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(54) **DEEP LEARNING DEVICE AND SYSTEM INCLUDING THE SAME**

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G06N 3/042 (2023.01)

(52) **U.S. Cl.**
CPC *G06N 3/042* (2023.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

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(57) **ABSTRACT**

A deep learning device and system including the same is provided. The deep learning device comprising processing circuitry configured to determine whether a received image is abnormal using an anomaly detection model; merge at least some vectors extracted from the anomaly detection model; input, to a probability approximation model, principal components generated by a principal component analysis (PCA) to detect whether out of distribution (OOD) occurs in data of the received image; store a result of the determinations; and extract at least some the data in which the OOD occurs, as target labeling, using a target labeling extraction model when a rate of the data in which the OOD occurs is greater than or equal to a threshold value, wherein the anomaly detection model determines whether the received image is abnormal using the target labeling.

20 Claims, 14 Drawing Sheets

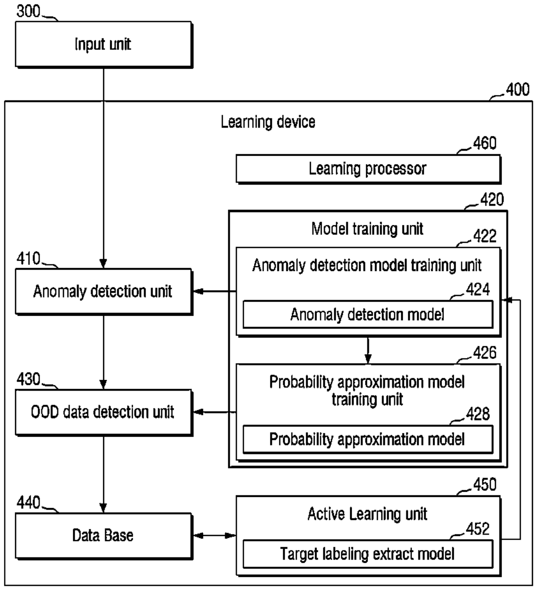

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FIG. 1

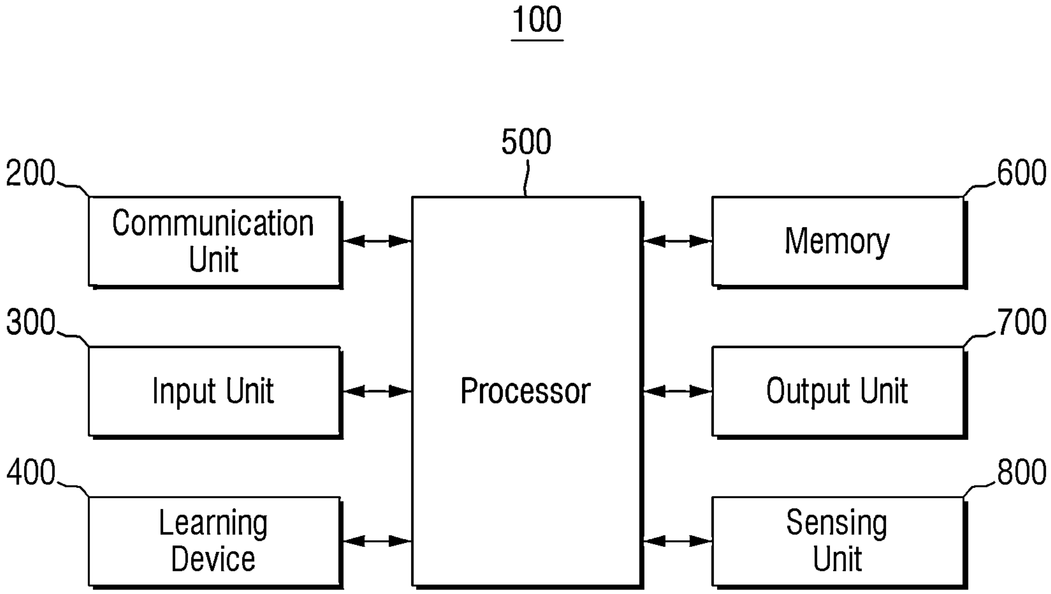

100
500
200
Communication Unit
300
Input Unit
400
Learning Device
Processor
600
Memory
700
Output Unit
800
Sensing Unit

