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(54) AI/ML FRAMEWORK FOR DISTRIBUTED APPLICATIONS AND FEDERATED LEARNING

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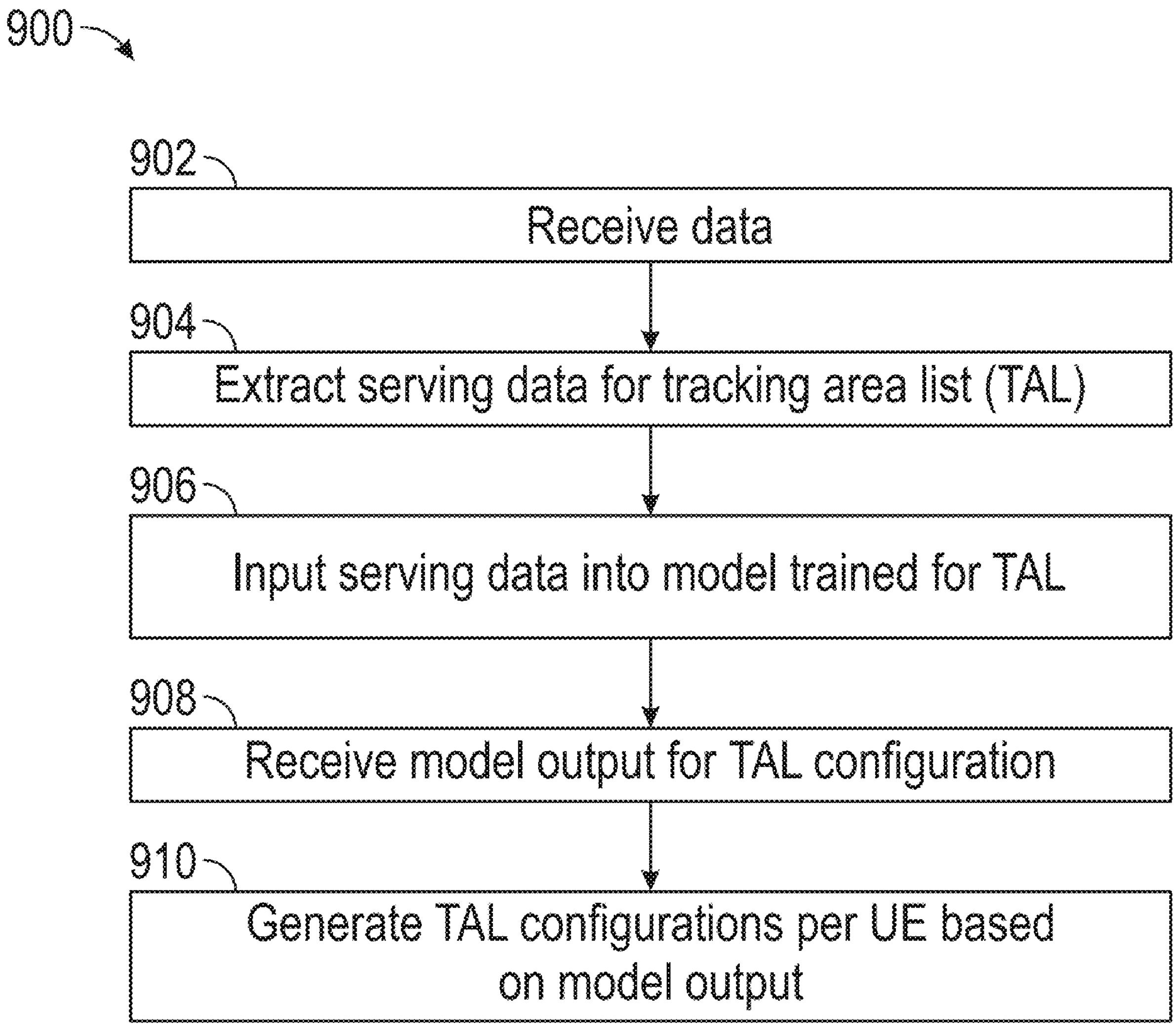
CPC *G06N 20/00* (2019.01)

(57) ABSTRACT

A service node of a communication network may receive event data from one or more gateway components. The service node may process the event data to generate processed and transmit the processed data to a central location of the communication network. The central location may receive data from a plurality of other service nodes and train a machine-learning (ML) model using the processed data and received data from the plurality of other service nodes. The trained ML model may be deployed at the service node and used for performing various actions at the service node.


900
902
Receive data
904
Extract serving data for tracking area list (TAL)
906
Input serving data into model trained for TAL
908
Receive model output for TAL configuration
910
Generate TAL configurations per UE based on model output

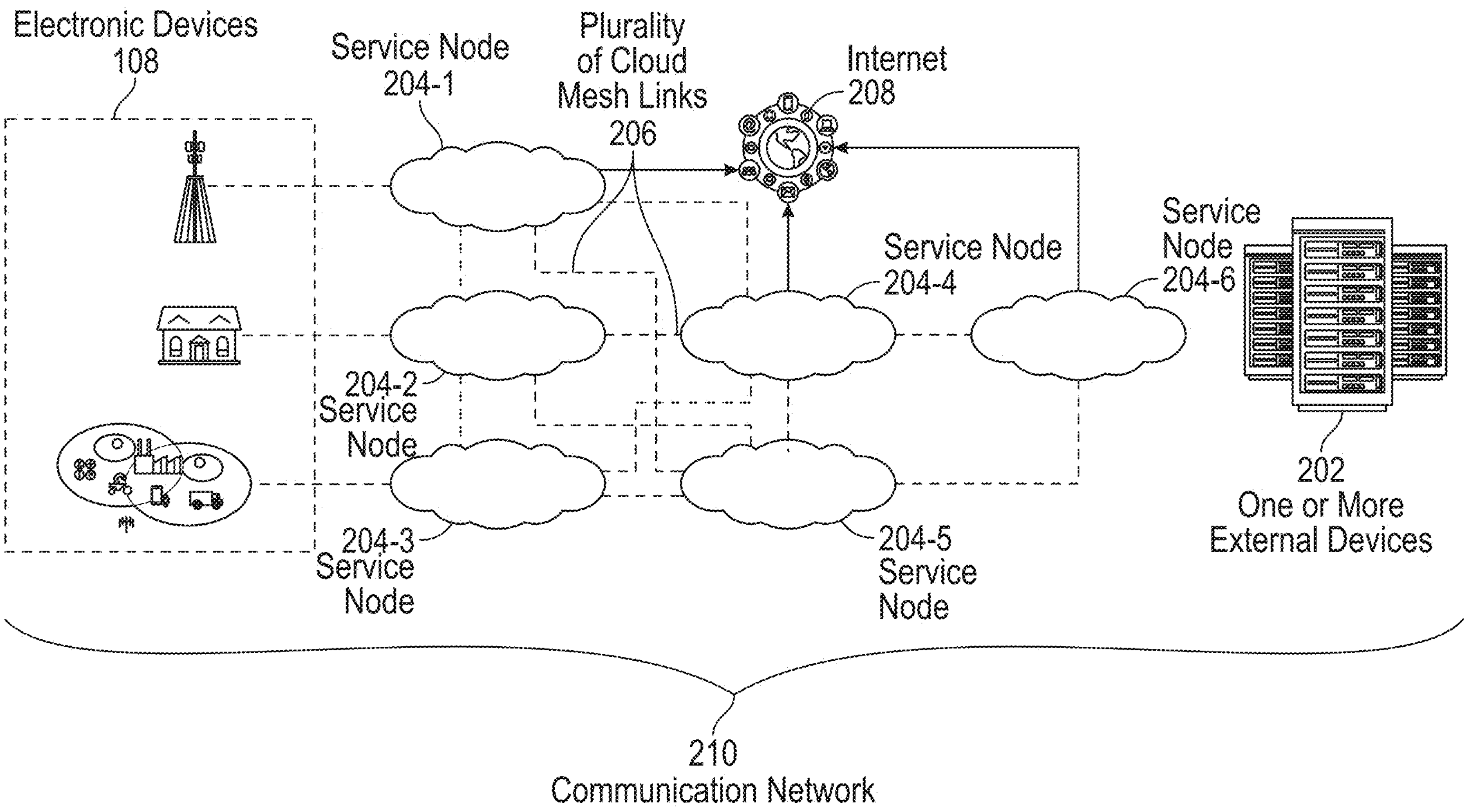

Electronic Devices
108
Service Node
204-1
Plurality
of Cloud
Mesh Links
206
Internet
208
Service Node
204-4
Service
Node
204-6
204-2
Service
Node
204-3
Service
Node
204-5
Service
Node
202
One or More
External Devices
210
Communication Network

FIG. 1

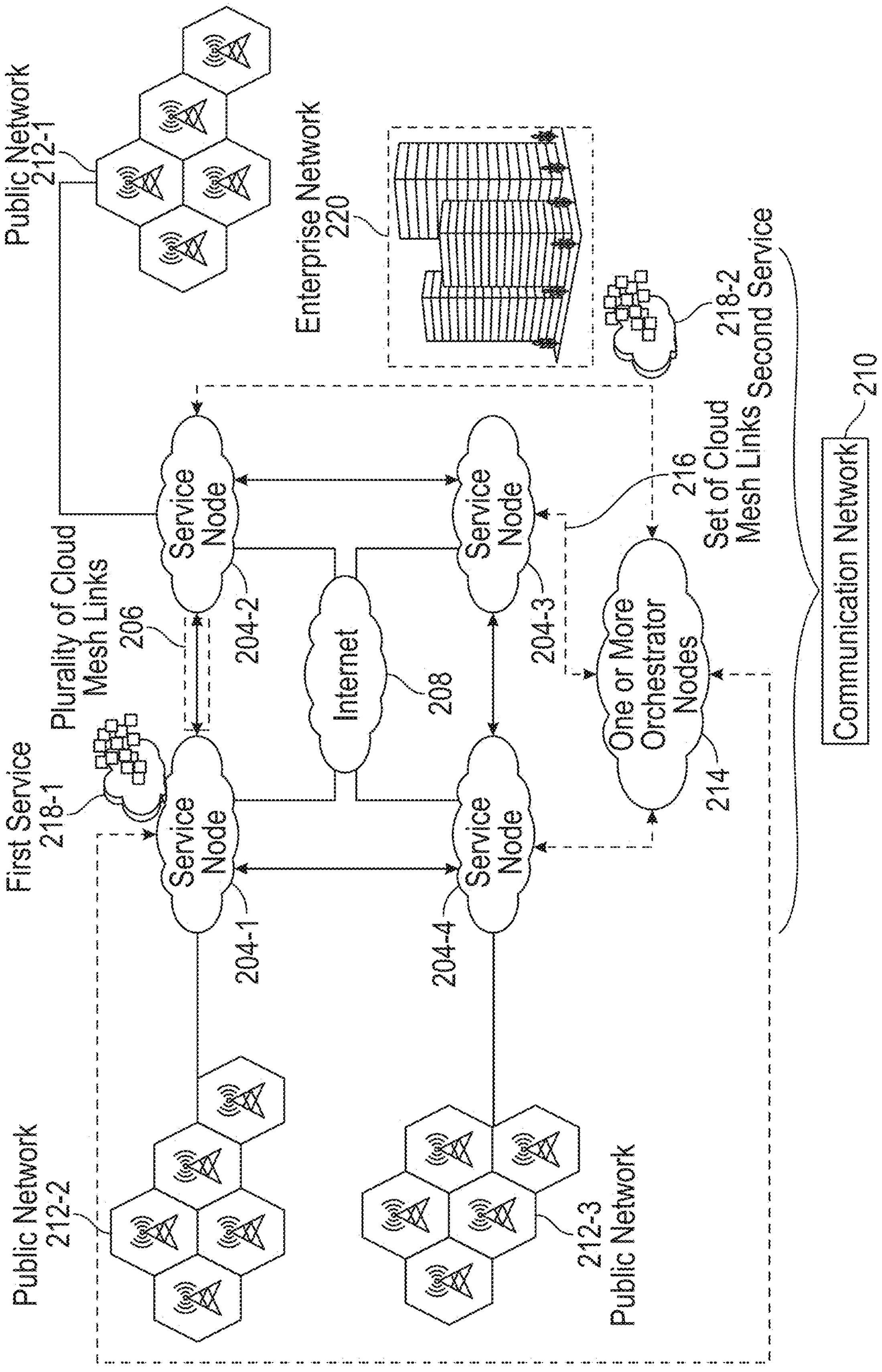

Public Network
212-2
Public Network
212-3
First Service
218-1
Plurality of Cloud
Mesh Links
206
Service
Node
204-1
Service
Node
204-4
Internet
208
Service
Node
204-2
Service
Node
204-3
One or More
Orchestrator
Nodes
214
216
Set of Cloud
Mesh Links
Public Network
212-1
Enterprise Network
220
218-2
Second Service
Communication Network
210

