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(54) **TRAINING A SUPERVISED MACHINE LEARNING MODEL FOR ANOMALY DETECTION**

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H04L 9/40	(2022.01)
H04L 41/16	(2022.01)

(52) **U.S. Cl.**
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(58) **Field of Classification Search**
CPC H04L 41/16; H04L 63/1425
See application file for complete search history.

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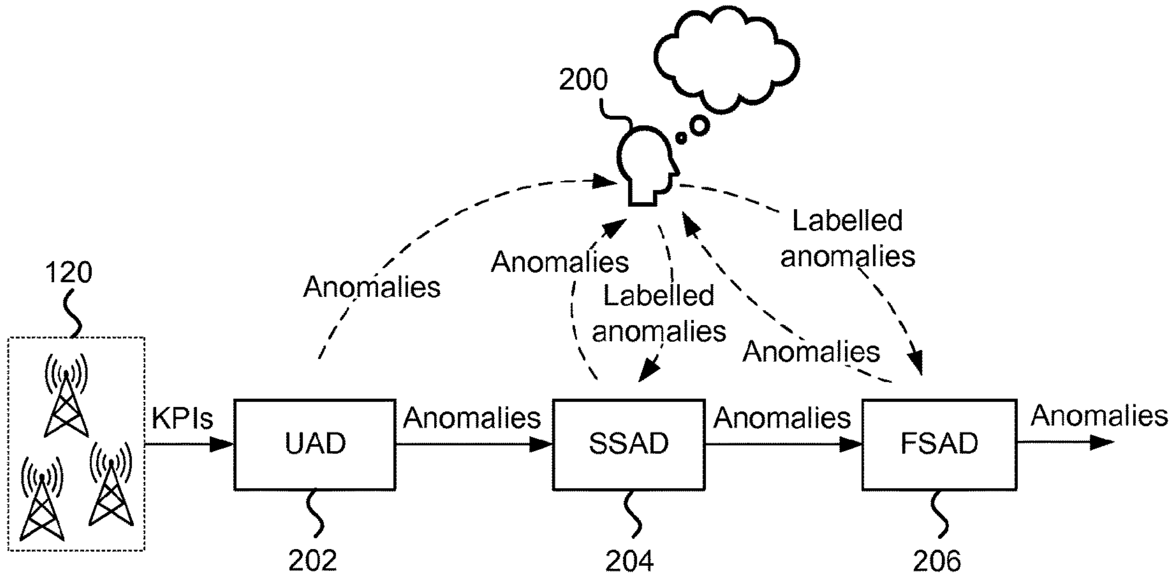
(57) **ABSTRACT**

Example embodiments may relate to training of a supervised machine learning model for anomaly detection in a communication network. A computer-implemented method may comprise: detecting, by an unsupervised machine learning model, a plurality of anomalies in performance indicator data of a communication network; receiving labels for a first subset of the plurality of anomalies and labelling the first subset of the plurality of anomalies with the labels; training, based on the labelled first subset of the plurality of anomalies, a semi-supervised machine learning model for labelling anomalies; labelling, by the semi-supervised machine learning model, a second subset of the plurality of anomalies; and training, based on the labelled first and second subsets of the plurality of anomalies, a supervised machine learning model for detecting and/or classifying anomalies in the performance indicator data.

15 Claims, 4 Drawing Sheets



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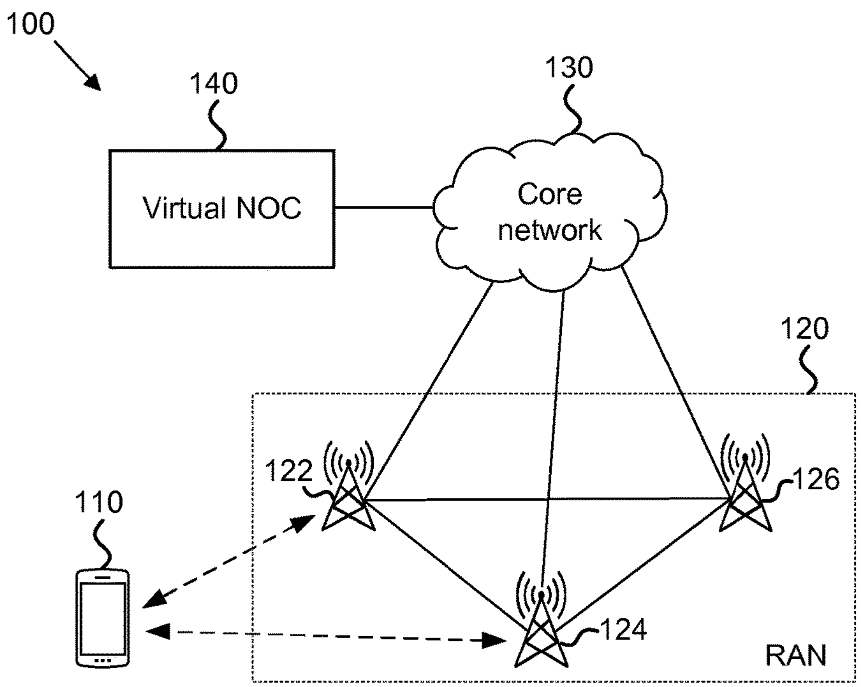
100
140
Virtual NOC
130
Core network
120
122
126
110
124
RAN

FIG. 1

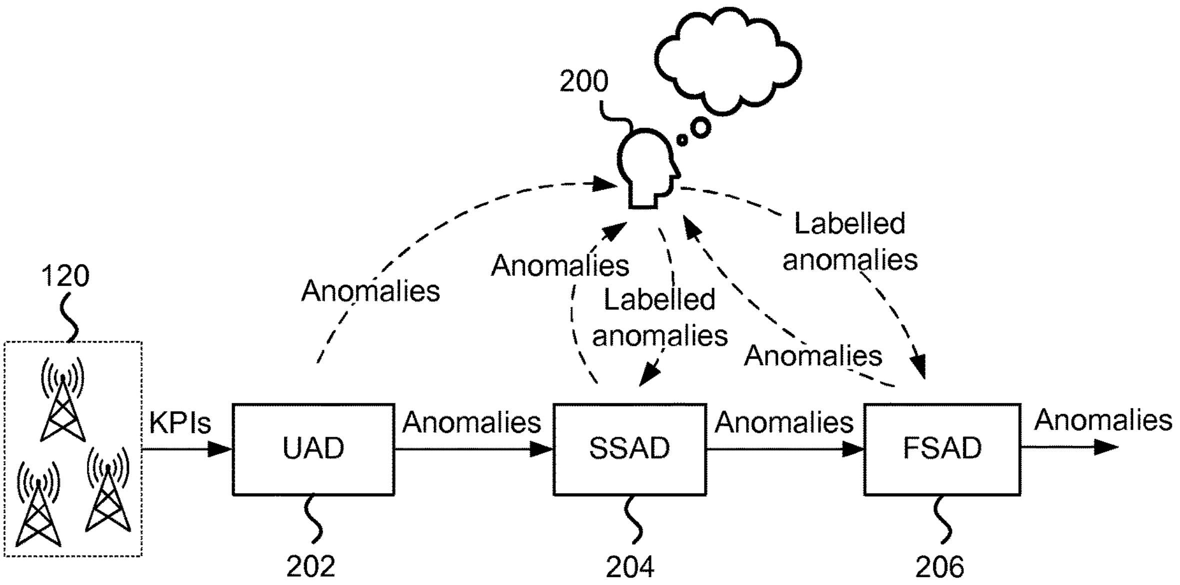
200
120
Anomalies
Anomalies
Labelled anomalies
Labelled anomalies
Anomalies
KPIs
UAD
Anomalies
SSAD
Anomalies
FSAD
Anomalies
202
204
206

