists, file_opened file_created, file_failed, file_read, directory_created, file_written, file_deleted, directory_removed, and file_recreated may be included in the behavior features relevant to the frequently visited paths and files in malicious list **640**.

[0078] Accordingly, to generate frequently visited files and paths **530** in feature vector **305** for each training and production sample, the dynamic information is collected by detonating the document in sandbox **130**. A count of how many times the document performs one of the relevant behavior features in a path of the malicious list **640** may be one dimension of feature vector **305**. A count of how many times the document performs one of the relevant behavior features in a path of the benign list **635** may be another dimension of feature vector **305**.

[0079] FIG. **7** illustrates a computing device **700**. The computing device **700** includes various components not included for ease of description in other computing devices discussed herein including, for example, endpoints **105**, network security system **125**, and destination domain servers **120**. Accordingly, computing device **700** may be endpoints **105**, network security system **125**, or destination domain servers **120** by incorporating the functionality described in each.

[0080] Computing device **700** is suitable for implementing processing operations described herein related to security enforcement and document malware detection, with which aspects of the present disclosure may be practiced. Computing device **700** may be configured to implement processing operations of any component described herein including the user system components (e.g., endpoints **105** of FIG. **1**). As such, computing device **700** may be configured as a specific purpose computing device that executes specific processing operations to solve the technical problems described herein including those pertaining to security enforcement and document malware detection. Computing device **700** may be implemented as a single apparatus, system, or device or may be implemented in a distributed manner as multiple apparatuses, systems, or devices. For example, computing device **700** may comprise one or more computing devices that execute processing for applications and/or services over a distributed network to enable execution of processing operations described herein over one or more applications or services. Computing device **700** may comprise a collection of devices executing processing for front-end applications/services, back-end applications/services, or a combination thereof. Computing device **700** includes, but is not limited to, a bus **705** communicably coupling processors **710**, output devices **715**, communication interfaces **720**, input devices **725**, power supply **730**, and memory **735**.

[0081] Non-limiting examples of computing device **700** include smart phones, laptops, tablets, PDAs, desktop computers, servers, blade servers, cloud servers, smart computing devices including television devices and wearable computing devices including VR devices and AR devices, e-reader devices, gaming consoles and conferencing systems, among other non-limiting examples.

[0082] Processors **710** may include general processors, specialized processors such as graphical processing units (GPUs) and digital signal processors (DSPs), or a combination. Processors **710** may load and execute software **740** from memory **735**. Software **740** may include one or more software components such as sandbox **130**, AI malware detection engine **135**, security policy enforcer **140**, endpoint routing client **110**, or any combination including other software components. In some examples, computing device **700** may be connected to other computing devices (e.g., display device, audio devices, servers, mobile devices, remote devices, VR devices, AR devices, or the like) to further enable processing operations to be executed. When executed by processors **710**, software **740** directs processors **710** to operate as described herein for at least the various processes, operational scenarios, and sequences discussed in the foregoing implementations. Computing device **700** may optionally include additional devices, features, or functionality not discussed for purposes of brevity. For example, software **740** may include an operating system that is executed on computing device **700**. Computing device **700** may further be utilized as endpoints **105** or any of the cloud computing systems in security environment **100** (FIG. **1**) including network security system **125** or may execute the method **400** of FIG. **4**.

[0083] Referring still to FIG. **7**, processors **710** may include a processor or microprocessor and other circuitry that retrieves and executes software **740** from memory **735**. Processors **710** may be implemented within a single processing device but may also be distributed across multiple processing devices or sub-systems that cooperate in executing program instructions. Examples of processors **710** include general purpose central processing units, microprocessors, graphical processing units, application specific processors, sound cards, speakers and logic devices, gaming devices, VR devices, AR devices as well as any other type of processing devices, combinations, or variations thereof.

[0084] Memory **735** may include any computer-readable storage device readable by processors **710** and capable of storing software **740** and data stores **745**. Data stores **745** may include data stores that maintain security policies used by security policy enforcer **140**, for example. Memory **735** may include volatile and nonvolatile, removable and non-removable media implemented in any method or technology for storage of information, such as computer readable instructions, data structures, program modules, cache memory, or other data. Examples of storage media include random access memory, read only memory, magnetic disks, optical disks, flash memory, virtual memory and non-virtual memory, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or other suitable storage media, except for propagated signals. In no case is the computer-readable storage device a propagated signal.