FIG. 2A

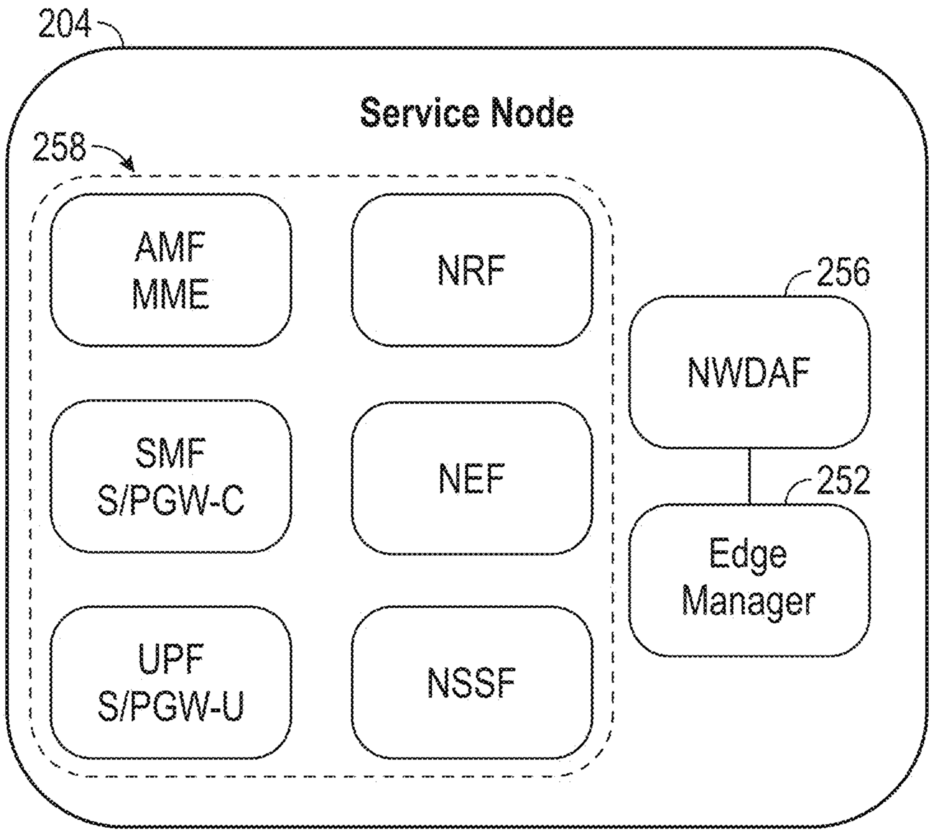

204
Service Node
258
AMF
MME
NRF
SMF
S/PGW-C
NEF
UPF
S/PGW-U
NSSF
256
NWDAF
252
Edge
Manager

FIG. 2B

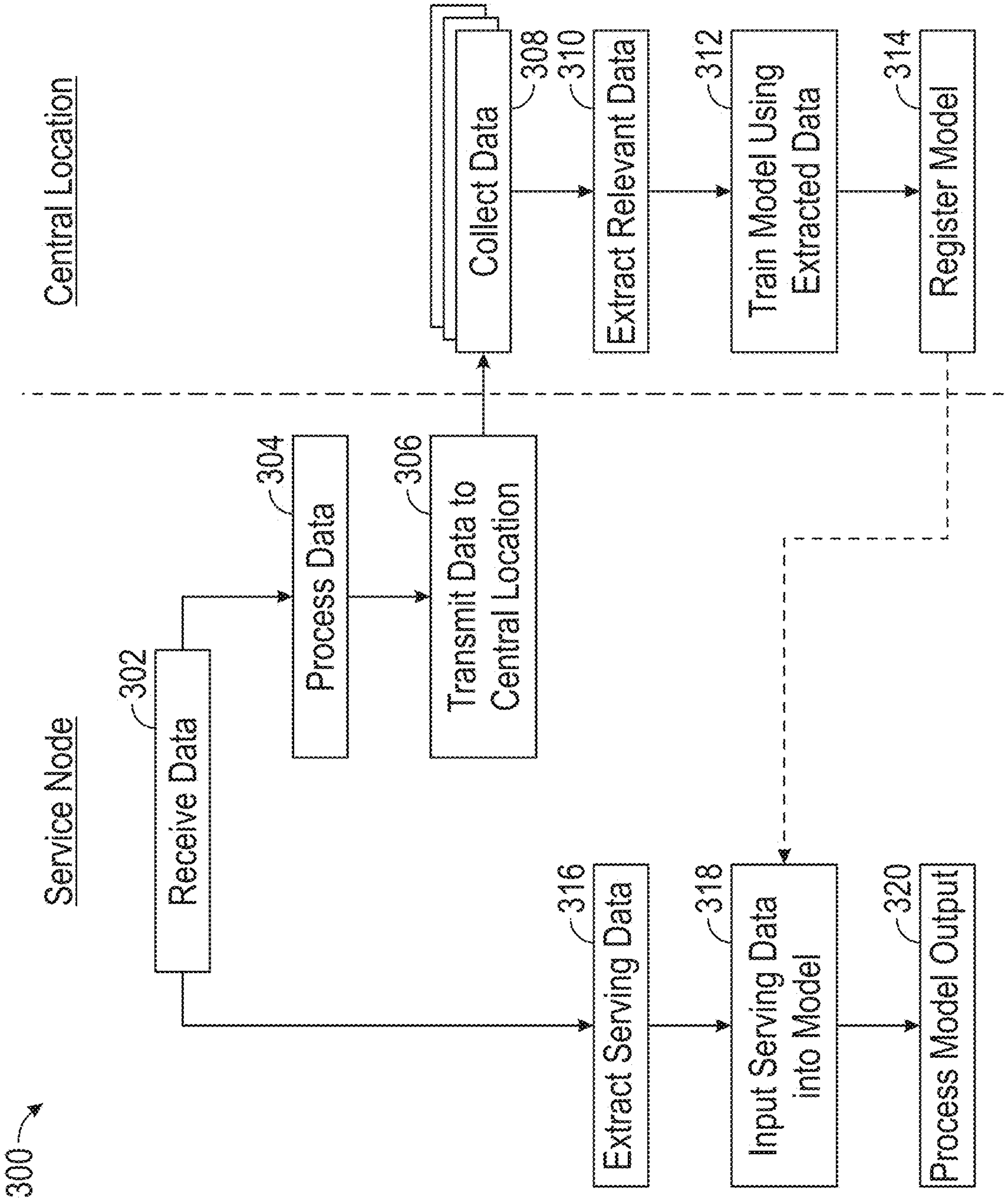

300
Service Node
Central Location
Receive Data
302
Process Data
304
Transmit Data to Central Location
306
Collect Data
308
Extract Relevant Data
310
Train Model Using Extracted Data
312
Register Model
314
Extract Serving Data
316
Input Serving Data into Model
318
Process Model Output
320

FIG. 3

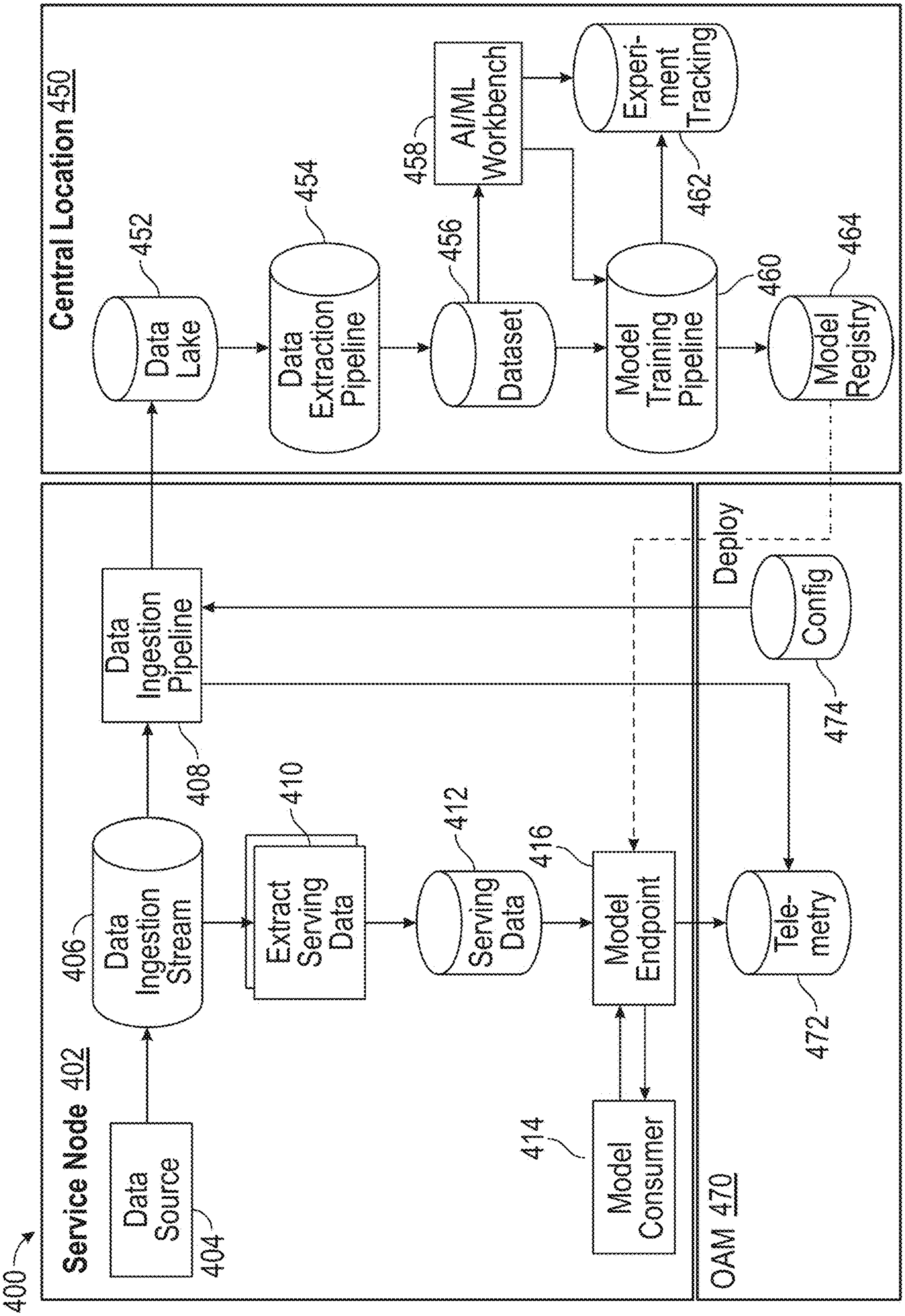

400
Service Node 402
Data Source
404
Data Ingestion Stream
406
Data Ingestion Pipeline
408
Extract Serving Data
410
Serving Data
412
Model Endpoint
416
Model Consumer
414
Central Location 450
Data Lake
452
Data Extraction Pipeline
454
Dataset
456
AI/ML Workbench
458
Experiment Tracking
462
Model Training Pipeline
460
Model Registry
464
Deploy
Config
474
Tele-metry
472
OAM 470

FIG. 4

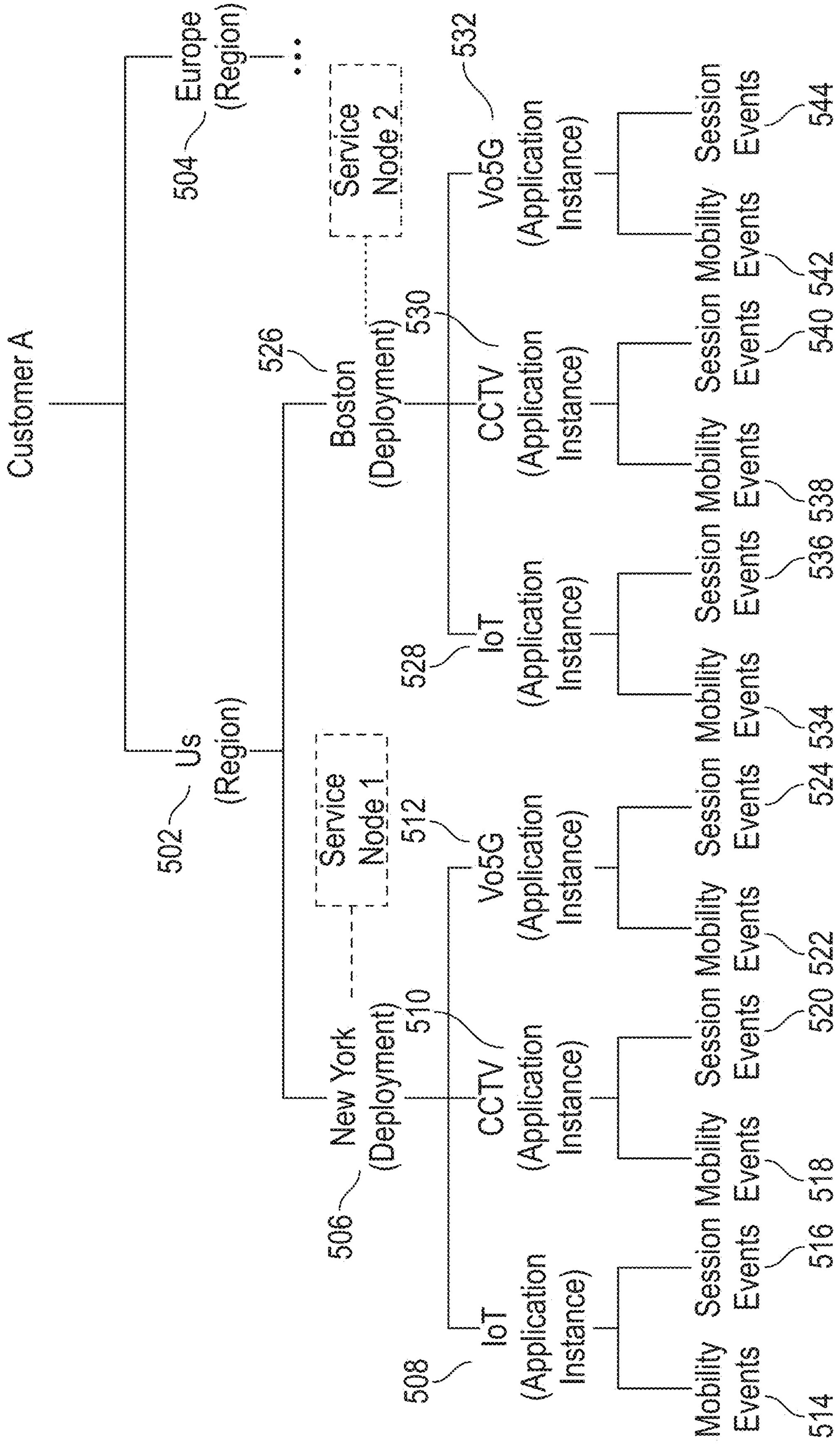

Customer A
502
Us (Region)
504
Europe (Region)
506
New York (Deployment)
Service Node 1
526
Boston (Deployment)
Service Node 2
508
IoT (Application Instance)
510
CCTV (Application Instance)
512
Vo5G (Application Instance)
528
IoT (Application Instance)
530
CCTV (Application Instance)
532
Vo5G (Application Instance)
Mobility Events
514
Session Events
516
Mobility Events
518
Session Events
520
Mobility Events
522
Session Events
524
Mobility Events
534
Session Events
536
Mobility Events
538
Session Events
540
Mobility Events
542
Session Events
544