FIG. 2

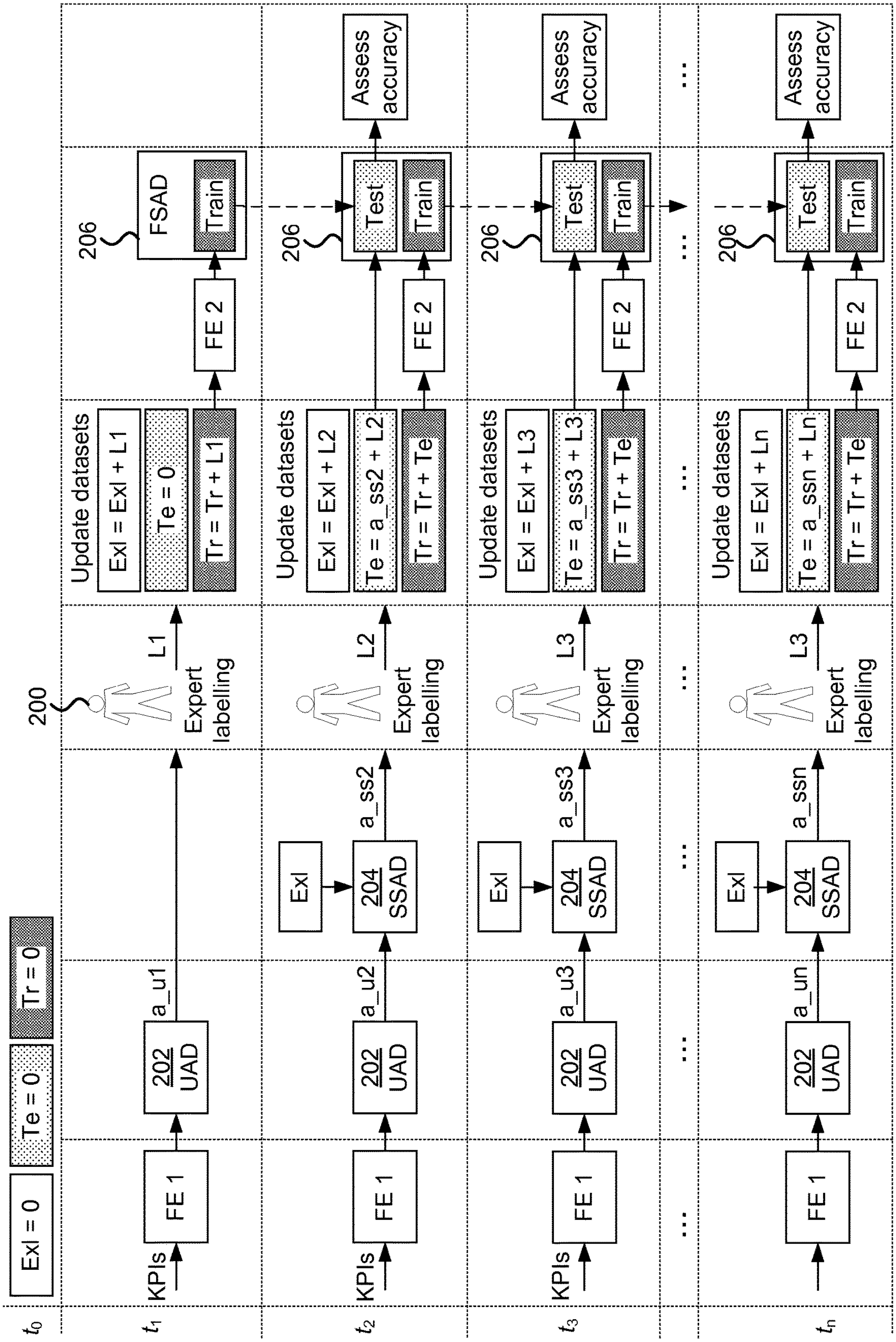
t_0
Exl = 0
Te = 0
Tr = 0
t_1
KPIs
FE 1
202
UAD
a_u1
200
Expert labelling
L1
Update datasets
Exl = Exl + L1
Te = 0
Tr = Tr + L1
FE 2
206
FSAD
Train
t_2
KPIs
FE 1
202
UAD
a_u2
Exl
204
SSAD
a_ss2
Expert labelling
L2
Update datasets
Exl = Exl + L2
Te = a_ss2 + L2
Tr = Tr + Te
FE 2
206
Test
Train
Assess accuracy
t_3
KPIs
FE 1
202
UAD
a_u3
Exl
204
SSAD
a_ss3
Expert labelling
L3
Update datasets
Exl = Exl + L3
Te = a_ss3 + L3
Tr = Tr + Te
FE 2
206
Test
Train
Assess accuracy
...
t_n
FE 1
202
UAD
a_un
Exl
204
SSAD
a_ssn
Expert labelling
L3
Update datasets
Exl = Exl + Ln
Te = a_ssn + Ln
Tr = Tr + Te
FE 2
206
Test
Train
Assess accuracy

FIG. 3

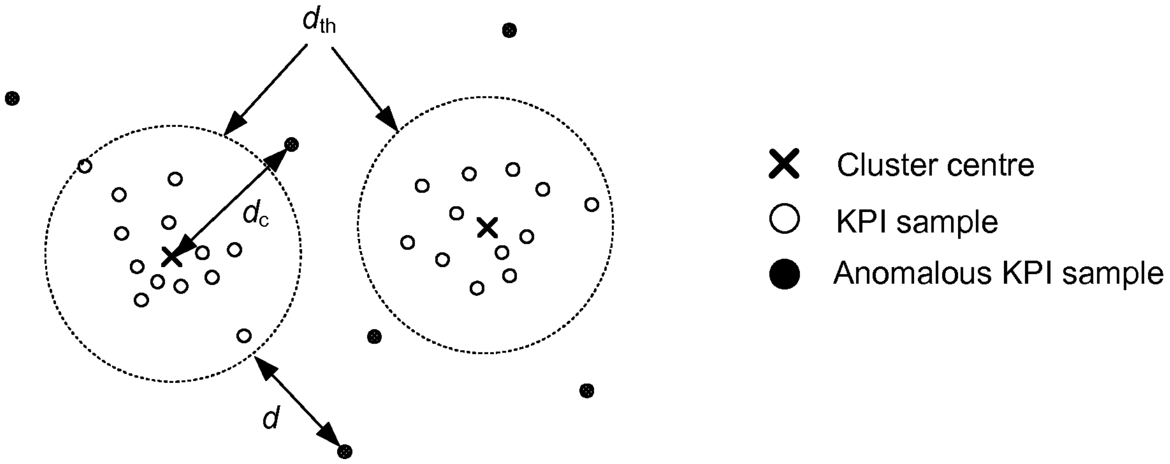
d_{th}
d_c
d
✕ Cluster centre
○ KPI sample
● Anomalous KPI sample