[0085] In addition to computer-readable storage devices, in some implementations, memory **735** may also include computer-readable communication media over which at least some of software **740** may be communicated internally or externally. Memory **735** may be implemented as a single storage device but may also be implemented across multiple storage devices or sub-systems co-located or distributed relative to each other. Memory **735** may include additional elements, such as a controller, capable of communicating with processors **710** or possibly other systems.

[0086] Software **740** may be implemented in program instructions and among other functions may, when executed by processors **710**, direct processors **710** to operate as described with respect to the various operational scenarios, sequences, and processes illustrated herein. For example, software **740** may include program instructions for executing document malware detection (e.g., AI malware detection engine **135**, AI model **230**, heuristic analyzer **235**, verdict engine **240**, data analyzer **225**, file retriever **215**, file detonator **220**, sandbox **130**) or security policy enforcement (e.g., security policy enforcer **140**) as described herein.

[0087] In particular, the program instructions may include various components or modules that cooperate or otherwise interact to conduct the various processes and operational scenarios described herein. The various components or modules may be embodied in compiled or interpreted instructions, or in some other variation or combination of instructions. The various components or modules may be executed in a synchronous or asynchronous manner, serially or in parallel, in a single threaded environment or multi-threaded, or in accordance with any other suitable execution paradigm, variation, or combination thereof. Software **740** may include additional processes, programs, or components, such as operating system software, virtual machine software, or other application software. Software **740** may also include firmware or some other form of machine-readable processing instructions executable by processors **710**.

[0088] In general, software **740** may, when loaded into processors **710** and executed, transform a suitable apparatus, system, or device (of which computing device **700** is representative) overall from a general-purpose computing system into a special-purpose computing system customized to execute specific processing components described herein as well as process data and respond to queries. Indeed, encoding software **740** on memory **735** may transform the physical structure of memory **735**. The specific transformation of the physical structure may depend on various factors in different implementations of this description. Examples of such factors may include, but are not limited to, the technology used to implement the storage media of memory **735** and whether the computer-storage media are characterized as primary or secondary storage, as well as other factors.

[0089] For example, if the computer readable storage device are implemented as semiconductor-based memory, software **740** may transform the physical state of the semiconductor memory when the program instructions are encoded therein, such as by transforming the state of transistors, capacitors, or other discrete circuit elements constituting the semiconductor memory. A similar transformation may occur with respect to magnetic or optical media. Other transformations of physical media are possible without departing from the scope of the present description, with the foregoing examples provided only to facilitate the present discussion.

[0090] Communication interfaces **720** may include communication connections and devices that allow for communication with other computing systems (not shown) over communication networks (not shown). Communication interfaces **720** may also be utilized to cover interfacing between processing components described herein. Examples of connections and devices that together allow for inter-system communication may include network interface cards or devices, antennas, satellites, power amplifiers, RF circuitry, transceivers, and other communication circuitry. The connections and devices may communicate over communication media to exchange communications with other computing systems or networks of systems, such as metal, glass, air, or any other suitable communication media. The aforementioned media, connections, and devices are well known and need not be discussed at length here.

[0091] Communication interfaces **720** may also include associated user interface software executable by processors **710** in support of the various user input and output devices discussed below. Separately or in conjunction with each other and other hardware and software elements, the user interface software and user interface devices may support a graphical user interface, a natural user interface, or any other type of user interface, for example, which enables front-end processing and including rendering of user interfaces, such as a user interface that is used by a user on endpoint **105**. Exemplary applications and services may further be configured to interface with processing components of computing device **700** that enable output of other types of signals (e.g., audio output, handwritten input) in conjunction with operation of exemplary applications or services (e.g., a collaborative communication application or service, electronic meeting application or service, or the like) described herein.

[0092] Input devices **725** may include a keyboard, a mouse, a voice input device, a touch input device for receiving a touch gesture from a user, a motion input device for detecting non-touch gestures and other motions by a user, gaming accessories (e.g., controllers and/or headsets) and other comparable input devices and associated processing elements capable of receiving user input from a user. Output devices **715** may include a display, speakers, haptic devices, and the like. In some cases, the input and output devices may be combined in a single device, such as a display capable of displaying images and receiving touch gestures. The aforementioned user input and output devices are well known in the art and need not be discussed at length here.