FIG. 5

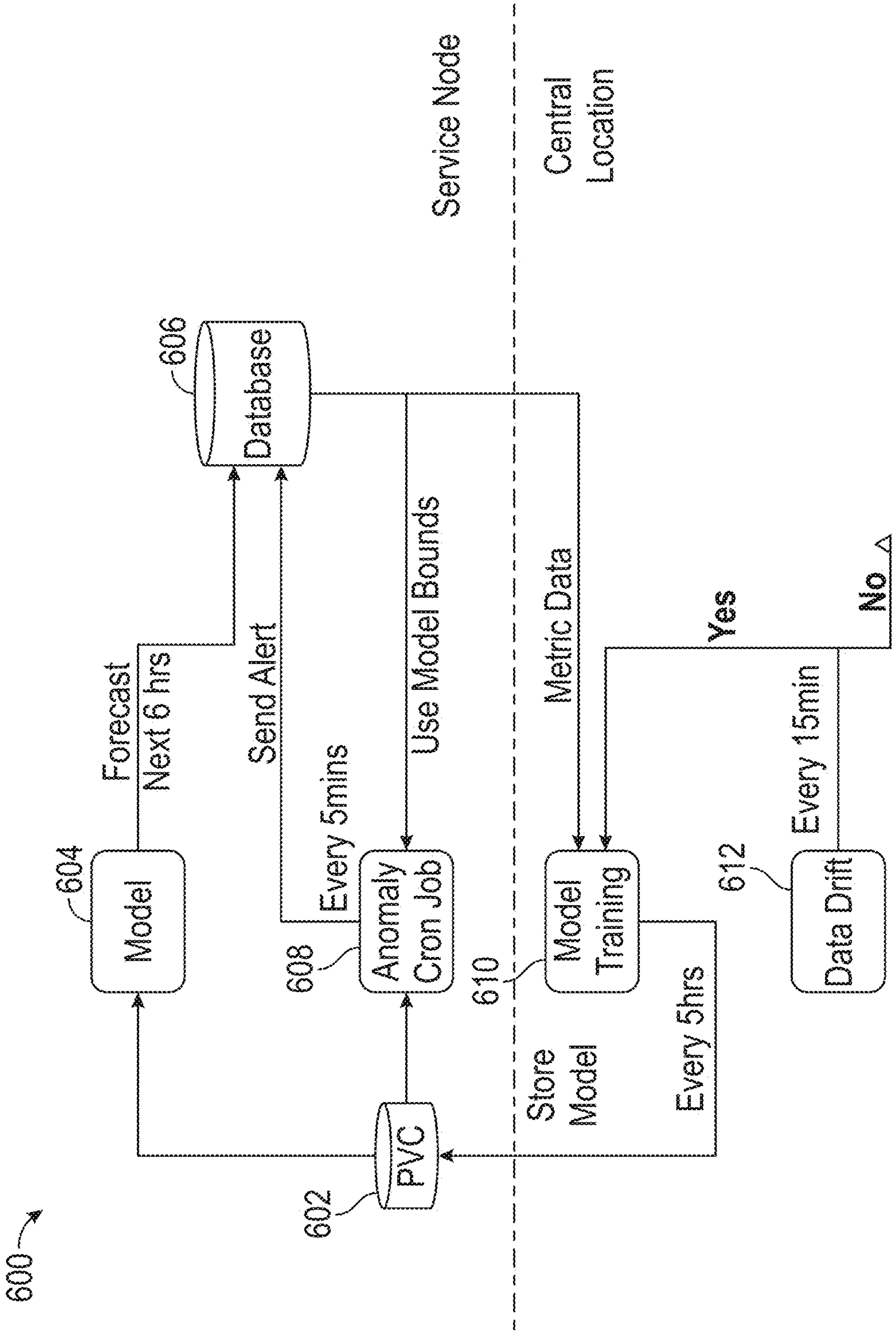

600
602
PVC
604
Model
Forecast
Next 6 hrs
606
Database
Send Alert
608
Anomaly
Cron Job
Every 5mins
Use Model Bounds
Service Node
Central
Location
Store
Model
Every 5hrs
610
Model
Training
Metric Data
Yes
No
612
Data Drift
Every 15min

FIG. 6

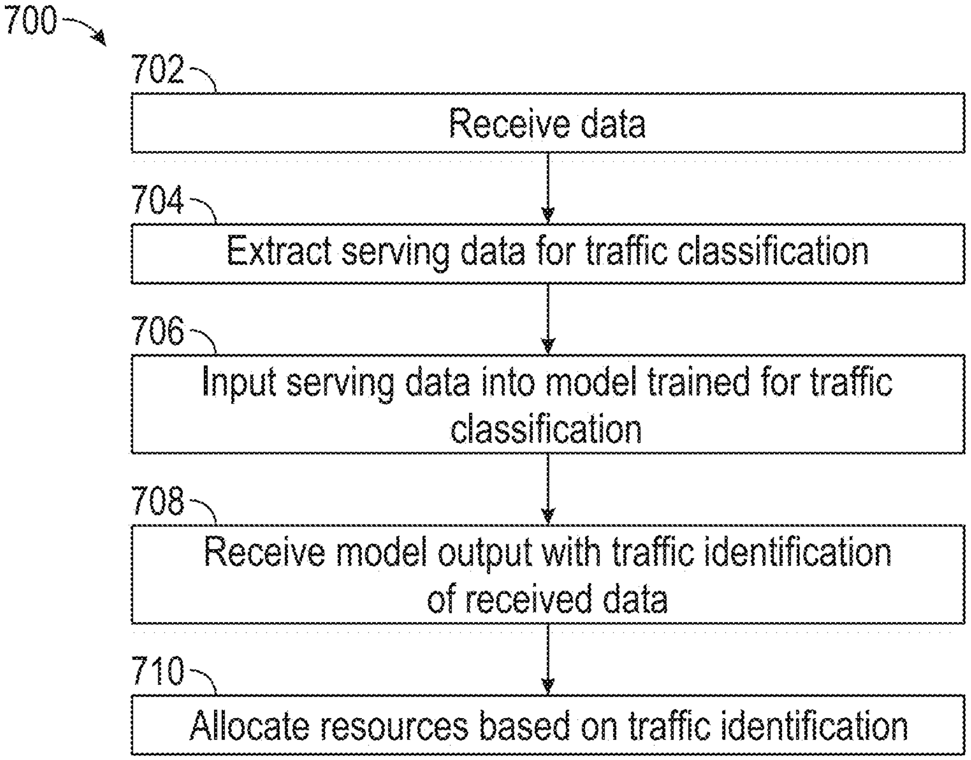

700
702
Receive data
704
Extract serving data for traffic classification
706
Input serving data into model trained for traffic classification
708
Receive model output with traffic identification of received data
710
Allocate resources based on traffic identification

FIG. 7

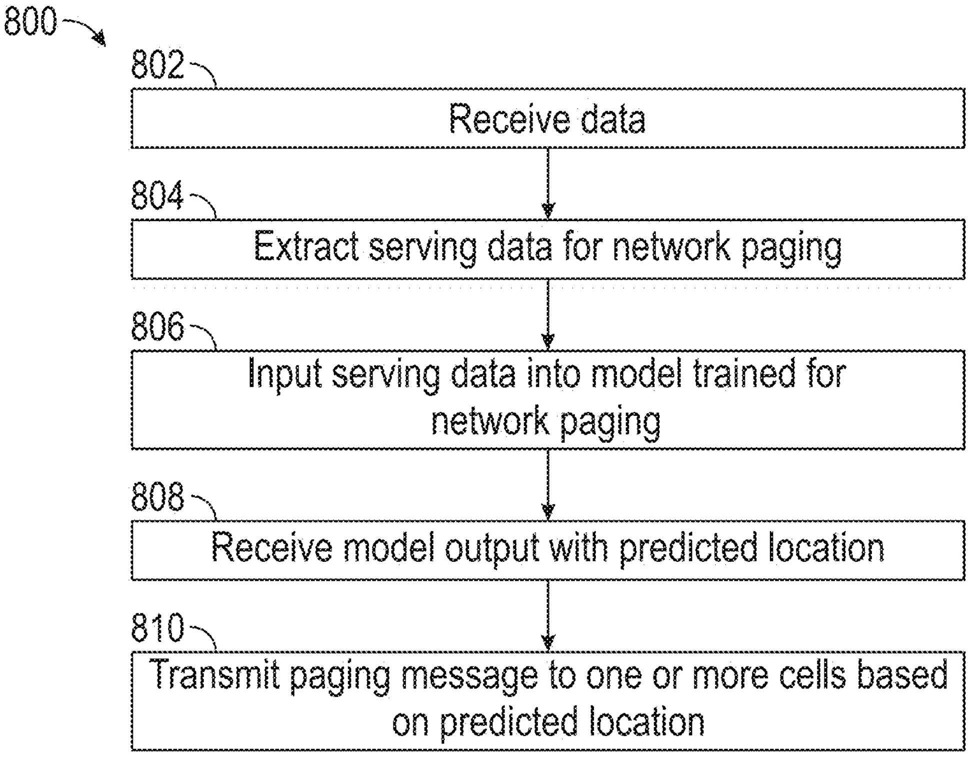

800
802
Receive data
804
Extract serving data for network paging
806
Input serving data into model trained for network paging
808
Receive model output with predicted location
810
Transmit paging message to one or more cells based on predicted location

FIG. 8

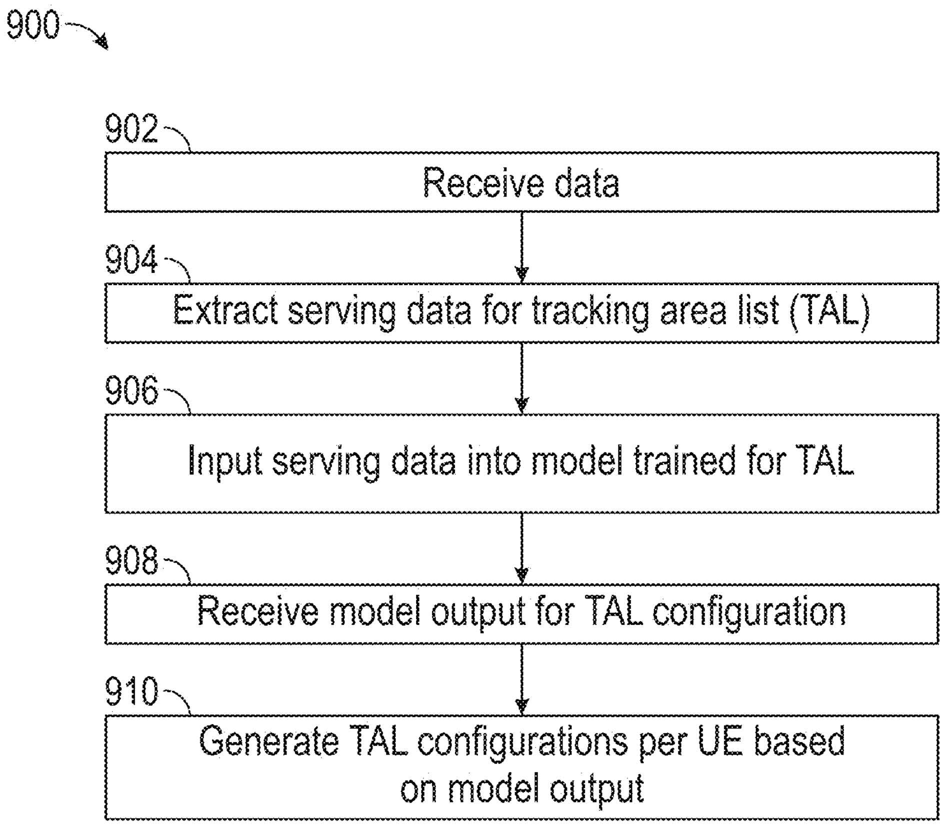

900
902
Receive data
904
Extract serving data for tracking area list (TAL)
906
Input serving data into model trained for TAL
908
Receive model output for TAL configuration
910
Generate TAL configurations per UE based on model output

FIG. 9

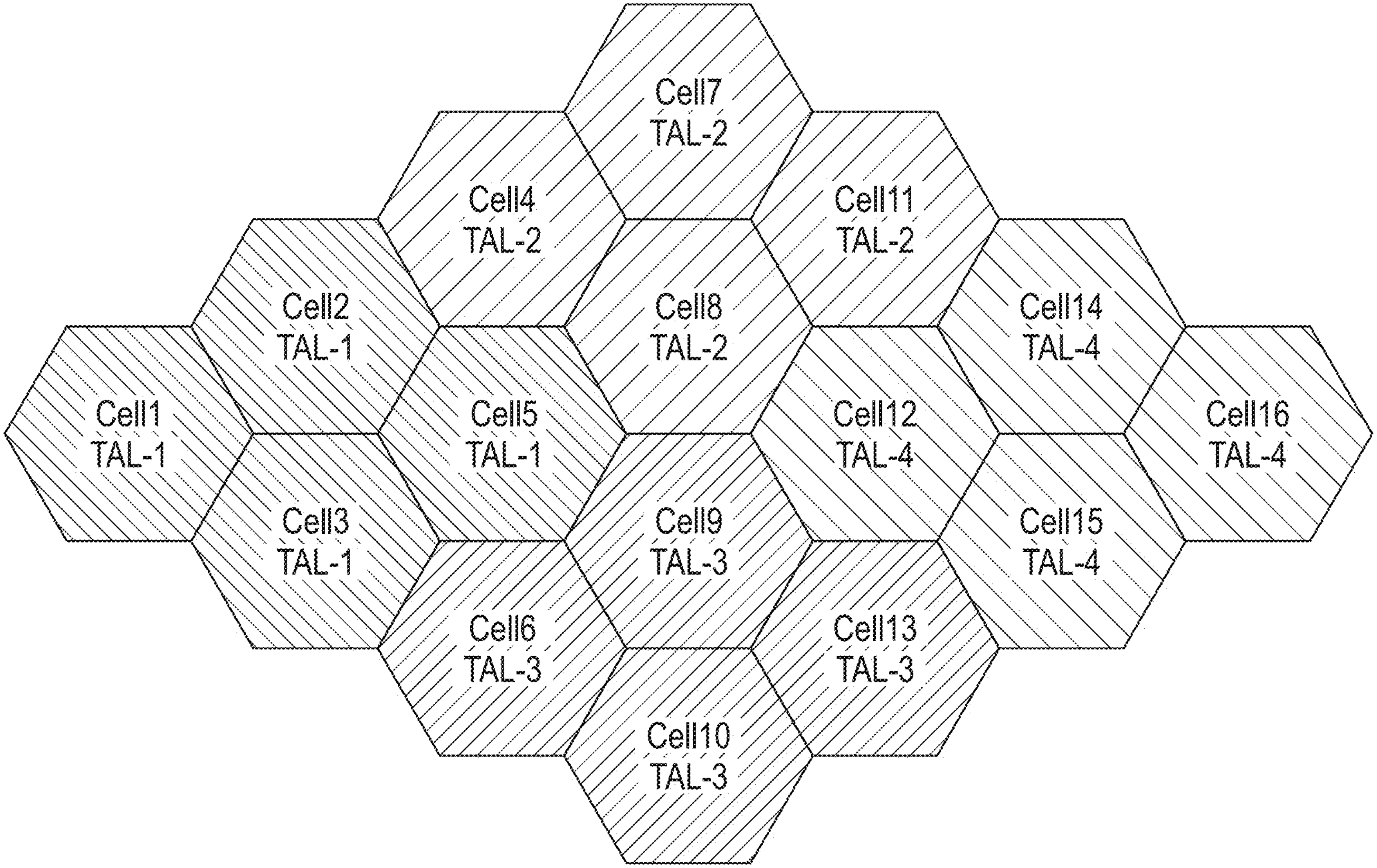

Cell7
TAL-2
Cell4
TAL-2
Cell11
TAL-2
Cell2
TAL-1
Cell8
TAL-2
Cell14
TAL-4
Cell1
TAL-1
Cell5
TAL-1
Cell12
TAL-4
Cell16
TAL-4
Cell3
TAL-1
Cell9
TAL-3
Cell15
TAL-4
Cell6
TAL-3
Cell13
TAL-3
Cell10
TAL-3