FIG. 4

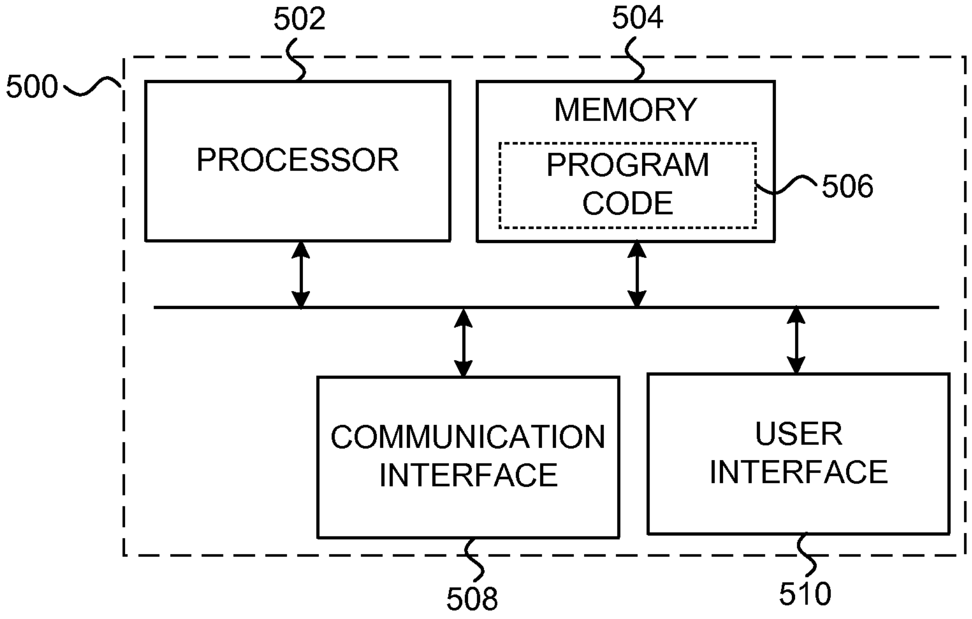
500
502
504
PROCESSOR
MEMORY
PROGRAM CODE
506
COMMUNICATION INTERFACE
USER INTERFACE
508
510

FIG. 5

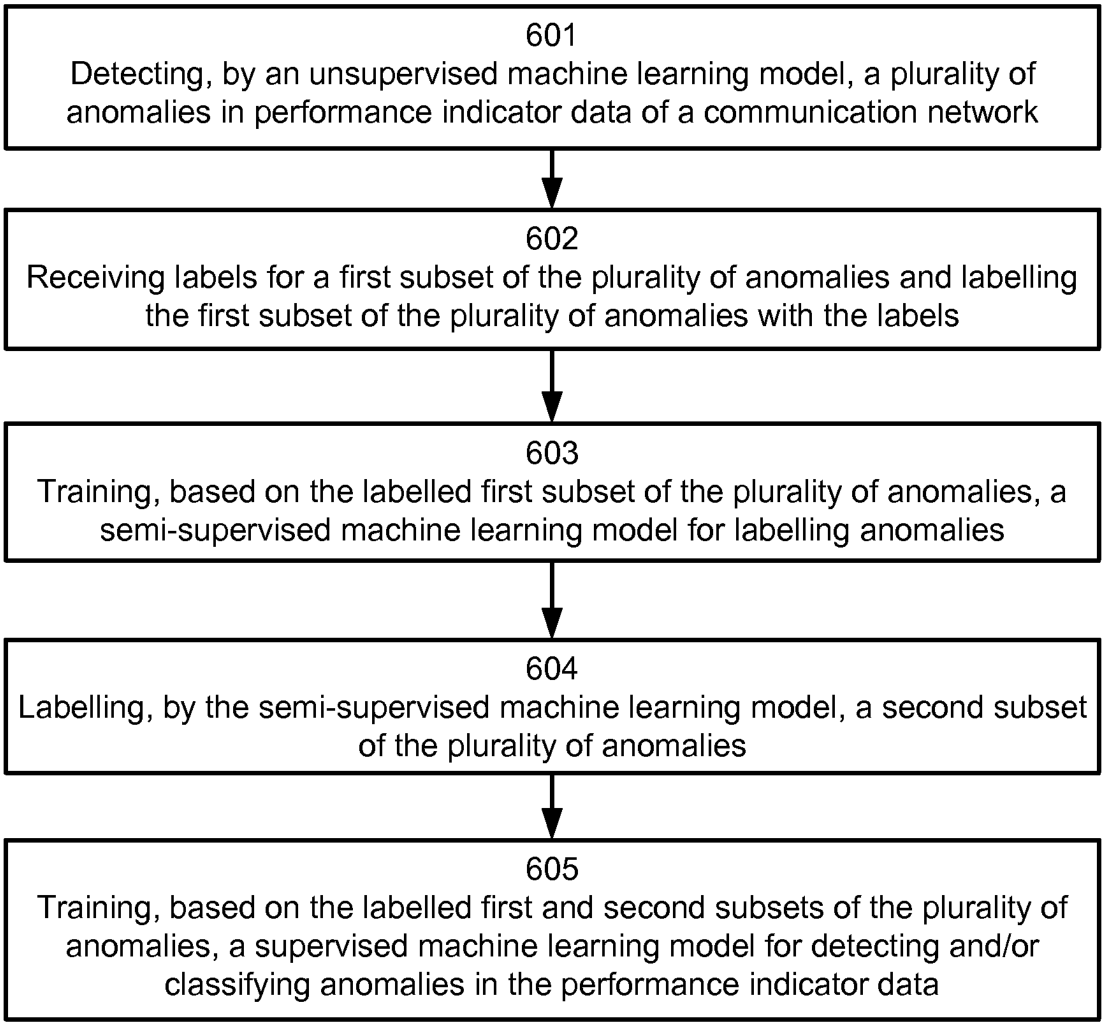
601
Detecting, by an unsupervised machine learning model, a plurality of anomalies in performance indicator data of a communication network
602
Receiving labels for a first subset of the plurality of anomalies and labelling the first subset of the plurality of anomalies with the labels
603
Training, based on the labelled first subset of the plurality of anomalies, a semi-supervised machine learning model for labelling anomalies
604
Labelling, by the semi-supervised machine learning model, a second subset of the plurality of anomalies
605
Training, based on the labelled first and second subsets of the plurality of anomalies, a supervised machine learning model for detecting and/or classifying anomalies in the performance indicator data

FIG. 6

TRAINING A SUPERVISED MACHINE LEARNING MODEL FOR ANOMALY DETECTION

TECHNICAL FIELD

Various example embodiments generally relate to the field of communication networks. Some example embodiments relate to machine learning models configured to detect or classify anomalies in performance indicator data of a communication network, or training such machine learning models.

BACKGROUND

Operation of a communication network may be analysed and optimised in many different ways, for example based on key performance indicators (KPI) of the network. Anomaly detection is a form of data analysis with a goal to identify rarely appearing phenomena in a set of data, for example events that significantly deviate from the rest of the data. Anomaly detection may be used in context of communication networks to detect undesired network behaviour, for example based on the KPIs. Detected anomalies may be then analysed and corrective actions may be performed accordingly.

SUMMARY

This summary is provided to introduce a selection of concepts in a simplified form that are further described below in the detailed description. This summary is not intended to identify key features or essential features of the claimed subject matter, nor is it intended to be used to limit the scope of the claimed subject matter.

Example embodiments of the present disclosure improve anomaly detection in a communication network. This benefit may be achieved by the features of the independent claims. Further example embodiments are provided in the dependent claims, the description, and the drawings.

According to a first aspect, a computer-implemented method is disclosed. The method may comprise: detecting, by an unsupervised machine learning model, a plurality of anomalies in performance indicator data of a communication network; receiving labels for a first subset of the plurality of anomalies and labelling the first subset of the plurality of anomalies with the labels; training, based on the labelled first subset of the plurality of anomalies, a semi-supervised machine learning model for labelling anomalies; labelling, by the semi-supervised machine learning model, a second subset of the plurality of anomalies; and training, based on the labelled first and second subsets of the plurality of anomalies, a supervised machine learning model for detecting and/or classifying anomalies in the performance indicator data.