[0093] Communication between computing device **700** and other computing systems (not shown), may occur over a communication network or networks and in accordance with various communication protocols, combinations of protocols, or variations thereof. Examples include intranets, internets, the Internet, local area networks, wide area networks, wireless networks, wired networks, virtual networks, software defined networks, data center buses, computing backplanes, or any other type of network, combination of network, or variation thereof. The aforementioned communication networks and protocols are well known and need not be discussed at length here. However, some communication protocols that may be used include, but are not limited to, the Internet protocol (IP, IPv4, IPv6, etc.), the transfer control protocol (TCP), and the user datagram protocol (UDP), as well as any other suitable communication protocol, variation, or combination thereof.

[0094] The computing device **700** has a power supply **730**, which may be implemented as one or more batteries. The power supply **730** may further include an external power source, such as an AC adapter or a powered docking cradle that supplements or recharges the batteries. In some embodiments, the power supply **730** may not include batteries and the power source may be an external power source such as an AC adapter.

[0095] The aforementioned discussion is presented to enable any person skilled in the art to make and use the technology disclosed and is provided in the context of a particular application and its requirements. Various modifications to the disclosed implementations will be readily apparent to those skilled in the art, and the general principles defined herein may be applied to other implementations and applications without departing from the spirit and scope of the technology disclosed. Thus, the technology disclosed is not intended to be limited to the implementations shown but is to be accorded the widest scope consistent with the principles and features disclosed herein.

[0096] Unless the context clearly requires otherwise, throughout the description and the claims, the words "comprise," "comprising," and the like are to be construed in an inclusive sense, as opposed to an exclusive or exhaustive sense; that is to say, in the sense of "including, but not limited to." As used herein, the terms "connected," "coupled," or any variant thereof means any connection or coupling, either direct or indirect, between two or more elements; the coupling or connection between the elements can be physical, logical, or a combination thereof. Additionally, the words "herein," "above," "below," and words of similar import, when used in this application, refer to this application as a whole and not to any particular portions of this application. Where the context permits, words in the above Detailed Description using the singular or plural number may also include the plural or singular number, respectively. The word "or" in reference to a list of two or more items covers all of the following interpretations of the word: any of the items in the list, all of the items in the list, and any combination of the items in the list.

[0097] The phrases "in some embodiments," "according to some embodiments," "in the embodiments shown," "in other embodiments," and the like generally mean the particular feature, structure, or characteristic following the phrase is included in at least one implementation of the present technology and may be included in more than one implementation. In addition, such phrases do not necessarily refer to the same embodiments or different embodiments.

[0098] The above Detailed Description of examples of the technology is not intended to be exhaustive or to limit the technology to the precise form disclosed above. While specific examples for the technology are described above for illustrative purposes, various equivalent modifications are possible within the scope of the technology, as those skilled in the relevant art will recognize. For example, while processes or blocks are presented in a given order, alternative implementations may perform routines having steps, or employ systems having blocks, in a different order, and some processes or blocks may be deleted, moved, added, subdivided, combined, and/or modified to provide alternative or subcombinations. Each of these processes or blocks may be implemented in a variety of different ways. Also, while processes or blocks are at times shown as being performed in series, these processes or blocks may instead be performed or implemented in parallel or may be performed at different times. Further any specific numbers noted herein are only examples: alternative implementations may employ differing values or ranges.

What is claimed is:

1. A cloud-based network security system, comprising a plurality of components executable by one or more processors, wherein the plurality of components comprises:

an isolated sandbox environment;

a file detonator configured to:

in response to receiving an access request for a document, opening the document in the isolated sandbox environment;

a data analyzer configured to:

extract dynamic information about the document and character strings from images in the document in the isolated sandbox environment;

an artificial intelligence model configured to:

predict whether or not the document contains malware based on the dynamic information;

a heuristic analyzer configured to:
generate a heuristic score based at least in part on comparing the character strings to a batch of keywords;
a verdict engine configured to:
classify the document as one of malicious or benign based at least in part on the prediction of the artificial intelligence model and the heuristic score; and
a security policy enforcer configured to:
implement a security policy based at least in part on the document classification from the verdict engine.

2. The cloud-based network security system of claim **1**, wherein the data analyzer is further configured to:
analyze behavior of the document in the isolated sandbox environment; and
extract the dynamic information from the behavior, wherein the dynamic information about the document comprises:
a set of behavior features exhibited by the document,
a size of a process tree spawned by opening the document, and
a set of signature features exhibited by the document.

3. The cloud-based network security system of claim **2**, wherein the set of behavior features comprises at least one of: visited files, visited paths, and pathways explored by processes in the isolated sandbox environment.