FIG. 10A

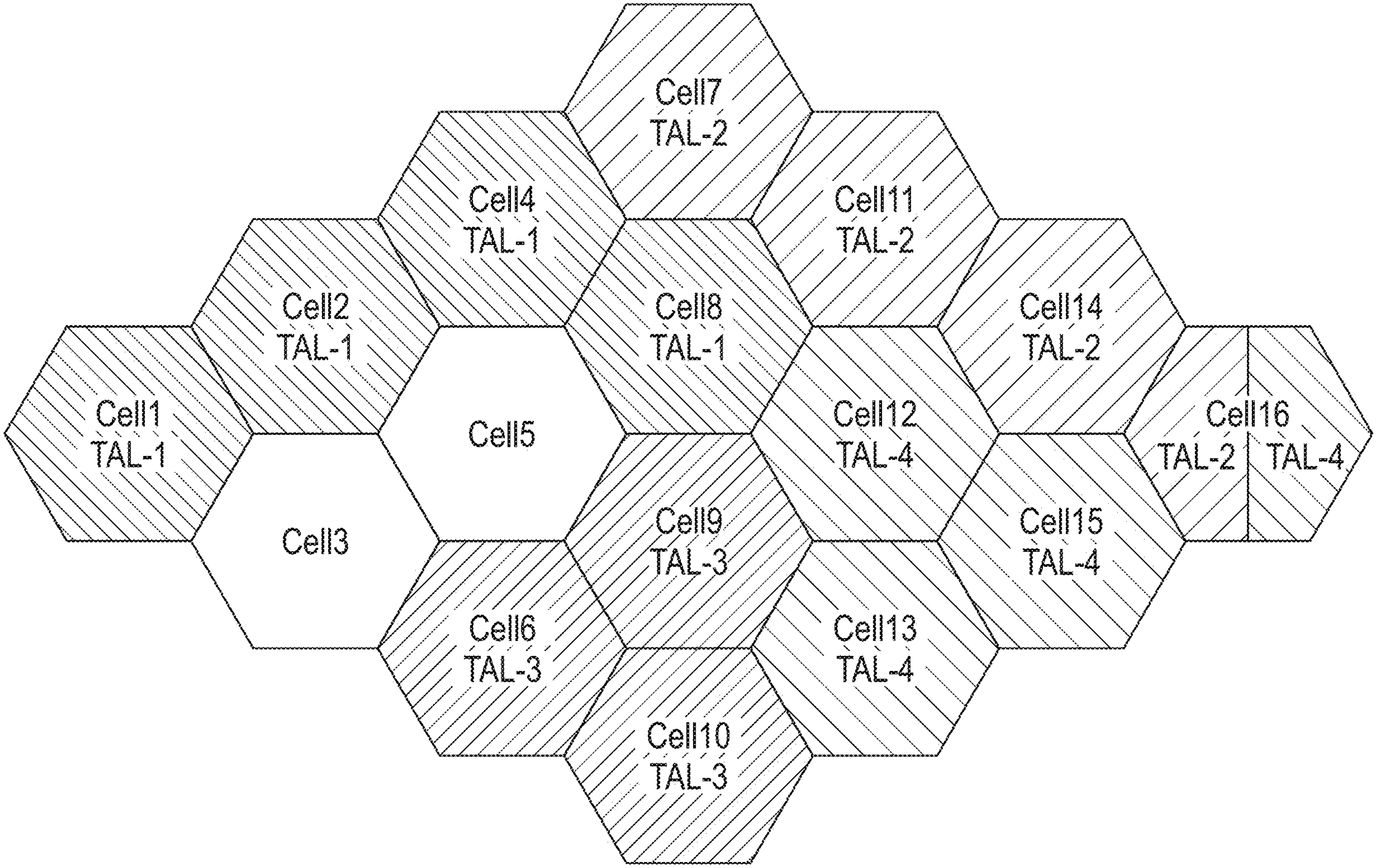

Cell1
TAL-1
Cell2
TAL-1
Cell3
Cell4
TAL-1
Cell5
Cell6
TAL-3
Cell7
TAL-2
Cell8
TAL-1
Cell9
TAL-3
Cell10
TAL-3
Cell11
TAL-2
Cell12
TAL-4
Cell13
TAL-4
Cell14
TAL-2
Cell15
TAL-4
Cell16
TAL-2
TAL-4

FIG. 10B

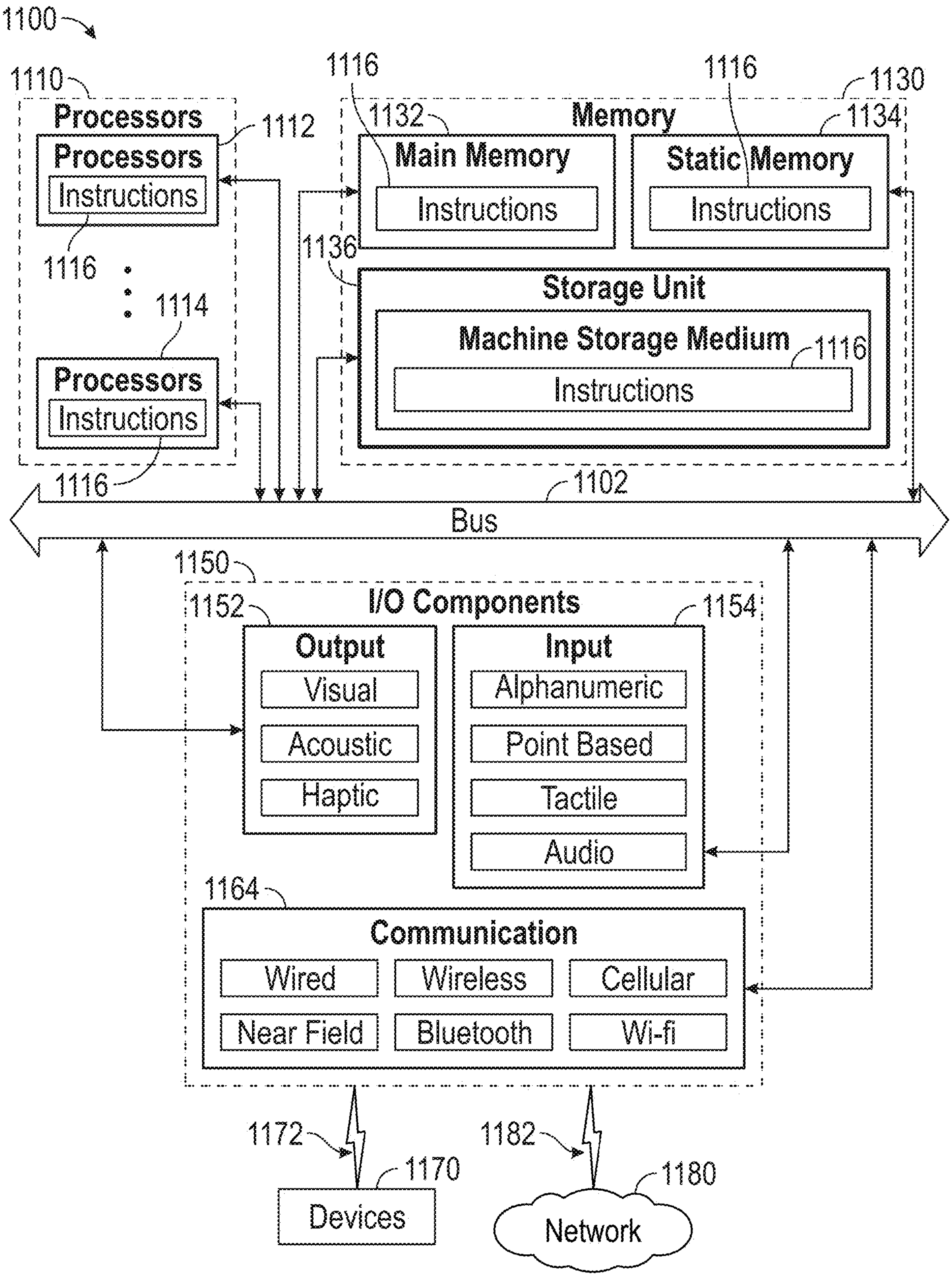

1100
1110
Processors
Processors
1112
Instructions
1116
1114
Processors
Instructions
1116
1116
1132
Memory
Main Memory
Instructions
1116
1130
1134
Static Memory
Instructions
1136
Storage Unit
Machine Storage Medium
1116
Instructions
1102
Bus
1150
I/O Components
1152
Output
Visual
Acoustic
Haptic
1154
Input
Alphanumeric
Point Based
Tactile
Audio
1164
Communication
Wired
Wireless
Cellular
Near Field
Bluetooth
Wi-fi
1172
1170
Devices
1182
1180
Network

FIG. 11

AI/ML FRAMEWORK FOR DISTRIBUTED APPLICATIONS AND FEDERATED LEARNING

CLAIM OF PRIORITY

[0001] This application claims the benefit of priority to U.S. Provisional Patent Application Ser. No. 63/556,121, filed on Feb. 21, 2024, and entitled "AIML Framework for Distributed Applications and Federated Learning," which is incorporated herein by reference in its entirety.

TECHNOLOGY FIELD

[0002] The present disclosure relates to telecommunications and network management technologies, specifically to dynamic network optimization using artificial intelligence (AI) and machine learning (ML) frameworks in distributed and federated learning environments.

BACKGROUND

[0003] In today's rapidly evolving digital landscape, the demand for robust and efficient network connectivity is more important than in the past. As technologies such as 5G, 6G, IoT, and edge computing continue to advance, traditional network infrastructures are struggling to keep pace with the increasing complexity and dynamic nature of modern telecommunications. Conventional systems often rely on static configurations and manual interventions, which can lead to inefficiencies, increased operational costs, and an inability to adapt swiftly to changing network conditions. These challenges are further compounded by the need for seamless integration across diverse environments, including public and private clouds, as well as edge locations.

[0004] Existing network management solutions frequently fall short in addressing the multifaceted requirements of contemporary digital ecosystems. They often lack the flexibility to efficiently allocate resources and ensure optimal performance across distributed environments.

SUMMARY

[0005] The present disclosure describes a method for operating a communication network, the method comprising: receiving, by a service node of the communication network, event data from one or more gateway components at the service node; processing the event data to generate processed data for transmission to a central location of the communication network, the processing comprising removing sensitive information and sampling the event data; transmitting, by the service node, the processed data to a central location, wherein the central location is configured to receive data from a plurality of other service nodes and to train a machine-learning (ML) model using the processed data and received data from the plurality of other service nodes, and wherein the central location is configured to deploy a ML model endpoint to the service node; extracting serving data from the event data; inputting the serving data into the ML model endpoint deployed at the service node from the central location; receiving a model output from the ML model endpoint; and processing the model output to perform an action at the service node.

[0006] The present disclosure also describes a system comprising at least one hardware processor; and at least one memory storing instructions that, when executed by the at least one hardware processor cause the at least one hardware processor to perform operations comprising: receiving, by a service node of the communication network, event data from one or more gateway components at the service node; processing the event data to generate processed data for transmission to a central location of the communication network, the processing comprising removing sensitive information and sampling the event data; transmitting, by the service node, the processed data to a central location, wherein the central location is configured to receive data from a plurality of other service nodes and to train a ML model using the processed data and received data from the plurality of other service nodes, and wherein the central location is configured to deploy a ML model endpoint to the service node; extracting serving data from the event data; inputting the serving data into the ML model endpoint deployed at the service node from the central location; receiving a model output from the ML model endpoint; and processing the model output to perform an action at the service node.

[0007] The present disclosure further describes a machine-storage medium embodying instructions that, when executed by a machine, cause the machine to perform operations comprising: receiving, by a service node of the communication network, event data from one or more gateway components at the service node; processing the event data to generate processed data for transmission to a central location of the communication network, the processing comprising removing sensitive information and sampling the event data; transmitting, by the service node, the processed data to a central location, wherein the central location is configured to receive data from a plurality of other service nodes and to train a ML model using the processed data and received data from the plurality of other service nodes, and wherein the central location is configured to deploy a ML model endpoint to the service node; extracting serving data from the event data; inputting the serving data into the ML model endpoint deployed at the service node from the central location; receiving a model output from the ML model endpoint; and processing the model output to perform an action at the service node.

BRIEF DESCRIPTION OF FIGURES

[0008] Various ones of the appended drawings merely illustrate example implementations of the present disclosure and should not be considered as limiting its scope.

[0009] FIG. **1** is a schematic representation of an exemplary cloud system autonomous data and signaling traffic management in a distributed infrastructure, in accordance with some embodiments of the present disclosure.

[0010] FIG. **2**A is a schematic representation of a cloud infrastructure for autonomous data and signaling traffic management in a distributed infrastructure, in accordance with some embodiments of the present disclosure.

[0011] FIG. **2**B is a simplified block diagram of an example service node, in accordance with some embodiments of the present disclosure.

[0012] FIG. **3** is a flow diagram for a method for training and using a ML algorithm in distributed locations across a networked environment, in accordance with some embodiments of the present disclosure.

[0013] FIG. **4** shows a distributed AI/ML framework designed to facilitate efficient data processing, model training, and deployment across a networked environment, in accordance with some embodiments of the present disclosure.

[0014] FIG. **5** shows an example of an organization structure of data stored in a data lake at a central location, in accordance with some embodiments of the present disclosure.

[0015] FIG. **6** shows an anomaly detection use case scenario using the AI/ML framework, in accordance with some embodiments of the present disclosure.

[0016] FIG. **7** is a flow diagram for a method for traffic classification using the AI/ML framework, in accordance with some embodiments of the present disclosure.

[0017] FIG. **8** is a flow diagram for a method for network paging optimization using the AI/ML framework, in accordance with some embodiments of the present disclosure.