According to an example embodiment of the first aspect, the method may comprise: performing a first feature extraction to extract features from the performance indicator data; and detecting, by the unsupervised machine learning model, the plurality of anomalies in the performance indicator data based on the extracted features of the performance indicator data.

According to an example embodiment of the first aspect, the method may comprise: determining an anomaly score or ranking for the plurality of anomalies; and determining the first subset of the plurality of anomalies based on the anomaly score or ranking.

According to an example embodiment of the first aspect, the method may comprise: determining the first subset of the plurality of anomalies based on uncertainty sampling of the plurality of anomalies.

According to an example embodiment of the first aspect, the method may comprise: receiving the labels for the first subset of the plurality of anomalies via a user interface.

According to an example embodiment of the first aspect, the method may comprise: outputting an indication of the labelling of the second subset of the plurality of anomalies via the user interface; receiving validation of the labelling of the second subset of the plurality of anomalies via the user interface, or updating at least one label of the second subset of the plurality of anomalies based on user input received via the user interface.

According to an example embodiment of the first aspect, the method may comprise: re-training the supervised machine learning model, in response to receiving further labels for the plurality of anomalies via the user interface and/or in response to labelling further anomalies of the plurality of anomalies by the semi-supervised machine learning model.

According to an example embodiment of the first aspect, the method may comprise: disabling the unsupervised machine learning model and the semi-supervised machine learning model, in response to determining that performance of the supervised anomaly detection exceeds performance of the semi-supervised machine learning model, and/or in response to determining that the re-training no longer improves the performance of the supervised machine learning model, wherein the performance of the supervised machine learning model and/or the performance of the semi-supervised machine learning model is evaluated based on a test dataset comprising the first and second subsets of the plurality of anomalies.

According to an example embodiment of the first aspect, the method may comprise: re-enabling the unsupervised machine learning model and/or the semi-supervised machine learning model and resuming re-training of the supervised machine learning model, in response to detecting a predetermined degradation in the performance of the supervised machine learning model, when evaluated with the test dataset.

According to an example embodiment of the first aspect, the method may comprise: detecting and/or classifying, by the supervised machine learning model, at least one anomaly in the performance indicator data.

According to an example embodiment of the first aspect, the method may comprise: outputting an indication of the detected and/or classified at least one anomaly in the performance indicator data.

According to an example embodiment of the first aspect, the method may comprise: outputting the indication of the detected and/or classified at least one anomaly via the user interface; and receiving validation of the detected and/or classified at least one anomaly via the user interface, or re-training the semi-supervised machine learning model, in response to receiving an indication of incorrect detection and/or classification of the at least one anomaly via the user interface.

According to an example embodiment of the first aspect, the method may comprise: adjusting at least one parameter of the communication network, in response to detecting and/or classifying the at least one anomaly in the performance indicator data.

According to a second aspect, an apparatus is disclosed. The apparatus may comprise means for performing any example embodiment of the method of the first aspect.

According to a third aspect, an apparatus is disclosed. The apparatus may comprise at least one processor; and at least one memory including computer program code; the at least one memory and the computer program code configured, when executed by the at least one processor, to cause the apparatus at least to perform any example embodiment of the method of the first aspect.

According to a fourth aspect, an apparatus is disclosed. The apparatus may comprise a computer-implemented supervised machine learning model obtainable by any example embodiment of the method of the first aspect.

According to a fifth aspect, a computer program or a computer program product is disclosed. The computer program or computer program product may comprise program code configured, when executed by a processor, to cause an apparatus at least to perform any example embodiment of the method of the first aspect.

According to a sixth aspect, a (non-transitory) computer readable medium is disclosed. The (non-transitory) computer readable medium may comprise computer program code configured, when executed by a processor, to cause an apparatus to perform any example embodiment of the method of the first aspect.

Any example embodiment may be combined with one or more other example embodiments. Many of the attendant features will be more readily appreciated as they become better understood by reference to the following detailed description considered in connection with the accompanying drawings.

DESCRIPTION OF THE DRAWINGS

The accompanying drawings, which are included to provide a further understanding of the example embodiments and constitute a part of this specification, illustrate example embodiments and together with the description help to understand the example embodiments. In the drawings:

FIG. **1** illustrates an example of a wireless communication network;

FIG. **2** illustrates an example of a system architecture for training a supervised machine learning model for detecting and/or classifying anomalies;

FIG. **3** illustrates an example of a step-by-step diagram for training a supervised machine learning model for detecting and/or classifying anomalies;

FIG. **4** illustrates an example of determining anomalous KPI samples and their anomaly scores;

FIG. **5** illustrates an example of an apparatus configured to practise one or more example embodiments; and

FIG. **6** illustrates an example of a method for training a machine learning model for detecting and/or classifying anomalies in performance indicator data of a communication network.

Like references are used to designate like parts in the accompanying drawings.

DETAILED DESCRIPTION

Reference will now be made in detail to example embodiments, examples of which are illustrated in the accompanying drawings. The detailed description provided below in connection with the appended drawings is intended as a description of the present examples and is not intended to represent the only forms in which the present example may be constructed or utilized. The description sets forth the functions of the example and the sequence of steps for constructing and operating the example. However, the same or equivalent functions and sequences may be accomplished by different examples.

Operational characteristics of a radio network may be analysed and optimized in many different ways, for example based on key performance indicators (KPI) collected from the radio access network (RAN). KPIs may include one or more of the following: a peak data rate, peak spectral efficiency, data rate experienced by a user equipment (UE), area traffic capacity, latency, connection density, average spectral efficiency, energy efficiency, reliability of transmission, a setup success rate, a connection drop rate, user average throughput, handover count, or a handover success rate. KPIs may be associated with a single cell or a group of cells and they may be collected for uplink and/or downlink. In general, KPIs may be collected from various network devices or elements and the KPIs may not include cell level KPIs. For example, user level KPIs may be used alternatively, or in addition to cell level KPIs. The methods disclosed herein may be therefore based on any suitable type of KPIs, and not only cell level KPIs. Collecting KPIs enables network operators to detect and correct anomalous behaviour in the network. Since the amount and type of KPIs may be high, it may be challenging for a human operator to detect anomalies and therefore machine learning may be exploited in anomaly detection.

An unsupervised machine learning model may analyse data in order to detect hidden structures or patterns within the data. In anomaly detection this may be exploited to identify samples of the input data set that appear to be inconsistent with the rest of the data set. Notably, unsupervised anomaly detection models may be operated without labelled training data, that is, without telling the model which samples of the data set should be considered as anomalous. Examples of machine learning models suitable for unsupervised anomaly detection include clustering techniques, such as KNN (k nearest neighbours), or outlier techniques such as isolation forest. For example, in case of KNN any KPI data having a distance higher than a threshold from the closest cluster centre may be regarded as anomalous. The distance may be also used to assess how anomalous the KPI data, for example to determine an anomaly score for the detected anomaly or a rank different anomalies based on how anomalous they are, as will be further described below. Performance (e.g., accuracy) of unsupervised machine learning models, for example in terms of number false positives in anomaly detection, may be worse than performance of semi-supervised or fully supervised anomaly detection methods. A false positive may refer to a situation, where an anomaly is detected even though the KPI data does not reflect any actual network anomaly.

In semi-supervised learning, a small amount of labelled training data may be combined with unlabelled training data to train a machine learning model. The resulting machine learning model may be called a semi-supervised machine learning model. For example, in transductive learning, a small amount of labelled data may be used to train the semi-supervised model to infer correct labels for the unlabelled data. Examples of semi-supervised machine learning models include generative models, such as for example generative adversarial networks, and graph-based models, such as for example label propagation models.

In supervised learning, training may be performed using labelled training data. The resulting machine learning model may be called a (fully) supervised machine learning model.