4. The cloud-based network security system of claim **2**, wherein the set of signature features comprises:
a signature vector having a dimension for each of a plurality of software signatures, wherein a value of each dimension indicates whether the document invoked the respective software signature in the isolated sandbox environment, and
severity scores for each of the software signatures the document invoked.

5. The cloud-based network security system of claim **2**, wherein the data analyzer is further configured to:
generate a feature vector representing the dynamic information; and
provide the feature vector as input to the artificial intelligence model.

6. The cloud-based network security system of claim **1**, wherein the artificial intelligence model comprises a gradient boosting tree algorithm.

7. The cloud-based network security system of claim **1**, wherein the data analyzer is further configured to:
analyze the document with optical character recognition.

8. The cloud-based network security system of claim **1**, wherein the heuristic analyzer is further configured to:
count all matches identified during the comparison of the character strings to the batch of keywords; and
use the count for the heuristic score.

9. The cloud-based network security system of claim **1**, wherein:
the heuristic analyzer is further configured to:
trigger a heuristic rule based on the heuristic score exceeding a threshold heuristic value;
the artificial intelligence model is further configured to:
generate a prediction score indicating the prediction; and
the verdict engine is further configured to:
classify document as malicious based on:
determining the heuristic rule is triggered; and
the prediction score exceeds a pre-defined prediction threshold value, and
classify the document as benign based on:
determining the heuristic rule is not triggered; or
the prediction score does not exceed the pre-defined prediction threshold value.

10. The cloud-based network security system of claim **1**, wherein:
the data analyzer is further configured to:
extract static information from the document; and
provide both the static information and the dynamic information as input to the artificial intelligence model.

11. A computer-implemented method, comprising:
in response to receiving an access request for a document, opening, by a cloud-based network security system, the document in an isolated sandbox environment;
extracting, by the cloud-based network security system, dynamic information about the document and character strings from images in the document in the isolated sandbox environment;
predicting, by an artificial intelligence model of the cloud-based network security system, whether or not the document contains malware based on the dynamic information;
generating, by a heuristic analyzer of the cloud-based network security system, a heuristic score based at least in part on comparing the character strings to a batch of keywords;
classifying, by a verdict engine of the cloud-based network security system, the document as one of malicious or benign based at least in part on the prediction of the artificial intelligence model and the heuristic score; and
implementing, by the cloud-based network security system, a security policy based at least in part on the document classification.

12. The computer-implemented method of claim **11**, wherein the extracting the dynamic information about the document comprises:
analyzing behavior of the document in the isolated sandbox environment; and
extracting data from the behavior, wherein the dynamic information about the document comprises:
a set of behavior features exhibited by the document,
a size of a process tree spawned by opening the document, and
a set of signature features exhibited by the document.

13. The computer-implemented method of claim **12**, wherein the set of behavior features comprises at least one of: visited files, visited paths, and pathways explored by processes in the isolated sandbox environment.

14. The computer-implemented method of claim **12**, wherein the set of signature features comprises:
a signature vector having a dimension for each of a plurality of software signatures, wherein a value of each dimension indicates whether the document invoked the respective software signature in the isolated sandbox environment, and
severity scores for each of the software signatures the document invoked.

15. The computer-implemented method of claim **12**, further comprising:
- generating a feature vector representing at least a portion of the dynamic information; and
- providing the feature vector as input to the artificial intelligence model.

16. The computer-implemented method of claim **11**, wherein the artificial intelligence model comprises a gradient boosting tree algorithm.

17. The computer-implemented method of claim **11**, wherein the extracting the character strings from the images in the document comprises analyzing the document with optical character recognition.

18. The computer-implemented method of claim **11**, wherein the heuristic score comprises a count of all matches identified during the comparison of the character strings to the batch of the keywords.

19. The computer-implemented method of claim **11**, wherein:
- a heuristic rule is triggered based on the heuristic score exceeding a threshold heuristic value;
- the prediction comprises a prediction score; and
- the verdict engine:
  - classifies the document as malicious based on:
    - determining the heuristic rule is triggered; and
    - the prediction score exceeds a pre-defined prediction threshold value, and
  - classifies the document as benign based on:
    - determining the heuristic rule is not triggered; or
    - the prediction score does not exceed the pre-defined prediction threshold value.

20. The computer-implemented method of claim **11**, further comprising:
- extracting static information from the document, wherein prediction of the artificial intelligence model is further based at least in part on the static information.

* * * * *