[0018] FIG. **9** is a flow diagram for a method for Tracking Area List optimization using the AI/ML framework, in accordance with some embodiments of the present disclosure.

[0019] FIG. **10**A shows an example of static Tracking Area Lists.

[0020] FIG. **10**B shows an example of optimized TAL configurations generated using the AI/ML framework, in accordance with some embodiments of the present disclosure.

[0021] FIG. **11** illustrates a diagrammatic representation of a machine in the form of a computer system within which a set of instructions may be executed for causing the machine to perform any one or more of the methodologies or techniques discussed herein, in accordance with some embodiments of the present disclosure.

DETAILED DESCRIPTION

[0022] In the rapidly evolving landscape of digital communications, the demand for robust, efficient, and scalable network solutions has become more pressing. As network technology transitions into an era characterized by unprecedented connectivity and digital innovation, existing network infrastructures are increasingly strained under the weight of burgeoning data traffic and diverse user demands. The advent of wireless and wireline network requirements such as but not limited to 4G, 5G, 6G technologies, while promising transformative capabilities, such as enhanced data transfer rates and support for a wide array of applications, has highlighted significant challenges in current network management and operation. Traditional mobile networks, with their centralized architectures and manual management processes, struggle to meet the dynamic requirements of modern digital ecosystems, leading to inefficiencies and increased operational costs.

[0023] Network management practices often rely on static configurations and manual interventions, which are not well-suited to the dynamic and distributed nature of contemporary network environments. These conventional approaches are typically resource-intensive, requiring significant human oversight and specialized skills to manage complex network operations. Furthermore, the lack of integration with advanced technologies, such as artificial intelligence (AI) and machine learning (ML), limits the ability of these systems to adapt to changing network conditions and user demands. This results in suboptimal resource utilization, increased latency, and potential service disruptions, which are particularly problematic in scenarios requiring low latency and high bandwidth, such as autonomous vehicles, smart cities, and immersive virtual reality applications.

[0024] The present framework addresses these challenges by utilizing an autonomous network management that leverages AI and ML to optimize network operations across wireless and wireline connectivity. This framework provides a comprehensive solution that integrates AI/ML-driven automation, predictive analytics, and dynamic resource allocation to enhance network performance and efficiency. By employing a decentralized architecture, the framework enables seamless deployment across hybrid and multi-cloud environments, supporting both centralized and edge-based network functions. This approach not only reduces the need for manual intervention but also ensures that network resources are utilized effectively, thereby minimizing operational costs and improving overall service quality. The framework can adapt to evolving network conditions and user demands positions this approach as a future-ready solution capable of supporting the next wave of digital innovation and connectivity.

[0025] FIG. **1** is a schematic representation of an example of a cloud system autonomous data and signaling traffic management in a distributed infrastructure, in accordance with some embodiments of the present disclosure. The cloud infrastructure **200** includes one or more external devices **202** communicatively coupled to a plurality of service nodes **204-1**, **204-2**, **204-3**, **204-4**, **204-5** . . . **204**-N via a transport network. For the sake of present description, the plurality of service nodes **204-1**, **204-2**, **204-3**, **204-4**, **204-5** . . . **204**-N have been represented as the plurality of service nodes **204**. In some embodiments of the present disclosure, the plurality of service nodes **204** may host a set of network functions including 4G, 5G, 6G or Wi-Fi network functions, such as Mobility Management Entity (MME), Signaling Gateway (SGW), Packet Gateway (PGW), Home Subscriber Server (HSS), Policy and Charging Rules Function (PCRF), Evolved Packet Data Gateway (ePDG), Trusted Wireless Access Gateway (TWAG), Centralized Unit (CU), Access & Mobility Management Function (AMF), Session Management Function (SMF), User Plane Function (UPF), Non-3GPP Interworking Function (N3IWF), Network Data Analytics Function (NWDAF), Network Repository Functions (NRF), Network Slicing Selection Function (NSSF), Network Exposure Function (NEF), Unified Data Management (UDM), Authentication Server Function (AUSF), Point Coordination Function (PCF) and the like. In some embodiments, the one or more external devices **202** may include one or more local servers, one or more cloud servers, compute nodes, content data network, internet, the set of network functions, one or more proxy servers and the like. The one or more external devices **202** are configured to host one or more services accessible by the plurality of service nodes **204**.

[0026] Further, each of the plurality of service nodes **204** may act as a computing system including a plurality of modules to handle various functionality, as described herein. In some embodiments of the present disclosure, the one or more data centers may correspond to private cloud, public cloud, hybrid cloud and the like. Furthermore, the plurality of service nodes **204** are connected with each other via a plurality of cloud mesh links **206**. The plurality of cloud mesh links **206** are secured ad hoc routing connections, such as Open Shortest Path First (OSPF) and the like between the plurality of service nodes **204**. In some embodiments of the present disclosure, the plurality of service nodes **204** may include multiple physical parameters characterizing the plurality of service nodes **204** and compute one or more system parameters, such as energy requirement, power utilization, processing type, processing power, configuration and the like. Further, each of the plurality of service nodes **204** may have their own state information and characteristics, such as delay, jitter, packet flow information, protocol parameter information, quality of experience and the like, known as one or more network function parameters. In some embodiments of the present disclosure, one or more external inputs or parameters are received by a computing system via internet **208**. Furthermore, the one or more system parameters, the one or more network function parameters and the one or more external inputs or parameters are one or more computing system parameters.

[0027] In some embodiments of the present disclosure, the service node **204-1**, the service node **204-2** and the service node **204-3** are far edge clouds at first level of hierarchy within the cloud infrastructure **200**. The first level of hierarchy corresponds to a first proximal distance from the one or more electronic devices **108**. Further, the service node **204-4** and the service node **204-5** are regional edge clouds at second level of hierarchy within the cloud infrastructure **200**. In some embodiments of the present disclosure, the second level of hierarchy corresponds to a second proximal distance from the one or more electronic devices **108**. In some embodiments of the present disclosure, the service node **204-6** is closer to the one or more external devices **202**. The service node **204-6** is at third level of hierarchy within the cloud infrastructure **200**. In some embodiments of the present disclosure, the third level of hierarchy corresponds to a third proximal distance from the one or more electronic devices **108**. In some embodiments of the present disclosure, the one or more external devices **202** may be main data center. In some embodiments of the present disclosure, each of the plurality of service nodes **204** is connected to the internet **208**, as shown in FIG. **1**.

[0028] Further, the cloud infrastructure **200** includes one or more orchestrator nodes connected to the plurality of service nodes **204** via a set of cloud mesh links. In some embodiments of the present disclosure, each of the one or more orchestrator nodes is an instance of a collective group of network functions hosted on the one or more data centers.

[0029] Furthermore, the cloud infrastructure **200** includes one or more electronic devices **108** associated with an organization connected to a communication network **210** via a communication channel. In some embodiments of the present disclosure, the communication network **210** may be private network, public network, smart city network, connected car network, Fixed Wireless Access (FWA) and the like. In some embodiments of the present disclosure, the one or more electronic devices **108** are connected to the plurality of service nodes **204**. The one or more electronic devices **108** may be used by one or more users associated with the organization to access the communication network **210** for accessing one or more services hosted on the internet **208**. In some embodiments of the present disclosure, the one or more external devices **202** are located nearby to the organization. In some embodiments of the present disclosure, the one or more electronic devices **108** may include a laptop computer, desktop computer, tablet computer, smartphone, wearable device, smart watch and the like. In some embodiments of the present disclosure, the one or more electronic devices **108** may also include a microprocessor, a server and the like. Further, the one or more electronic devices **108** include a local browser, a mobile application or a combination thereof. The one or more users may use a web application via the local browser, the mobile application or a combination thereof to communicate with the computing system. In some embodiments of the present disclosure, the one or more electronic devices **108** may access the computing system via a radio access network.

[0030] In some embodiments of the present disclosure, the computing system receives a request from the one or more electronic devices **108** within the communication network **210** to access the one or more services hosted on the one or more external devices **202** or a set of services hosted on the internet **208**. Further, the computing system determines one or more network parameters based on the received request, one or more device parameters and the one or more computing system parameters by using a trained Machine Learning (ML) model. The computing system also determines current network demand within the cloud infrastructure **200** based on the received request by using the trained based ML model. The computing system determines one or more service nodes at multiple levels of hierarchy within the cloud infrastructure **200** from the plurality of service nodes **204** based on the determined one or more network parameters and the determined current network demand by using the trained ML model. In an embodiment of the present disclosure, the one or more service nodes at first level of hierarchy within the cloud infrastructure **200** are service node **204-1**, service node **204-2** and service node **204-3**, service node **204-4**, service node **204-5** and service node **204-6**. Furthermore, the computing system dynamically establishes one or more cloud mesh links between the determined one or more service nodes **204-1**, **204-2**, **204-3**, **204-4**, **204-5** and **204-6** at the multiple levels of hierarchy and the one or more external devices **202** based on the determined one or more network parameters and the current network demand by using the trained ML model. The multiple levels of hierarchy comprise first level, second level, third level of hierarchy and the like. The computing system processes the received request by providing access of the one or more services hosted on the one or more external devices **202** to the one or more electronic devices **108** via the established one or more cloud mesh links.

[0031] FIG. **2**A is a schematic representation of a cloud infrastructure **200** for autonomous data and signaling traffic management in a distributed infrastructure, in accordance with some embodiments of the present disclosure. The cloud infrastructure **200** includes the plurality of service nodes **204-1**, **204-2**, **204-3** and **204-4**. For the sake of present description, the plurality of service nodes **204-1**, **204-2**, **204-3** and **204-4** have been represented as the plurality of service nodes **204**. The service node **204-3** is an enterprise cloud associated with the organization. Further, the service node **204-4** is a far edge cloud located at a distant position from the organization. The cloud infrastructure **200** includes the one or more electronic devices **108** associated with the organization connected to the communication network **210** via the communication channel. In some embodiments of the present disclosure, the communication network **210** is a 4G, 5G, 6G and WiFi network with the set of network functions including multiple 4G, 5G, 6G and WiFi network functions running on variety of cloud and compute infrastructures. Furthermore, the cloud infrastructure **200** includes a first public network **212-1**, a second public network **212-2** and a third public network **212-3** to communicatively couple the one or more external devices **202** to the plurality of service nodes **204**. In some embodiments of the present disclosure, the second public network **212-2** is shorter public network. The plurality of service nodes **204** are connected with each other via the plurality of cloud mesh links **206** and the internet **208**. Further, the one or more orchestrator nodes **214** are connected to the plurality of service nodes **204** via a set of cloud mesh links **216**. The one or more external devices **202** host a first service **218-1** and a second service **218-2** accessible by the plurality of service nodes **204**. In some embodiments of the present disclosure, the plurality of service nodes **204** may also be communicatively coupled with one or more operator networks to achieve seamless integration of the one or more electronic devices **108** with the one or more operator networks.

[0032] In some embodiments of the present disclosure, the computing environment **200** is applicable in telecommunication, healthcare, manufacturing, transport, public safety domains and the like. As described above, the computing environment **200** includes the plurality of service nodes **204-1**, **204-2**, **204-2** and **204-4**. For the sake of present description, the plurality of service nodes **204-1**, **204-2**, **204-3** and **204-4** have been represented as the plurality of service nodes **204**. The service node **204-3** is an enterprise cloud associated with the organization. Further, the service node **204-4** is a far edge cloud located at a distant position from the organization. The computing environment **200** includes one or more electronic devices **108** associated with the organization connected to the enterprise network **220** via the private communication channel. In some embodiments of the present disclosure, the enterprise network is a 4G or 5G or 6G or WiFi network and the like. Furthermore, the computing environment includes a first public network **206-1**, a second public network **206-2** and a third public network **206-3** to communicatively couple the one or more external devices **202** to the plurality of service nodes **204**. In some embodiments of the present disclosure, the second public network **206-2** is shorter public network. The plurality of service nodes **204** are connected with each other via the network **212** and internet **224**. Further, the one or more orchestrator nodes **214** are connected to the plurality of service nodes **204** via the network **212**. In some embodiments of the present disclosure, the network **212** may be the one or more cloud mesh links. The one or more external devices **202** host a first public network application **226-1** and a second public network application **226-2** accessible by the plurality of service nodes **204**.

[0033] FIG. 2B is a simplified block diagram of an example service node **204**, in accordance with some embodiments of the present disclosure. Service node **204** may include an edge manager **252**, a network data analytics function (NWDAF) **256**, and shared slice components **258**. The shared slice components **258** may include any network function including 4G, 5G, 6G or Wi-Fi network functions, such as Access & Mobility Management Function (AMF), Mobility Management Entity (MME), Signaling Gateway (SGW), Packet Gateway (PGW), Home Subscriber Server (HSS), Policy and Charging Rules Function (PCRF), Evolved Packet Data Gateway (ePDG), Trusted Wireless Access Gateway (TWAG), Centralized Unit (CU), Session Management Function (SMF), User Plane Function (UPF), Non-3GPP Interworking Function (N3IWF, Network Repository Functions (NRF), Network Slicing Selection Function (NSSF), Network Exposure Function (NEF), Unified Data Management (UDM), Authentication Server Function (AUSF), Point Coordination Function (PCF) and the like.

[0034] The edge manager **252** may facilitate interactions with other service nodes and networks, such as private networks and other public networks. The edge manager **252** may communicate with other service nodes (and their respective edge managers) using a communication interface, such as a Cloud Mesh link. The communication interface may be based on webservices, for example, REST based webservices. Edge managers may act as routing agents. In some embodiments, edge managers may take the role of one or more network functions such as S1 proxy, NgAP proxy, Mobility Management Entity (MME), Signaling Gateway (SGW), Packet Gateway (PGW), Access & Mobility Management Function (AMF), Session Management Function (SMF), User Plane Function (UPF), Non-3GPP Interworking Function (N3IWF), Network Repository Functions (NRF), Network Slicing Selection Function (NSSF), Network Exposure Function (NEF) and the like.

[0035] The NWDAF **256** may collect usage data, analyze the usage data for network slices, and generate predicted usage information regarding resources, as described in further detail herein. The NWDAF **256** may execute machine-learning algorithms, as described herein. The NWDAF **256** may continuously analyze the parameters of each network slice and predict the usage or congestion that may occur at a future time. The prediction results as well as other data may be exchanged via a cloud mesh link with other service nodes.

[0036] Service nodes **204** may be provided as public and/or private networks or a combination thereof. For example, as explained in detail below, a service node **204** may be provided as a public network but may provide network slices for a private network in accordance with the dynamic network slice management techniques described herein. Likewise, for example, a service node **204** may be provided as a private network but may provide network slices for a public network in accordance with the dynamic network slicing techniques described herein.