Examples of supervised machine learning models include classifiers, e.g. neural networks, which may be trained to predict a class of a data sample from a given set of classes, for example to classify data as anomalous or not (cf. detect an anomaly) and optionally select a class for a detected anomaly. In general, detecting an anomaly may refer to detecting presence of an anomaly, for example classifying data as anomalous or not. Classification may refer to determining a class (e.g., a type) of a detected anomaly and/or assigning a label indicative of the class to an anomaly.

Semi- and fully supervised machine learning models may be trained by comparing the output of the model to the desired output (labels), which may be also referred to as ground-truth data. An output of the model may for example comprise a probability distribution over the set of anomalies, for example as a vector where each element of the vector represents a probability of the input data of the model to belong to a certain class of anomalies (e.g. a coverage hole, interference, call drops caused by handover failures). Antenna uptilting may be applied as a corrective action for anomalies belonging to the class of coverage hole. Antenna downtilting may be applied as a corrective action for anomalies belonging to the class of interference. Update (e.g., optimization) of handover parameters may be applied as a corrective action for anomalies belonging to the class of call drops due to handover failures. In the simplest case, the output of the model may comprise a two-element vector that represents probabilities of the input data being anomalous or not. Training of a machine learning model may include iteratively updating parameters of the model until it is able to perform the task with sufficient accuracy. A loss function, comprising for example the KPIs as input data and the labels as ground truth data, may be provided to assess performance of the model. For example, in case of anomaly classification, the loss function may compare the desired classes (ground truth data) to the class predicted by the ML model. Parameters of the model may be updated at each iteration such that the loss function decreases, that is, the output of the model becomes closer to the desired output.

In continuous network monitoring solutions, the identified KPI anomalies may be configured to cause synthetic alarms, which may be processed further automatically, e.g., correlating occurrence of the detected anomalies with other data such as maintenance or service logs, weather data, or the like. Alternatively, or additionally, the alarms may be processed manually by a human operator, including expert analysis in order to determine corrective action(s) to be taken. In continuous KPI monitoring, anomaly detection may be performed based on network KPIs from time to time, for example periodically or at specific time intervals, as configured by the network automation system, for example every 6, 12, 24, or 48 hours.

Some anomalies may be generated by intentional network changes, such as for example adjustments made by automated algorithms, or by unusual user mobility and traffic patterns, or even weather conditions. Such anomalies may not require any action. Anomalies may be however also caused by equipment faults or misconfiguration and it may be desired to correct such anomalies. In order to automate this process and make it as reliable as possible, for example by reducing the number of false alarms, it may be desired to increase accuracy of KPI anomaly detection beyond performance of purely unsupervised machine learning methods.

A target for network automation may be to automatically detect network faults and to determine the underlying fault causing the problem (e.g. misconfigured handover parameters). However, many of the statistical anomalies identified in KPI data may not be indicative of any severe problem that would degrade customer experience. It may be therefore desired to avoid such anomalies triggering alarms, for example to be processed in a virtual network operation centre (NOC). Furthermore, KPI time series are inherently noisy, especially at individual cell level, and the network may be constantly changing, thereby bringing up new kinds of problems. Furthermore, the number of monitored KPIs may be large.

Performance of unsupervised anomaly detection may be improved by semi-supervised or fully supervised training methods. However, the amount of labelled training data available for such training may be small. Experts may be capable of analysing and resolving only a limited number of anomalies due to the time-consuming manual work associated therewith. Moreover, the resolved anomalies may not be systematically recorded, for example in a database. It may be also difficult to hardcode rules for distinguishing problem situations from non-problematic anomalies, for example because each KPI may need to be treated independently. It may be therefore difficult to set up accurate rules for distinguishing between problem situations and non-problematic anomalies.

Example embodiments of the present disclosure provide a three-step approach for training a machine learning model for detection and/or classification of anomalies in KPI data. The disclosed approach is based on interplay of unsupervised and supervised machine learning models. Expert-in-the-loop input may be used for validating outputs of the models at various stages and hence to generate labels for further training. The disclosed architecture implements a hierarchical solution that ends with a successful domain specific anomaly detection, even when no labelled data is initially available. The solution may increasingly rely on use of labels once they start coming from the expert or the semi-supervised model.

An unsupervised machine learning model may be provided at a first step. This step may provide only limited accuracy, as described above. However, this step may be beneficial for initializing the system, for example because anomalies may be rare, and it may not be practical for a human user (cf. expert) to find them from raw unfiltered KPI data. At least some of the anomalies detected by the unsupervised machine learning mode may be provided to the user for labelling.

A semi-supervised machine learning model may be provided at a second step. The semi-supervised machine learning model may combine the results of the unsupervised method with information drawn from small number of labelled data provided by the user. Thanks to the labels, the accuracy of anomaly detection/classification may be improved when compared to the unsupervised stage. The accuracy of the semi-supervised machine learning model may be improved over time as the number of labels provided by the user increases.

A (fully) supervised machine learning model may be provided at a third step. The supervised machine learning model may use the labelled anomalies from the user but also labels produced by the semi-supervised machine learning model. Enriching the input labels with the output of the semi-supervised machine learning model enables the supervised model to learn faster. At this step, the accuracy of the model may be further improved. Accuracy of a machine learning model may refer to its ability to reflect semantic understanding of anomalies in telco KPIs, as interpreted by the human user.

FIG. **1** illustrates an example of a wireless communication network. Communication network **100** may comprise one or more devices, which may be also referred to as client nodes, user nodes, or user equipment (UE). An example of a device is UE **110**, which may communicate with one or more access nodes of a radio access network (RAN) **120**. An access node may be also referred to as an access point or a base station. Access nodes **122**, **124**, **126** of RAN **120** may for example comprise 5th generation access nodes (gNB). Communications between UE **110** and access nodes **122**, **124**, **126** may be bidirectional and hence any of these entities may be configured to operate as a transmitter, and/or a receiver.

An access node may provide communication services within one or more cells, which may correspond to geographical area(s) within coverage of the access node. Communication network **100** may further comprise a core network **130**, which may comprise various network functions (NF) for establishing, configuring, and controlling data communication sessions of UE **110**. A virtual NOC **140** may be configured to perform network optimization based on various information (e.g. KPIs) gathered form RAN **120** and/or core network **130**, as will be further described below. Training of the ML model(s) may be performed by virtual NOC **140**, or in general by a training system comprising at least one apparatus configured to perform the training. Trained ML model(s) may be deployed for inference phase at any suitable network device, for example associated with virtual NOC **140**. Furthermore, a network automation system (not shown) may be configured to control operational parameters of communication network **100**, for example RAN **120**, based on detected anomalies. The network automation system may be implemented as part of virtual NOC **140**, or be communicatively coupled to virtual NOC **140**, for example to received information about detected anomalies.

Communication network **100** may be configured for example in accordance with the 4th or 5th generation (4G, 5G) digital cellular communication network, as defined by the 3rd Generation Partnership Project (3GPP). In one example, communication network **100** may operate according to 3GPP (4G) LTE (Long-Term Evolution) or 3GPP 5G NR (New Radio). It is however appreciated that example embodiments presented herein are not limited to these example networks and may be applied in any present or future wireless or wired communication networks, or combinations thereof, for example other type of cellular networks, short-range wireless networks, multicast networks, fiber networks, or the like.

FIG. **2** illustrates an example of a system architecture for training a supervised machine learning model for detecting and/or classifying anomalies. Unsupervised anomaly detector (UAD) **202** may receive KPIs from a communication network, for example RAN **120**. UAD **202** may be configured to perform anomaly detection for the KPI data. KPI data detected as anomalous may be presented to user **200** via a user interface. Alternatively, or additionally, the anomalous KPI data may be provided to a semi-supervised anomaly detector (SSAD) **204**. User **200** may label at least part of the anomalous KPI data and provide the labelled anomalies to SSAD **204**. These labelled anomalies may comprise a first subset of the anomalies detected by UAD **202**.

SSAD **204** may be trained in a semi-supervised manner, using the labelled anomalies received from user **200**. SSAD **204** may be trained for detecting and/or labelling (classifying) anomalies in KPI data. SSAD **204** may be used to detect and/or label the KPI data that has been detected by UAD **202** as anomalous. It is noted that accuracy of UAD **202** may be relatively low, for example compared to accuracy of SSAD **204** or supervised anomaly detection methods in general, thereby resulting in a large amount of KPI data to be processed by SSAD **204**. Thanks to semi-supervised training, accuracy of SSAD **204** may be higher than accuracy of UAD **202**. As noted above, SSAD **204** may be trained not only to detect anomalies but also to classify them, e.g., to generate labels for the anomalies detected by UAD **202**.

Labels generated by SSAD **204** may be presented to user **200** via the user interface to enable user **200** to verify/correct the labels generated by SSAD **204**. User **200** may also continue to label the anomalous KPI data received from UAD **202**. User **200** may provide the anomalies labelled by user **200** and/or SSAD **204** to a fully supervised anomaly detector (FSAD) **206**. Anomalies labelled by SSAD **204** may comprise a second subset of the anomalies initially detected by UAD **202**. The second subset may not include anomalies of the first subset.

FSAD **206** may be trained in a supervised manner, using the labelled anomalies received from user **200**, including the anomalies originally labelled by SSAD **204**. After training, FSAD **206** may independently detect and/or classify anomalies in KPI data, for example KPI data identified as anomalous by UAD **202** and/or SSAD **204**, or raw KPI data of RAN **120**. The output of FSAD **206**, for example anomalies detected and/or classified by FSAD **206**, may be presented to user **200**. User **200** may verify/correct labels generated by FSAD **206**. The corrected labels may be used for further training of FSAD **206**.

UAD **202**, SSAD **204**, and FSAD **206** are provided as examples of unsupervised, semi-supervised, and supervised ML models, and they may be implemented as any suitable type/structure of machine learning models, as described above.

FIG. **3** illustrates an example of a step-by-step diagram for training a supervised machine learning model for detecting and/or classifying anomalies. Operations are described for different time instants or periods t_0 to t_n. Initially no labeled data may be available. Training of the ML model(s) may be performed by a training system, for example using the architecture of FIG. **2**.

At to, a set of expert labels Exl may be initialized as an empty data set. Similarly, a training data set, Tr, and a test data set, Te, may be initialized as empty data sets. Training may be therefore initiated without training data or associated labels.

At t_1, UAD **202** may detect anomalies from the KPI data, resulting in a set of candidate anomalies, a_ul. The KPI data may be provided in any suitable format, for example as a time series of KPI measurements, structured for example as vector(s) or tensor(s) with suitable dimensions. Optionally, a first feature extraction (FE 1) may be performed for the KPI data before anomaly detection by UAD **202**. Feature extraction may include any suitable operation to pre-process the KPI data, for example to remove irregularities in the KPI data. This may be done by means of statistical operations or otherwise summarizing the KPI data. Alternatively, or additionally, a feature extractor model such as a neural network may be used. The first feature extraction may provide as output the extracted features of the KPI data. The set of candidate anomalies, a_ul, may comprise the KPI data or the extracted features detected as anomalous by UAD **202**.

Since set a_ul may include a large number of candidate anomalies detected by UAD **202**, it may be beneficial to filter set a_ul before presenting it to user **200**. An anomaly score or ranking may be therefore defined for the detected anomalies. An anomaly score or ranking may be determined for example based on how far each anomaly is from being considered as normal KPI data and not anomalous. An example of determining an anomaly score is illustrated in FIG. **4**. In case of KNN the anomaly score may comprise the distance (d_c) from closest cluster centre (x) or the distance (d) to a threshold distance d_{th} (from the cluster centre) used for determining whether the KPI data is anomalous. The distances may be determined using any suitable measure of similarity between vectors or tensors. In case of isolation forest, an anomaly score/ranking may be determined for example based on the number of partitions in the algorithm to isolate the KPI sample.

In one example, the most anomalous cases, as determined by the anomaly score/ranking, may be selected to the set of candidate anomalies, a_ul. This may be beneficial because it enables user **200** to quickly label the candidate anomalies. Alternatively, set a_ul may be determined based on uncertainty sampling of the anomalies detected by UAD **202**, or by any other suitable active learning type of label querying from user **200**. In uncertainty sampling, labels may be queried from user **200** for anomalies, for which the current prediction is most uncertain. For example, set a_ul may be selected to include borderline anomalous cases. This way user **200** may be presented cases which may be more difficult to classify. The most anomalous data may be directly provided to SSAD **204**, because it may be more likely that SSAD **204** is able to correctly label the most anomalous data. This may speed up label generation, because input form user **200** may not be needed for many of the anomalies detected by UAD **202**.

Referring back to FIG. **3**, set a_ul may be presented to user **200** via a user interface. User **200** may perform expert labelling for at least part of set a_ul, thereby generating a set of labelled anomalies, L1. Labels of set L1 may be received via the user interface and be associated with respective anomalous data. The set of expert labels, Exl, may be updated with the labelled anomalies (Exl=Exl+L1). The training data set, Tr, may be updated with the received set of labelled anomalies (Tr=Tr+L1).

FSAD **206** may be then trained based on the training data set, Tr. However, a second feature extraction (FE 2) may be performed before inputting the training data set, Tr, to FSAD **206**. The second feature extraction may be however different from the first feature extraction, for example to account for different input dimensions of SSAD **204** and FSAD **206**.

At t_2, UAD **202** may perform anomaly detection similar to t_1, to output a set of candidate anomalies, a_u2. Set a_u2 may be provided to SSAD **204**, which may be trained in a semi-supervised manner using the set of labelled data, L1, obtained at t_1. SSAD **204** may perform anomaly detection and at least partially also labelling of set a_u2 to obtain another set of anomalies, a_ss2. At least part of set a_ss2 may be presented to user **200**. For example, an indication of the labels generated by SSAD **204** may be output via the user interface. User **200** may validate labelling of SSAD **204**, update any incorrect labels, or label still unlabelled anomalies of set a_ss2, to obtain another set of labels, L2. Validation of the labelling by SSAD **204** may be received from user **200** via the user interface. Labels of set a_ss2 may be updated based on user input received from user **200** via the user interface. User **200** may provide an indication of the incorrect labelling by SSAD **204** via the user interface. In response to receiving the indication of incorrect labelling, the training system may determine to re-train SSAD **204**. Training of FSAD **206** with labels generated by SSAD **204** may be suspended, for example until re-training of SSAD **204** is completed. This improves training by enabling user **200** to control label generation by SSAD **204**. For example, erroneous labels generated too early with insufficiently performing SSAD **204** may be avoided.

The set of expert labels may be updated as Exl=Exl+L2. The training data set may be updated as Tr=Tr+L2. Training of FSAD **206** may continue with the updated training data set, Tr. The output of SSAD **204** and label set L2 may be added to the test data set: Te=a_ss2+L2.