[0037] Network slice management performed by service nodes enables multiple isolated and independent virtual (logical) networks to exist together. In other words, a plurality of virtual networks, i.e., slices, may be created using resources of the same physical network infrastructure. A slice includes shared network components that provides end-to-end connection enabling multiplexing of virtualized and independent logical networks using logical separation. In some embodiments, each network slice may be based on a set of parameters that are part of the SLA of the slice. For example, the set of parameters may include minimum guaranteed bandwidth, maximum end-to-end latency for data packets, guaranteed quality-of-service (QOS), simultaneous maximum number of users, and so on.

[0038] Service nodes **204** may be provided in the same or different edge locations. In some embodiments, a network slice may be managed at each edge location. Resources available at each edge location may be limited, and, therefore, these edge locations may not have endless resources to statically provision each slice and provide the guaranteed SLA.

[0039] In some embodiments, machine-learning algorithms may be used for various operations in a mesh network of service nodes located at one or more edge locations, such as dynamic network slicing management, anomaly detection, traffic classification, mobile network paging optimization, tracking area list (TAL) optimization, Discontinuous Reception (DRX) silence period prediction, UE radio context optimization, handover optimization, intelligent application-edge selection, abnormal activity detection (e.g., for IoT), and efficient microservice resource management. For example, the edge locations may be at different geographic locations, though service nodes may be connected in a mesh network or other suitable types of network configuration. In some embodiments, the machine-learning algorithm executed used for predicting various operations and may include linear regression algorithm, decision tree algorithm, time series analysis, K-means clustering, etc. In some embodiments, neural network-based machine-learning algorithm, such as artificial neural network (ANN) and/or recurrent neural network (RNN), etc., may also be used. The AI/ML algorithms may be executed using suitable processing architectures. For example, the AI/ML algorithms may be executed using a processing architecture including different types and combinations of processing units, such as Central Processing Unit (CPU), Graphics Processing Unit (GPU), Data Processing Unit (DPU), Tensor Processing Unit (TPU), etc.

[0040] In some examples, the ML algorithms may be deployed in a distributed manner in the service node locations, as described above, but may be trained at a centralized location. The centralized location may collect data from the various service node locations and may train and update the model with the collected data from the different locations. The trained and updated models may then be deployed to at the service node locations to perform various operations, as descried herein. This distributed and federated framework allows fast, autonomous decisions to be made at the service node locations using the locally-deployed ML algorithms while training the ML algorithms with more data from the distributed locations, improving the accuracy of the ML algorithms.

[0041] FIG. **3** is a flow diagram for a method **300** for training and using a ML algorithm in distributed locations across a networked environment, in accordance with some embodiments of the present disclosure. Portions of the method **300** are performed at a distributed location, such as a service node as described herein, and other portions are performed at a central location, such as an orchestrator node as described herein.

[0042] At operation **302**, data is received at a service node. In some examples, the data may be received from gateway components. The gateway components may include different network functions, such as AMF, SMF, UPF. The data may include published events from the network functions, such as mobility events, session events, data events, etc. The received data is used for training a ML model as well as using a locally-deployed ML model to perform a particular operation, such as dynamic network slicing management, anomaly detection, traffic classification, mobile network paging optimization, TAL optimization, DRX silence period prediction, UE radio context optimization, handover optimization, intelligent application-edge selection, abnormal activity detection (e.g., for IoT), and efficient microservice resource management.

[0043] The model training will be described first. At operation **304**, the data is processed for transmission to the central location. The processing may include signal processing, such as filtering, aggregating, and sampling. For example, the received data may include hundreds of mobility events collected during a session. Transmitting all mobility events may be cumbersome and consume significant bandwidth. Therefore, a portion of the mobility events, such as 10%, may be sampled for transmission. The sampled events may undergo other processing, such as removal of sensitive information, such as personal identification information (PII).

[0044] At operation **306**, the processed data is transmitted from the service node to the central location. In some examples, the data may be transmitted using cloud mesh links as described herein. In some examples, continuous data transfer may be avoided. For example, batch data transfer may be utilized instead of single data transfer. The number of events per batch of data may be configurable. The processed data may be pushed from the edge location (service node) to the central location via SFTP. In some examples, sensitive information (e.g., IP addresses) may be masked before transmission. For example, sensitive information may be anonymized before being pushed to the central location.

[0045] At operation **308**, the received data from the service node may be collected at the central location. The central location may also receive data from other service nodes in the network. The central location may store the collected data from the different distributed location in a database, such as a data lake. The collected data include raw data from the various sources and stored in a centralized repository in structured, semi-structured, or unstructured format.

[0046] At operation **310**, relevant data may be extracted for a particular ML model that is to be trained. As mentioned above, the collected data include raw data from the different sources. Training a ML model with all the collected data from the distributed location would consume significant resources, such as processing resources and time, and may not lead to an accurate ML model. Thus, relevant data for the particular ML model may be extracted for ML model training to conserve resources and increasing accuracy of the ML model. For example, data extracted for an anomaly detection model may be different than the data extracted for a traffic-classification model. The extracted data may be customized for the corresponding model.

[0047] At operation **312**, the model is trained using the extracted data. The ML model may include one or more of linear regression algorithm, decision tree algorithm, time series analysis, K-means clustering, etc. The ML model may include ANN, RNN, or other types of neural networks. For example, the ML model may be provided as a multi-layered machine learning model. For example, the ML model may include a plurality of observable layers with a plurality of hidden layers, such as an input layer, a feature extraction layer, a features relationship layer, and a decision layer. The extracted data may be sent to the input layer. The ML model may, in an iterative fashion, train its biases and coefficients in its layers. The decision layer may output a decision regarding the particular operation, such as the presence or absence of an anomaly. The training of the ML model may be a supervised and/or unsupervised process. For example, in a supervised process, labels for anomaly or no anomaly may be added to the extracted data. The labels may then be set as reference outputs. The ML model may adjust its biases and coefficients in its layers to generate an output for each set of extracted data substantially matching its respective reference output (e.g., anomaly or no anomaly). The ML model training may include hyperparameter tuning, cross-validation, and model selection.

[0048] At operation **314**, the trained model is registered in a model registry. For example, the trained model is stored in a model database. The trained model may be an updated or new version of a prior model. The model database may store different types of models that have been trained at the central location. The registered model may then be deployed at the different distributed locations (e.g., service nodes). For example, the updated or newer version of the model may be transmitted and installed at the distributed locations. The model registry may maintain version control of the trained models, allowing for rollback to previous versions if needed.

[0049] Next, using the trained model at the distributed location is described. At operation **316**, serving data for the particular model is extracted from the received data (e.g., from operation **302**) at the service node. Different models may use different serving data for operation. For example, for a traffic-classification model, the serving data may include metadata for the first thirty packets in a session received from the UPF. The first thirty packets may form a packet signature of the traffic type.

[0050] At operation **318**, the serving data is inputted into the deployed model in the service node. The model may generate a prediction output based on the serving data. In a traffic classification scenario, the output may be a traffic type. In an anomaly detection scenario, the output may be the presence or absence of an anomaly. In a network paging optimization scenario, the output may be a predicted location of the UE and so on.

[0051] At operation **320**, the model output is processed by the service node. For example, the service node may perform an action based on the model output. In an anomaly detection scenario, the service node may generate an alert if an anomaly is detected. In a traffic classification scenario, the service node may allocate a specified number and type of resources based on the type of traffic detected.

[0052] Method **300** is described above with respect to the training, deployment, and use of one ML algorithm for illustration purposes only. A plurality of ML algorithms may be trained, deployed, and used contemporaneously. Multiple iterations of method **300**, or at least portions of method **300**, may be performed in parallel for the different ML algorithms. For example, one ML algorithm may be for dynamic network slicing management, another ML algorithm for anomaly detection, and another one for traffic classification, and so on.

[0053] FIG. **4** shows a distributed AI/ML framework **400** designed to facilitate efficient data processing, model training, and deployment across a networked environment, in accordance with some embodiments of the present disclosure. The framework **400** may be distributed across one or more service nodes **402**, a central location **450**, and Operations, Administration, and Maintenance (OAM) **470**. This framework **400** is structured to handle data from multiple sources, process the data, utilize the processed data for ML model training, deployment of the trained ML model, and utilizing the deployed ML model.

[0054] The service node **402** includes a data source **404**. The data source **404** may include one or more gateway components. The gateway components may include different network functions, such as AMF, SMF, UPF. The data source **404** may include event hubs and batch uploads, which generate or publish events, such as mobility events, session events, data events, etc. For example, the data source **404** may include gateway components deployed at edge locations (service node **402**), such as Kubernetes applications.

[0055] The data source **404** is coupled to a data ingestion stream **406**. The data ingestion stream **406** may include a queue of the generated events. The data ingestion stream **406** may be provided as a streaming interface to ingest events generated by the data source **404**. The ingested events may be organized as an event stream.

[0056] A data ingestion pipeline **408** is coupled to the data ingestion stream **406**. The data ingestion pipeline **408** may process and prepare the data for transmission to the central location **450**. The data ingestion pipeline **408** may be provided as one more computation tasks of a cloud processing platform. The data ingestion pipeline **408** may perform processing operations, such as filtering, aggregating, and sampling. For example, ingested data may include hundreds of mobility events collected during a session. Transmitting all mobility events to the central location **150** may be cumbersome and consume significant bandwidth. Therefore, a portion of the mobility events, such as 10%, may be sampled by the data ingestion pipeline **408**. The sampled events may undergo other processing, such as removal or masking of sensitive information.

[0057] The data ingestion pipeline **408** may transmit the processed data to the central location **450**. In some examples, the data may be transported securely over HTTPS/TLS over the internet.

[0058] The received data from the service node **402** is stored in a data lake **452** in the central location **450**. The data lake **452** may be a centralized repository that stores large volumes of raw data from the various service nodes. The collected data include raw data from the various sources and stored in a centralized repository in structured, semi-structured, or unstructured format. The collected data from the different locations may be partitioned by customer, deployment, and namespace and stored in the data lake **452**.

[0059] A data extraction pipeline **454** may extract relevant data to train the particular ML model. As mentioned above, the collected data include raw data from the different sources. Training a ML model with all of the collected data would consume significant resources, such as processing resources and time, and may not lead to an accurate ML model. Thus, relevant data for the particular ML model may be extracted for ML model training to conserve resources and increasing accuracy of the ML model. For example, data extracted for an anomaly detection model may be different than the data extracted for a traffic-classification model. The extracted data may be customized for the corresponding model. The extracted data may be stored in a dataset **456**. An AI/ML workbench **458**, model training pipeline **460**, and experiment tracking **462** may train the ML model. The AI/ML workbench **458** may serve as a platform for data scientists and engineers to explore data, develop models, and conduct experiments. The model training pipeline **460** may handle the training of machine learning models using the prepared datasets **456**, while experiment tracking **462** may monitor the performance and outcomes of various training runs.

[0060] The trained model is stored and registered in model registry **464**. The trained model may be packed as serving endpoint containers. The ML model may be deployed in the service node **402**. The model registry **464** may store different types of models that have been trained at the central location. The registered model may then be deployed at the different distributed locations (e.g., service nodes). For example, the updated or newer version of the model may be transmitted and installed at the distributed locations.

[0061] Referring back to the service node **402**, once the data is ingested, the extract serving data **410** component extracts relevant data for immediate use, storing the information in the serving data DB **412**. This serving data DB **412** serves as a repository for data that is actively used by the model endpoint **416**, which is the deployed model from the central location **450**. The model endpoint **416** also interfaces with a model consumer **414**. The model consumer **414** may be an application or service (e.g., anomaly detection, traffic classifier) and utilize the predictions or outputs generated by the model endpoint **416**, integrating these results into applications or services.

[0062] The OAM **470** may be used to oversee the entire framework, for example the performance of the model endpoint **416**. The OAM **570** may collect telemetry information **472**. OAM **470** may collect telemetry from serving containers like model performance, data skew, model drift, etc. These telemetries may be used to trigger model training pipeline **460** as appropriate. A configuration database **474** may store configuration settings. The configuration settings may include settings for the data ingestion pipeline **408**, such as which data to filter, aggregate, and/or sample. Overall, this distributed AI/ML framework **400** is designed to optimize data processing and model deployment, providing a scalable and efficient solution for modern data-driven applications.

[0063] As mentioned above, the data lake **452** may store data from the different service nodes in a curated multi-tenant format. The collected data from the different locations may be partitioned by customer, deployment, and namespace. For example, each customer may be assigned with a resource group.

[0064] FIG. **5** shows an example of an organization structure of data stored in a data lake at a central location, in accordance with some embodiments of the present disclosure. The data shown in FIG. **5** is for one customer, which may be a retail provider in this example. As shown, the data is organized and stored in a hierarchical structure. Customer A's data is first organized by regions, such as US region **502** and Europe region **504**. Details of the Europe region **504** are not shown for brevity, and the organization structure of the data in the Europe region **504** may be the same as or similar to the US region **502**, which is described and shown in more detail.

[0065] Under the US region **502**, the data is organized by different deployments, such as a New York deployment **506** and Boston deployment **526**. Under the New York deployment **506** the data is organized by applications, such as IoT application **508**, CCTV application **510**, and Voice over 5G (Vo5G) application **512**. Each application includes the events. For example, IoT application **508** includes mobility events **514** and session events **516**. CCTV application **510** includes mobility events **518** and session events **520**. Vo5G application **512** includes mobility events **522** and session events **524**. Other events may be included, such as data events.

[0066] Likewise, the Boston deployment **526** includes an IoT application **528**, CCTV application **530**, and Vo5G application **532**. Each application includes the events. For example, IoT application **528** includes mobility events **534** and session events **536**. CCTV application **530** includes mobility events **538** and session events **540**. Vo5G application **532** includes mobility events **542** and session events **544**.

[0067] The AI/ML framework described herein can be used in different use cases. The use cases may include different applications or services, such as dynamic network slicing management, anomaly detection, traffic classification, mobile network paging optimization, TAL optimization, DRX silence period prediction, UE radio context optimization, handover optimization, intelligent application-edge selection, abnormal activity detection (e.g., for IoT), and efficient microservice resource management.

[0068] For example, the telecom industry generates massive amounts of telemetry data from networks, including performance counters, traffic metrics, and equipment logs. Accurate forecasting and anomaly detection in this data can be important for ensuring network reliability, minimizing downtime, and enhancing customer experience. The AI/ML framework can enable building scalable and efficient models tailored to telecom network telemetry, leveraging the temporal nature of the data for both predictive insights and fault detection.