Accuracy of FSAD **206** may be tested with the test data set, Te. For example, performance of SSAD **204** and FSAD **206** may be evaluated with the test data set, using the anomalous data of Te as input to both SSAD **204** and FSAD **206** and using the associated labels as ground truth data. Performance of SSAD **204** and FSAD **206** may be compared, for example based on the number of correctly detected/classified anomalies. If performance of FSAD **206** exceeds performance of SSAD **204**, SSAD **204** and/or UAD **202** may be disabled. Disabling a machine learning model, such as for example UAD **202** or SSAD **204**, may comprise terminating execution of the model. Anomaly detection may be subsequently performed by FSAD **206** without UAD **202** and/or SSAD **204**. UAD **202** and SSAD **204** may be advantageously used for training FSAD **206**. However, UAD **202** and/or SSAD **204** may be disabled to save power and computing resources, once FSAD **206** has been sufficiently trained.

It is also possible to assess accuracy of FSAD **206** without comparing its performance to SSAD **204**. For example, (re)-training of FSAD **206** may be determined to be completed, if the training no longer improves performance of FSAD **206**, for example in terms of the number of correctly detected/classified anomalies in the test data set, Te. UAD **202** and/or SSAD **204** may be then disabled, as described above. As a result of the operations at t_1 and t_2, training data set Te may include anomalies labelled by user **200** (cf. first subset of anomalies) and SSAD **204** (cf. second subset of anomalies).

In the example of FIG. **3**, the training system may determine at t_2 that accuracy of FSAD **206** is not yet sufficient. Hence, training and testing of FSAD **206** may continue at t_3 similar to t_2, by detecting more anomalies with UAD **202**, detecting/labelling more anomalies with SSAD **204** or by user **200**, and further training FSAD with the expanded set of labelled training data Tr. In general, training may be performed for n steps t_1 to t_n. The gradually increasing amount of labelled training data may progressively improve performance of FSAD **206**. FSAD **206** may be thus re-trained, in response to receiving further labels for the anomalies from user **200** and/or SSAD **204**. Once accuracy of FSAD **206** is good enough, UAD **202** and SSAD **204** may be disabled, as described above. It is however possible to keep UAD **202** enabled while performing inference with FSAD **206**, in order to reduce the amount of data to be processed by FSAD **206**.

Performance of FSAD **206** may be monitored during inference phase, for example after disabling UAD **202** and SSAD **204**. If performance of FSAD **206** with the test data set, Te, is detected to degrade, UAD **202** and/or SSAD **204** may be re-enabled to resume re-training of FSAD **206**. Performance of FSAD **206** may be for example compared to a predetermined level of degradation, provided for example as a threshold for degradation in the number of correctly detected/classified anomalies in the test data set, Te. UAD **202** and/or SSAD **204** may be re-enabled if performance of SSAD has degraded more than the predetermined limit for degradation. The predetermined limit may be preconfigured at a device configured to perform the training of FSAD **206**, for example stored at its memory. Re-enabling a ML model may comprise resuming execution of the ML model. UAD **202** and SSAD **204** may therefore start detecting and labelling more anomalies for training FSAD **206**.

Whenever using FSAD **206** for inference, that is, detecting and/or classifying anomaly(ies) in KPI data, an output may be provided by the network device comprising FSAD **206** in order to inform a human operator about the detected anomaly and optionally its classification. The human operator may then determine necessary actions for recovering from the anomaly(ies). For example, the human operator may adjust parameter(s) of communication network **100**, for example RAN **120**. The indication of the detected/classified anomaly may for example include a visual indication (e.g. on a display), a sound, or other alert. Alternatively, or additionally, the output may be provided to the network automation system such as virtual NOC **140**, for example as an alert signal, which may cause the network automation system to perform, or cause performance of, corrective action(s) in order to recover from the anomaly. Corrective action(s) may depend on the class of anomaly in question. A corrective action may comprise adjustment of parameter(s) of communication network **100**.

Anomalies detected/classified by FSAD **206** may be validated by user **200** during inference phase. For example, user **200** may provide validation of an anomaly detected/classified by FSAD **206** via the user interface. User **200** may also provide to the training system, via the user interface, an indication of incorrect labelling by FSAD **206**. Based on the feedback from user **200**, for example the indication of incorrect labelling or a ratio between validly and incorrectly labelled anomalies, as indicated by user **200**, the training system may determine to re-train FSAD **206**. This improves anomaly detection by FSAD **206** by enabling further training based on feedback during the inference phase.

FIG. **5** illustrates an example embodiment of an apparatus, for example a server, configured to perform one or more example embodiments. Apparatus **500** may be for example used to implement virtual NOC **140**, a training system, and/or a network automation system. Apparatus **500** may comprise at least one processor **502**. The at least one processor **502** may comprise, for example, one or more of various processing devices or processor circuitry, such as for example a co-processor, a microprocessor, a controller, a digital signal processor (DSP), a processing circuitry with or without an accompanying DSP, or various other processing devices including integrated circuits such as, for example, an application specific integrated circuit (ASIC), a field programmable gate array (FPGA), a microcontroller unit (MCU), a hardware accelerator, a special-purpose computer chip, or the like.

Apparatus **500** may further comprise at least one memory **504**. The at least one memory **504** may be configured to store, for example, computer program code or the like, for example operating system software and application software. The at least one memory **504** may comprise one or more volatile memory devices, one or more non-volatile memory devices, and/or a combination thereof. For example, the at least one memory **504** may be embodied as magnetic storage devices (such as hard disk drives, floppy disks, magnetic tapes, etc.), optical magnetic storage devices, or semiconductor memories (such as mask ROM, PROM (programmable ROM), EPROM (erasable PROM), flash ROM, RAM (random access memory), etc.).

Apparatus **500** may further comprise a communication interface **508** configured to enable apparatus **500** to transmit and/or receive information to/from other devices, functions, or entities, for example network functions of core network **130** or another (remote) device operated by user **200**. Communication interface **510** may be for example used to transmit indication(s) of detected and/or classified anomalies to the other device, for example for labelling by user **200**, and/or to receive labels for the presented anomalies from the other device.

Apparatus **500** may further comprise a user interface **510** comprising an input device and/or an output device. The input device may take various forms such a keyboard, a mouse, a touch screen, or one or more embedded control buttons. The output device may for example comprise a display, a speaker, a vibration motor, or the like. User interface **510** may be for example used to present detected and/or classified anomalies to user **200**, and/or to receive labels for the presented anomalies.

When apparatus **500** is configured to implement some functionality, some component and/or components of apparatus **500**, such as for example the at least one processor **502** and/or the at least one memory **504**, may be configured to implement this functionality. Furthermore, when the at least one processor **502** is configured to implement some functionality, this functionality may be implemented using (computer) program code **506** comprised, for example, in the at least one memory **504**.

The functionality described herein may be performed, at least in part, by one or more computer program product components such as for example software components. According to an embodiment, the apparatus comprises a processor or processor circuitry, such as for example a microcontroller, configured by the program code when executed to execute the embodiments of the operations and functionality described. A computer program or a computer program product may therefore comprise instructions for causing, when executed, apparatus **500** to perform the method(s) described herein. Alternatively, or in addition, the functionality described herein can be performed, at least in part, by one or more hardware logic components. For example, and without limitation, illustrative types of hardware logic components that can be used include Field-programmable Gate Arrays (FPGAs), application-specific Integrated Circuits (ASICs), application-specific Standard Products (ASSPs), System-on-a-chip systems (SOCs), Complex Programmable Logic Devices (CPLDs), Graphics Processing Units (GPUs).

A ML model, for example a neural network, may be implemented by software and/or hardware. For example, parameters (e.g. weights) of a neural network may be stored at the at least on memory **504** and structured such that flow of input data through layers of the neural network is implemented, when executing associated program instructions.