[0069] The AI/ML framework may utilize statistics machine learning for predictive analytics and anomaly detection in telemetry datasets. The AI/ML framework may utilize metrics from mobility, session and UPF along with common metrics like memory usage, CPU utilization, etc. The AI/ML framework can be tailored for applications in IoT, industrial monitoring, and system diagnostics, enabling real-time insights and scalable deployment in production environments.

[0070] FIG. **6** shows an anomaly detection use case scenario using an AI/ML framework **600**, in accordance with some embodiments of the present disclosure. A persistent storage, such as a persistent volume control (PVC) **602**, may store and deploy a trained model **604**. The storage of the model **604** in PVC **602** enables preserving the model **604** across different sessions making the model **604** accessible by other components.

[0071] The PVC may deploy the model **604** and input serving data for anomaly detection. The model **604** may generate a forecast of the network traffic for a specified time interval (e.g., next 6 hours) based on the serving data. Predictions made by the model **604** may be based on historical data and refined on an ongoing basis through the training process to enhance accuracy The forecast may be stored in database **606**. For example, the lower and upper bounds of the forecast may be stored in the database **606**.

[0072] The PVC **602** may also input current serving data (e.g., current session data) in an anomaly cron job **608**, which may be a scheduled task that runs automatically at a set time or interval (e.g., every 5 minutes). The anomaly cron job **608** may also receive the forecast generated by the model **604**, such as the lower and upper bounds of the forecast. The anomaly cron job **608** may compare the current conditions to the forecast, and if the current conditions differ by more than a specified threshold, the anomaly cron job **608** may generate an alert indicating the presence of an anomaly and notifying relevant systems or personnel of the detected anomaly. This alerting mechanism may enable prompt response of the detected anomaly and mitigation of potential issues within the network.

[0073] Metric data stored in the database **606** may be transmitted to central location for model training **610**. A data drift component **612** may monitor data changes over time. The data drift component **612**, for example, may check for any significant deviations in the data patter at 15-minute intervals. When data drift is detected, the model training **610** is activated. Model training **610** may then update the model to accommodate the new data patterns, ensuring that the model remains accurate and effective in detecting anomalies. The trained model may be stored in the PVC **602** with a data time tag for version control. This training process helps maintain the relevance and accuracy of the model in a dynamic data environment. The use of the AI/ML framework enhances the network's capability to adapt to changing data patterns and maintain high levels of accuracy in anomaly detection.

[0074] Next, another use case scenario of traffic classification is discussed. Network traffic is rapidly evolving over time make network management more difficult. For example, new apps and new app versions can be continuously deployed and introduce drift in traffic. Thus, conventional solutions (even conventional ML based approaches) may not scale well. Collecting large, labeled network-traffic datasets is a cumbersome and time-consuming process. In fact, capturing network-traffic traces, splitting them in traffic objects and associating labels to them, often requires dedicated setups and introduces user-privacy and business-sensitivity issues.

[0075] Furthermore, because most of the network traffic is being encrypted, the traditional deep-packet-inspecting (DPI) solutions are becoming obsolete. Traffic classification using the AI/ML framework described herein leverages advanced ML techniques to accurately categorize network traffic, including encrypted traffic, which traditional DPI methods struggle to analyze. The framework employs a ML model to identify and generalize traffic patterns with high accuracy, even in the presence of novel or previously unseen traffic types. By continuously collecting data from production environments (e.g., service nodes) and utilizing a model evaluation pipeline, the framework ensures that the traffic classification models are regularly updated and optimized for performance. This approach not only enhances network security by enabling precise identification of traffic types but also optimizes quality of service by allowing network operators to prioritize and manage traffic based on real-time insights. The AI/ML framework's ability to adapt to evolving traffic patterns and integration with existing network infrastructure make AI/ML framework a robust solution for modern network management challenges.

[0076] FIG. **7** is a flow diagram for a method **700** for traffic classification using the AI/ML framework, in accordance with some embodiments of the present disclosure. At operation **702**, data is received at a service node. For traffic classification, data may be received from the UPF. The data may include encrypted and unencrypted traffic data.

[0077] At operation **704**, serving data for traffic classification is extracted at the service node. For example, the serving data may include metadata such as packet sizes, flow statistics, and inter-arrival times of packets. The serving data may include an initial set of packets in an encrypted data session, such as the first **30** or **50** packets. The serving data may include the time duration of the initial set of packets. For example, the serving data may include the time between the transmission of the first and second packet, and between the transmission of the second packet and the third packet, and so on. The serving data may also include direction of the packets. For example, the direction may indicate that the packets are being transmitted from the network to the UE or vice versa. The serving data may also include the size of the packets. A digital signature may be generated based on metadata of the initial set of packets and may be used as serving data.

[0078] At operation **706**, the serving data may be inputted into a ML model deployed in the service node. The ML model may have been trained for traffic classification at a central location using training data collected from various distributed locations as described herein. For example, the ML model may include a deep neural network that was trained using digital signatures of various traffic types using traffic-type labels. For example, video streaming may have a first type of digital signature while video gaming may have a second type of digital signature and social media websites may have a third type of digital signature and so on. The model may be periodically trained using real-time traffic data from the different service nodes, as described herein. New versions or updates to the model may be deployed at the service node as appropriate. For example, changes in traffic pattern may trigger deployment of new or updated model to the service nodes.

[0079] At operation **708**, a model output is received with a traffic type identification. The model may generate a traffic type identification of the serving data. In some cases, the model may identify an unknown or new traffic type, which was not previously classified. The model may then classify the new traffic type. The data for the new traffic type is collected at the central location, and the model may be updated accordingly.

[0080] At operation **710**, the service node allocates resources, such as network slices, based on the traffic identification. For example, the service node may allocate a certain amount and type of resources for video streaming traffic as compared to social media website traffic.

[0081] Network paging optimization is another use case scenario of the AI/ML framework as described herein. Network paging optimization using the AI/ML framework can be a transformative approach to managing the signaling overhead in mobile networks, particularly in LTE, 5G, and future 6G environments. Traditionally, when a UE is in an idle state, the location of the UE is known only at the Tracking Area (TA) level, which can lead to inefficient paging processes. For example, the network may broadcast a paging message in a large number of cells. The AI/ML framework addresses this problem by employing ML models to predict the most likely current location of a UE based on historical mobility patterns and real-time data. This predictive capability allows the network to target paging messages more accurately, reducing the need to broadcast messages across multiple cell towers and thereby conserving radio resources and minimizing UE power consumption. By optimizing the paging process, the framework significantly enhances network performance and user experience, particularly in scenarios where UEs frequently transition between idle and active states.

[0082] FIG. **8** is a flow diagram for a method **800** for network paging optimization using the AI/ML framework, in accordance with some embodiments of the present disclosure. At operation **802**, data is received at a service node. For network paging optimization, data may be received from the MME and AMF. The data may include mobility events and session events.

[0083] At operation **804**, serving data for network paging optimization is extracted at the service node. For example, the serving data may include historical mobility event information of the UE. The serving data may include the time and other information that can impact the mobility of the UE. For example, previous location of UE received in various signaling messages may be extracted and used to predict the probable next location.

[0084] At operation **806**, the serving data may be inputted into a ML model deployed in the service node. The ML model may have been trained for predicting UE location using training data collected from various distributed locations as described herein. For example, the ML model may be a deep neural network that was trained using historical mobility information. The model may be periodically trained using real-time mobility data from the different service nodes, as described herein. New versions or updates to the model may be deployed at the service node as appropriate. For example, changes in mobility pattern may trigger deployment of new or updated model to the service nodes.

[0085] At operation **808**, a model output is received with a predicted location of the UE based on the inputted serving data. The predicted location may include a particular cell or a set of cells.

[0086] At operation **810**, the service node may transmit a paging message to the UE based on the predicted location. For example, the service node may transmit a paging message using a cell tower in the predicted cell or using a set of cell towers corresponding to the predicted set of cells.

[0087] The AI/ML framework's ability to dynamically learn and adapt to changing network conditions increases the effectiveness in network paging optimization. The framework can continuously ingest data from network events, such as mobility and session events, and uses this data to train and refine its predictive models at the central location, which are then deployed at the service nodes. These models can identify patterns and trends in UE movement, allowing the network to anticipate where a UE is likely to be located when it needs to be paged. This proactive approach not only reduces the signaling load on the network but also decreases the latency associated with establishing connections, which is especially important for applications requiring low latency and high reliability. Furthermore, the integration of the AI/ML framework with existing network infrastructure ensures that the ML models can be deployed seamlessly, providing a scalable solution that can evolve alongside advancements in mobile network technology.

[0088] TAL optimization is another use case scenario of the AI/ML framework as described herein. In communication networks, a Tracking Area (TA) is a logical grouping of cells UE can move freely without updating its location. TALs are lists of Tas that a UE can traverse without triggering a location update. The TALs, in conventional systems, typically are generic and static lists clustering nearby cells without taking into account historical mobility patterns. FIG. **10**A shows an example of static Tracking Area Lists. Here, TAL-1 includes cells 1, 2, 3, and 5. TAL-2 includes cells 4, 7, 8, and 11. TAL-3 includes cells 6, 9, 10, and 13. TAL-4 includes cells 12, 14, 15, and 16. These TALs may be used for all UEs without any customization or optimization based on the particular travel patterns of the UEs. In accurate TALs can lead to frequent location updates, which can lead to a ping-pong effect and signaling storms degrading network performance.

[0089] TAL optimization using the AI/ML framework can address the challenges of managing signaling overhead in mobile networks. The AI/ML framework can address these issues by employing ML models to optimize the configuration of TALs. By analyzing historical mobility patterns and real-time data, the framework can generate the most efficient TAL configuration for each UE, balancing the trade-off between paging overhead and location update overhead. This optimization can reduce unnecessary signaling, conserve network resources, and enhance overall network efficiency.

[0090] FIG. **9** is a flow diagram for a method **900** for TAL optimization using the AI/ML framework, in accordance with some embodiments of the present disclosure. At operation **902**, data is received at a service node. For TAL optimization, data may be received from the MME and AMF. The data may include mobility events and session events.

[0091] At operation **904**, serving data for network paging optimization is extracted at the service node. For example, the serving data may include historical mobility event information of the UE. The serving data may include the time and other information that can impact the mobility of the UE. The serving data may include UE past location trails based on events and data received from the MME and AMF.

[0092] At operation **906**, the serving data may be inputted into a ML model deployed in the service node. The ML model may have been trained for generating TALs customized for UEs using training data collected from various distributed locations as described herein. For example, the ML model may be a deep neural network that was trained using historical mobility information. The model may be periodically trained using real-time mobility data from the different service nodes, as described herein. New versions or updates to the model may be deployed at the service node as appropriate. For example, changes in mobility pattern may trigger deployment of new or updated model to the service nodes.

[0093] At operation **908**, a model output is received. The model output may include information for TAL configuration for the UE. For the example, the model output may include a predicted mobility pattern of the UE based on the inputted serving data. The predicted mobility pattern may include a set of cells.

[0094] At operation **910**, the service node may generate a TAL configuration for the UE based on the model output. For example, generate a TAL customized for the UE based on the predicted mobility pattern, such as including the set of cells in the predicted mobility pattern.

[0095] FIG. **10**B shows an example of optimized TAL configurations generated using the AI/ML framework, in accordance with some embodiments of the present disclosure. Here, the TALs are not generic, static lists, but customized list for UEs that have been optimized based on the predicted mobility patterns by the AI/ML framework. Here, TAL-1 corresponds to a customized TAL for UE**1**. TAL-1 includes cells 1, 2, 4, and 8. TAL-2 corresponds to a customized TAL for UE**2**. TAL-2 includes cells 7, 11, 14, and 16. TAL-3 corresponds to a customized TAL for UE**3**. TAL-3 incudes cells 6, 9, and 10. TAL-4 corresponds to a customized TAL for UE**4**. TAL-4 includes cells 12, 13, 15, and 16.

[0096] The AI/ML framework's ability to adapt to dynamic network conditions can improve TAL optimization and thus improving network performance. By continuously collecting and analyzing data on UE movements and network performance, the framework refines its predictive models to accommodate changes in user behavior and network topology. This allows the framework to provide real-time recommendations for TAL configurations that minimize signaling overhead while maintaining optimal network performance. The integration of AI-driven insights into TAL management allows the network to respond swiftly to changes in user mobility patterns, reducing latency and improving the quality of service for end-users. Additionally, the framework's scalability and compatibility with existing network infrastructure provides robustness and can evolve alongside technological advancements and increasing demands for connectivity.

[0097] FIG. **11** illustrates a representation of a machine **1100** in the form of a computer system within which a set of instructions may be executed for causing the machine **1100** to perform any one or more of the methodologies and techniques discussed herein. Specifically, FIG. **11** shows a diagrammatic representation of the machine **1100** in the example form of a computer system, within which instructions **1116** (e.g., software, a program, an application, an applet, an app, or other executable code) for causing the machine **1100** to perform any one or more of the methodologies discussed herein may be executed. For example, the instructions **1116** may cause the machine **1100** to execute any one or more operations of any one or more of the methods described herein. As another example, the instructions **1116** may cause the machine **1100** to implement portions of the data flows described herein. In this way, the instructions **1116** transform a general, non-programmed machine into a particular machine **1100** (e.g., service nodes, orchestrator nodes, edge managers, etc.) that is specially configured to carry out any one of the described and illustrated functions in the manner described herein.

[0098] In alternative embodiments, the machine **1100** operates as a standalone device or may be coupled (e.g., networked) to other machines. In a networked deployment, the machine **1100** may operate in the capacity of a server machine or a client machine in a server-client network environment, or as a peer machine in a peer-to-peer (or distributed) network environment. The machine **1100** may comprise, but not be limited to, a server computer, a client computer, a personal computer (PC), a tablet computer, a laptop computer, a netbook, a smart phone, a mobile device, a network router, a network switch, a network bridge, or any machine capable of executing the instructions **1116**, sequentially or otherwise, that specify actions to be taken by the machine **1100**. Further, while only a single machine **1100** is illustrated, the term "machine" shall also be taken to include a collection of machines **1100** that individually or jointly execute the instructions **1116** to perform any one or more of the methodologies discussed herein.

[0099] The machine **1100** includes processors **1110**, memory **1130**, and input/output (I/O) components **1150** configured to communicate with each other such as via a bus **1102**. In an example embodiment, the processors **1110** (e.g., a central processing unit (CPU), a reduced instruction set computing (RISC) processor, a complex instruction set computing (CISC) processor, a graphics processing unit (GPU), a digital signal processor (DSP), an application-specific integrated circuit (ASIC), a radio-frequency integrated circuit (RFIC), another processor, or any suitable combination thereof) may include, for example, a processor **1112** and a processor **1114** that may execute the instructions **1116**. The term "processor" is intended to include multi-core processors **1110** that may comprise two or more independent processors (sometimes referred to as "cores") that may execute instructions **1116** contemporaneously. Although FIG. **11** shows multiple processors **1110**, the machine **1100** may include a single processor with a single core, a single processor with multiple cores (e.g., a multi-core processor), multiple processors with a single core, multiple processors with multiple cores, or any combination thereof.

[0100] The memory **1130** may include a main memory **1132**, a static memory **1134**, and a storage unit **1136**, all accessible to the processors **1110** such as via the bus **1102**. The main memory **1132**, the static memory **1134**, and the storage unit **1136** store the instructions **1116** embodying any one or more of the methodologies or functions described herein. The instructions **1116** may also reside, completely or partially, within the main memory **1132**, within the static memory **1134**, within the storage unit **1136**, within at least one of the processors **1110** (e.g., within the processor's cache memory), or any suitable combination thereof, during execution thereof by the machine **1100**.

[0101] The I/O components **1150** include components to receive input, provide output, produce output, transmit information, exchange information, capture measurements, and so on. The specific I/O components **1150** that are included in a particular machine **1100** will depend on the type of machine. For example, portable machines such as mobile phones will likely include a touch input device or other such input mechanisms, while a headless server machine will likely not include such a touch input device. It will be appreciated that the I/O components **1150** may include many other components that are not shown in FIG. **11**. The I/O components **1150** are grouped according to functionality merely for simplifying the following discussion and the grouping is in no way limiting. In various example embodiments, the I/O components **1150** may include output components **1152** and input components **1154**. The output components **1152** may include visual components (e.g., a display such as a plasma display panel (PDP), a light emitting diode (LED) display, a liquid crystal display (LCD), a projector, or a cathode ray tube (CRT)), acoustic components (e.g., speakers), other signal generators, and so forth. The input components **1154** may include alphanumeric input components (e.g., a keyboard, a touch screen configured to receive alphanumeric input, a photo-optical keyboard, or other alphanumeric input components), point-based input components (e.g., a mouse, a touchpad, a trackball, a joystick, a motion sensor, or another pointing instrument), tactile input components (e.g., a physical button, a touch screen that provides location and/or force of touches or touch gestures, or other tactile input components), audio input components (e.g., a microphone), and the like.

[0102] Communication may be implemented using a wide variety of technologies. The I/O components **1150** may include communication components **1164** operable to couple the machine **1100** to a network **1180** or devices **1170** via a coupling **1182** and a coupling **1172**, respectively. For example, the communication components **1164** may include a network interface component or another suitable device to interface with the network **1180**. In further examples, the communication components **1164** may include wired communication components, wireless communication components, cellular communication components, and other communication components to provide communication via other modalities. The devices **1170** may be another machine or any of a wide variety of peripheral devices (e.g., a peripheral device coupled via a universal serial bus (USB)). For example, as noted above, the machine **1100** may correspond to any one of the service nodes, edge managers, orchestrator nodes, etc., described herein, and the devices **1170** may include any other of these systems and devices.

[0103] The various memories (e.g., **1130**, **1132**, **1134**, and/or memory of the processor(s) **1110** and/or the storage unit **1136**) may store one or more sets of instructions **1116** and data structures (e.g., software) embodying or utilized by any one or more of the methodologies or functions described herein. These instructions **1116**, when executed by the processor(s) **1110**, cause various operations to implement the disclosed embodiments.

[0104] As used herein, the terms "machine-storage medium," "device-storage medium," and "computer-storage medium" mean the same thing and may be used interchangeably in this disclosure. The terms refer to a single or multiple storage devices and/or media (e.g., a centralized or distributed database, and/or associated caches and servers) that store executable instructions and/or data. The terms shall accordingly be taken to include, but not be limited to, solid-state memories, and optical and magnetic media, including memory internal or external to processors. Specific examples of machine-storage media, computer-storage media, and/or device-storage media include non-volatile memory, including by way of example semiconductor memory devices, e.g., erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), field-programmable gate arrays (FPGAs), and flash memory devices; magnetic disks such as internal hard disks and removable disks; magneto-optical disks; and CD-ROM and DVD-ROM disks. The terms "machine-storage media," "computer-storage media," and "device-storage media" specifically exclude carrier waves, modulated data signals, and other such media, at least some of which are covered under the term "signal medium" discussed below.

[0105] In various example embodiments, one or more portions of the network **1180** may be an ad hoc network, an intranet, an extranet, a virtual private network (VPN), a local-area network (LAN), a wireless LAN (WLAN), a wide-area network (WAN), a wireless WAN (WWAN), a metropolitan-area network (MAN), the Internet, a portion of the Internet, a portion of the public switched telephone network (PSTN), a plain old telephone service (POTS) network, a cellular telephone network, a wireless network, a Wi-Fi® network, another type of network, or a combination of two or more such networks. For example, the network **1180** or a portion of the network **1180** may include a wireless or cellular network such as those defined by various standard-setting organizations, other long-range protocols, or other data transfer technology.

[0106] The instructions **1116** may be transmitted or received over the network **1180** using a transmission medium via a network interface device (e.g., a network interface component included in the communication components **1164**) and utilizing any one of a number of well-known transfer protocols (e.g., hypertext transfer protocol (HTTP)). Similarly, the instructions **1116** may be transmitted or received using a transmission medium via the coupling **1172** (e.g., a peer-to-peer coupling) to the devices **1170**. The terms "transmission medium" and "signal medium" mean the same thing and may be used interchangeably in this disclosure. The terms "transmission medium" and "signal medium" shall be taken to include any intangible medium that is capable of storing, encoding, or carrying the instructions **1116** for execution by the machine **1100**, and include digital or analog communications signals or other intangible media to facilitate communication of such software. Hence, the terms "transmission medium" and "signal medium" shall be taken to include any form of modulated data signal, carrier wave, and so forth. The term "modulated data signal" means a signal that has one or more of its characteristics set or changed in such a manner as to encode information in the signal.

[0107] The terms "machine-readable medium," "computer-readable medium," and "device-readable medium" mean the same thing and may be used interchangeably in this disclosure. The terms are defined to include both machine-storage media and transmission media. Thus, the terms include both storage devices/media and carrier waves/modulated data signals.

[0108] The various operations of example methods described herein may be performed, at least partially, by one or more processors that are temporarily configured (e.g., by software) or permanently configured to perform the relevant operations. Similarly, the methods described herein may be at least partially processor-implemented. For example, at least some of the operations of the methods described herein may be performed by one or more processors. The performance of certain of the operations may be distributed among the one or more processors, not only residing within a single machine, but also deployed across a number of machines. In some example embodiments, the processor or processors may be located in a single location (e.g., within a home environment, an office environment, or a server farm), while in other embodiments the processors may be distributed across a number of locations.

[0109] Although the embodiments of the present disclosure have been described with reference to specific example embodiments, it will be evident that various modifications and changes may be made to these embodiments without departing from the broader scope of the inventive subject matter. Accordingly, the specification and drawings are to be regarded in an illustrative rather than a restrictive sense. The accompanying drawings that form a part hereof show, by way of illustration, and not of limitation, specific embodiments in which the subject matter may be practiced. The embodiments illustrated are described in sufficient detail to enable those skilled in the art to practice the teachings disclosed herein. Other embodiments may be used and derived therefrom, such that structural and logical substitutions and changes may be made without departing from the scope of this disclosure. This Detailed Description, therefore, is not to be taken in a limiting sense, and the scope of various embodiments is defined only by the appended claims, along with the full range of equivalents to which such claims are entitled.

[0110] Such embodiments of the inventive subject matter may be referred to herein, individually and/or collectively, by the term "invention" merely for convenience and without intending to voluntarily limit the scope of this application to any single invention or inventive concept if more than one is in fact disclosed. Thus, although specific embodiments have been illustrated and described herein, it should be appreciated that any arrangement calculated to achieve the same purpose may be substituted for the specific embodiments shown. This disclosure is intended to cover any and all adaptations or variations of various embodiments. Combinations of the above embodiments, and other embodiments not specifically described herein, will be apparent, to those of skill in the art, upon reviewing the above description.

[0111] In this document, the terms "a" or "an" are used, as is common in patent documents, to include one or more than one, independent of any other instances or usages of "at least one" or "one or more." In this document, the term "or" is used to refer to a nonexclusive or, such that "A or B" includes "A but not B," "B but not A," and "A and B," unless otherwise indicated. In the appended claims, the terms "including" and "in which" are used as the plain-English equivalents of the respective terms "comprising" and "wherein." Also, in the following claims, the terms "including" and "comprising" are open-ended; that is, a system, device, article, or process that includes elements in addition to those listed after such a term in a claim is still deemed to fall within the scope of that claim.

What is claimed is:

1. A method for operating a communication network, the method comprising:

receiving, by a service node of the communication network, event data from one or more gateway components at the service node;

processing the event data to generate processed data for transmission to a central location of the communication network, the processing comprising removing sensitive information and sampling the event data;

transmitting, by the service node, the processed data to a central location, wherein the central location is configured to receive data from a plurality of other service nodes and to train a machine-learning (ML) model using the processed data and received data from the plurality of other service nodes, and wherein the central location is configured to deploy a ML model endpoint to the service node;

extracting serving data from the event data;

inputting the serving data into the ML model endpoint deployed at the service node from the central location;

receiving a model output from the ML model endpoint; and

processing the model output to perform an action at the service node.

2. The method of claim **1**, wherein the model output comprises a forecast of network traffic comprising an upper bound and a lower bound of the forecast, wherein the method further comprising:

performing a scheduled task to determine current network conditions;

comparing the current network conditions to the upper bound and the lower bound of the forecast;

in an event the current network conditions are outside the upper bound and the lower bound of the forecast, detecting an anomaly; and

generating an alert based on the detected anomaly.

3. The method of claim **1**, wherein the model output comprises traffic identification of the event data.

4. The method of claim **3**, wherein the event data is encrypted, and wherein the serving data comprises metadata for an initial set of packets in a data session, wherein the metadata comprises at least one of packet sizes, flow statistics, or inter-arrival times of packets.

5. The method of claim **1**, wherein the model output comprises a predicted location of a user equipment (UE), and wherein the action comprises transmitting a paging message from one or more cell towers based on the prediction location.

6. The method of claim **1**, wherein the model output comprises a mobility pattern of a UE, and wherein the action comprises generating a customized tracking area list (TAL) for the UE based on the mobility pattern.

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

transmitting telemetry information related to performance of the deployed model endpoint, wherein the telemetry information is used to trigger model training at the central location.

8. A system comprising:

at least one hardware processor; and

at least one memory storing instructions that, when executed by the at least one hardware processor, cause the at least one hardware processor to perform operations comprising:

receiving, by a service node of a communication network, event data from one or more gateway components at the service node;

processing the event data to generate processed data for transmission to a central location of the communication network, the processing comprising removing sensitive information and sampling the event data;

transmitting, by the service node, the processed data to a central location, wherein the central location is configured to receive data from a plurality of other service nodes and to train a machine-learning (ML) model using the processed data and received data from the plurality of other service nodes, and wherein the central location is configured to deploy a ML model endpoint to the service node;

extracting serving data from the event data;

inputting the serving data into the ML model endpoint deployed at the service node from the central location;

receiving a model output from the ML model endpoint; and

processing the model output to perform an action at the service node.

9. The system of claim **8**, wherein the model output comprises a forecast of network traffic comprising an upper bound and a lower bound of the forecast, wherein the operations further comprising:

performing a scheduled task to determine current network conditions;

comparing the current network conditions to the upper bound and the lower bound of the forecast;

in an event the current network conditions are outside the upper bound and the lower bound of the forecast, detecting an anomaly; and

generating an alert based on the detected anomaly.

10. The system of claim **8**, wherein the model output comprises traffic identification of the event data.

11. The system of claim **10**, wherein the event data is encrypted, and wherein the serving data comprises metadata for an initial set of packets in a data session, wherein the metadata comprises at least one of packet sizes, flow statistics, or inter-arrival times of packets.

12. The system of claim **8**, wherein the model output comprises a predicted location of a user equipment (UE), and wherein the action comprises transmitting a paging message from one or more cell towers based on the prediction location.

13. The system of claim **8**, wherein the model output comprises a mobility pattern of a UE, and wherein the action comprises generating a customized tracking area list (TAL) for the UE based on the mobility pattern.

14. The system of claim **8**, the operations further comprising:

transmitting telemetry information related to performance of the deployed model endpoint, wherein the telemetry information is used to trigger model training at the central location.

15. A machine-storage medium embodying instructions that, when executed by a machine, cause the machine to perform operations comprising:

receiving, by a service node of a communication network, event data from one or more gateway components at the service node;

processing the event data to generate processed data for transmission to a central location of the communication network, the processing comprising removing sensitive information and sampling the event data;

transmitting, by the service node, the processed data to a central location, wherein the central location is configured to receive data from a plurality of other service nodes and to train a machine-learning (ML) model using the processed data and received data from the plurality of other service nodes, and wherein the central location is configured to deploy a ML model endpoint to the service node;

extracting serving data from the event data;

inputting the serving data into the ML model endpoint deployed at the service node from the central location;

receiving a model output from the ML model endpoint; and

processing the model output to perform an action at the service node.

16. The machine-storage medium of claim **15**, wherein the model output comprises a forecast of network traffic comprising an upper bound and a lower bound of the forecast, wherein the operations further comprising:

performing a scheduled task to determine current network conditions;

comparing the current network conditions to the upper bound and the lower bound of the forecast;

in an event the current network conditions are outside the upper bound and the lower bound of the forecast, detecting an anomaly; and

generating an alert based on the detected anomaly.

17. The machine-storage medium of claim **15**, wherein the model output comprises traffic identification of the event data.

18. The machine-storage medium of claim **17**, wherein the event data is encrypted, and wherein the serving data comprises metadata for an initial set of packets in a data session, wherein the metadata comprises at least one of packet sizes, flow statistics, or inter-arrival times of packets.

19. The machine-storage medium of claim **15**, wherein the model output comprises a predicted location of a user equipment (UE), and wherein the action comprises transmitting a paging message from one or more cell towers based on the prediction location.

20. The machine-storage medium of claim **15**, wherein the model output comprises a mobility pattern of a UE, and wherein the action comprises generating a customized tracking area list (TAL) for the UE based on the mobility pattern.

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