In general, apparatus **500** comprises means for performing at least one method described herein. In one example, the means comprises the at least one processor **502**, the at least one memory **504** including program code **506** configured to, when executed by the at least one processor, cause the apparatus **500** to perform the method. In general, computer program instructions may be executed on means providing generic processing functions. Such means may be embedded for example in a personal computer, a smart phone, a network device, or the like. The method(s) may be thus computer-implemented, for example based on algorithm(s) executable by the generic processing functions, an example of which is the at least one processor **502**.

Apparatus **500** may comprise a computing device such as for example a server, a network device, a network function device, or the like. Although apparatus **500** is illustrated as a single device it is appreciated that, wherever applicable, functions of apparatus **500** may be distributed to a plurality of devices, for example to implement example embodiments as a cloud computing service.

FIG. **6** illustrates an example of a computer-implemented method for training a machine learning model for detecting and/or classifying anomalies in performance indicator data of a communication network.

At **601**, the method may comprise detecting, by an unsupervised machine learning model, a plurality of anomalies in performance indicator data of a communication network.

At **602**, the method may comprise receiving labels for a first subset of the plurality of anomalies and labelling the first subset of the plurality of anomalies with the labels.

At **603**, the method may comprise training, based on the labelled first subset of the plurality of anomalies, a semi-supervised machine learning model for labelling anomalies.

At **604**, the method may comprise labelling, by the semi-supervised machine learning model, a second subset of the plurality of anomalies.

At **605**, the method may comprise training, based on the labelled first and second subsets of the plurality of anomalies, a supervised machine learning model for detecting and/or classifying anomalies in the performance indicator data.

Further features of the method directly result for example from the functionalities of virtual NOC **140**, the training system, and/or the network automation system as described throughout the specification and in the appended claims, and are therefore not repeated here. Different variations of the method may be also applied, as described in connection with the various example embodiments.

An apparatus, such as for example a server or a network device may be configured to implement one or more network functions or entities, may be configured to perform or cause performance of any aspect of the method(s) described herein. Further, a computer program, a computer program product, or a (non-transitory) computer readable medium may comprise instructions for causing, when executed, an apparatus to perform any aspect of the method(s) described herein. Further, an apparatus may comprise means for performing any aspect of the method(s) described herein. According to an example embodiment, the means comprises at least one processor, and memory including program code, the at least one processor, and program code configured to, when executed by the at least one processor, cause performance of any aspect of the method(s). An apparatus, a computer program (product), or a (non-transitory) computer-readable medium may comprise, e.g. stored therein, a machine learning model obtainable by the method(s).

Any range or device value given herein may be extended or altered without losing the effect sought. Also, any embodiment may be combined with another embodiment unless explicitly disallowed.

Although the subject matter has been described in language specific to structural features and/or acts, it is to be understood that the subject matter defined in the appended claims is not necessarily limited to the specific features or acts described above. Rather, the specific features and acts described above are disclosed as examples of implementing the claims and other equivalent features and acts are intended to be within the scope of the claims.

It will be understood that the benefits and advantages described above may relate to one embodiment or may relate to several embodiments. The embodiments are not limited to those that solve any or all of the stated problems or those that have any or all of the stated benefits and advantages. It will further be understood that reference to 'an' item may refer to one or more of those items.

The steps or operations of the methods described herein may be carried out in any suitable order, or simultaneously where appropriate. Additionally, individual blocks may be deleted from any of the methods without departing from the scope of the subject matter described herein. Aspects of any of the example embodiments described above may be combined with aspects of any of the other example embodiments described to form further example embodiments without losing the effect sought.

The term 'comprising' is used herein to mean including the method, blocks, or elements identified, but that such blocks or elements do not comprise an exclusive list and a method or apparatus may contain additional blocks or elements.

Although subjects may be referred to as 'first' or 'second' subjects, this does not necessarily indicate any order or importance of the subjects. Instead, such attributes may be used solely for the purpose of making a difference between subjects.

It will be understood that the above description is given by way of example only and that various modifications may be made by those skilled in the art. The above specification, examples and data provide a complete description of the structure and use of exemplary embodiments. Although various embodiments have been described above with a certain degree of particularity, or with reference to one or more individual embodiments, those skilled in the art could make numerous alterations to the disclosed embodiments without departing from scope of this specification.

The invention claimed is:

1. A computer-implemented method, comprising:

detecting, by an unsupervised machine learning model, a plurality of anomalies in performance indicator data of a communication network;

receiving labels for a first subset of the plurality of anomalies and labelling the first subset of the plurality of anomalies with the labels;

training, based on the labelled first subset of the plurality of anomalies, a semi-supervised machine learning model for labelling anomalies;

labelling, by the semi-supervised machine learning model, a second subset of the plurality of anomalies;

training, based on the labelled first and second subsets of the plurality of anomalies, a supervised machine learning model for detecting and/or classifying anomalies in the performance indicator data; and

disabling the unsupervised machine learning model and/or the semi-supervised machine learning model, in response to determining that performance of the supervised machine learning model exceeds performance of the semi-supervised machine learning model.

2. The method according to claim **1**, further comprising:

performing a first feature extraction to extract features from the performance indicator data; and

detecting, by the unsupervised machine learning model, the plurality of anomalies in the performance indicator data based on the extracted features of the performance indicator data.

3. The method according to claim **1**, further comprising:

determining an anomaly score or ranking for the plurality of anomalies; and

determining the first subset of the plurality of anomalies based on the anomaly score or ranking.

4. The method according to claim **1**, further comprising:

determining the first subset of the plurality of anomalies based on uncertainty sampling of the plurality of anomalies.

5. The method according to claim **1**, further comprising:

receiving the labels for the first subset of the plurality of anomalies via a user interface.

6. The method according to claim **5**, further comprising:

outputting an indication of the labelling of the second subset of the plurality of anomalies via the user interface;

receiving validation of the labelling of the second subset of the plurality of anomalies via the user interface, or

updating at least one label of the second subset of the plurality of anomalies based on user input received via the user interface.

7. The method according to claim **1**, further comprising:

re-training the supervised machine learning model, in response to receiving further labels for the plurality of anomalies via a user interface and/or in response to labelling further anomalies of the plurality of anomalies by the semi-supervised machine learning model.

8. The method according to claim **7**, further comprising:

disabling the unsupervised machine learning model and the semi-supervised machine learning model further in response to determining that the re-training no longer improves the performance of the supervised machine learning model, wherein the performance of the supervised machine learning model and/or the performance of the semi-supervised machine learning model is evaluated based on a test dataset comprising the first and second subsets of the plurality of anomalies.

9. The method according to claim **8**, further comprising:

re-enabling the unsupervised machine learning model and/or the semi-supervised machine learning model and resuming re-training of the supervised machine learning model, in response to detecting a predetermined degradation in the performance of the supervised machine learning model, when evaluated with the test dataset.

10. The method according to claim **1**, further comprising:

detecting and/or classifying, by the supervised machine learning model, at least one anomaly in the performance indicator data.

11. The method according to claim **10**, further comprising:

outputting an indication of the at least one anomaly in the performance indicator data.

12. The method according to claim **11**, further comprising:

outputting the indication of the at least one anomaly via a user interface; and

receiving validation of the at least one anomaly via the user interface, or

re-training the supervised machine learning model, in response to receiving an indication of incorrect detection and/or classification of the at least one anomaly via the user interface.

13. The method according to claim **10**, further comprising:

adjusting at least one parameter of the communication network, in response to detecting and/or classifying the at least one anomaly in the performance indicator data.

14. A non-transitory computer-readable medium comprising a computer-implemented supervised machine learning model obtainable by the method of claim **1**.

15. A non-transitory computer-readable medium comprising program code configured to, when executed by a processor, cause an apparatus at least to perform the method according to claim **1**.

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