FIG. 2

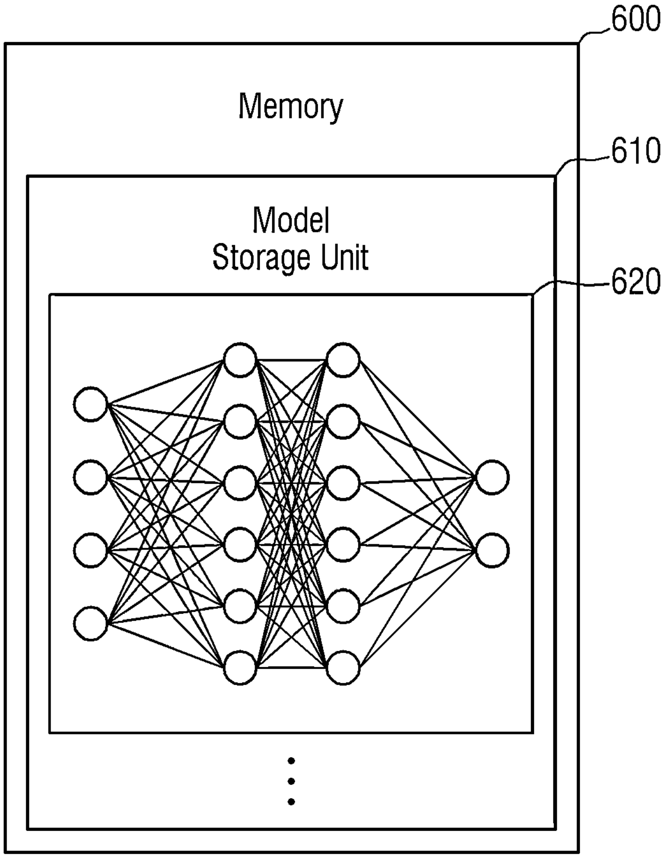


FIG. 3

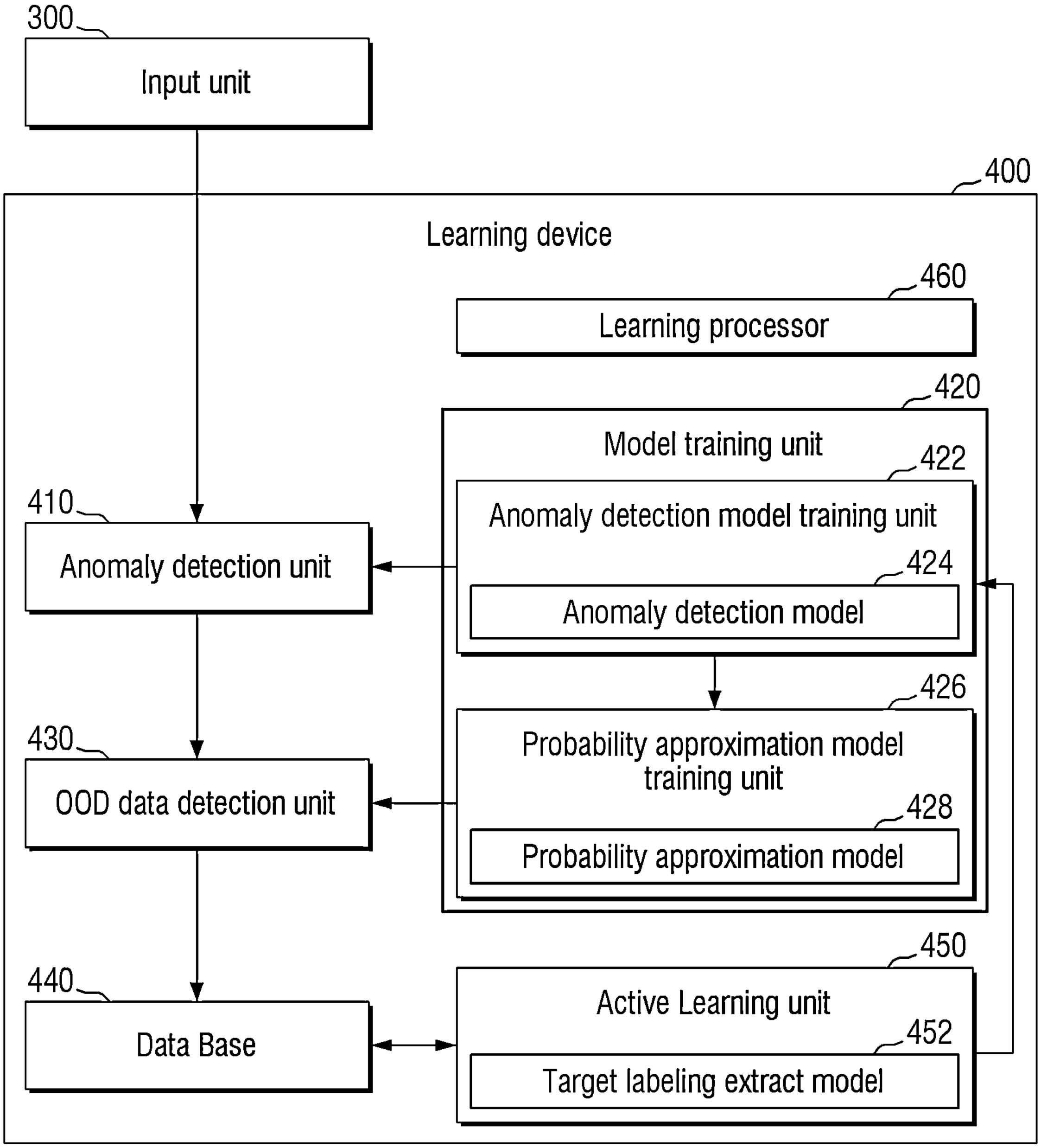

300
Input unit
400
Learning device
460
Learning processor
420
Model training unit
422
Anomaly detection model training unit
424
Anomaly detection model
410
Anomaly detection unit
426
Probability approximation model training unit
428
Probability approximation model
430
OOD data detection unit
450
Active Learning unit
452
Target labeling extract model
440
Data Base

FIG. 4

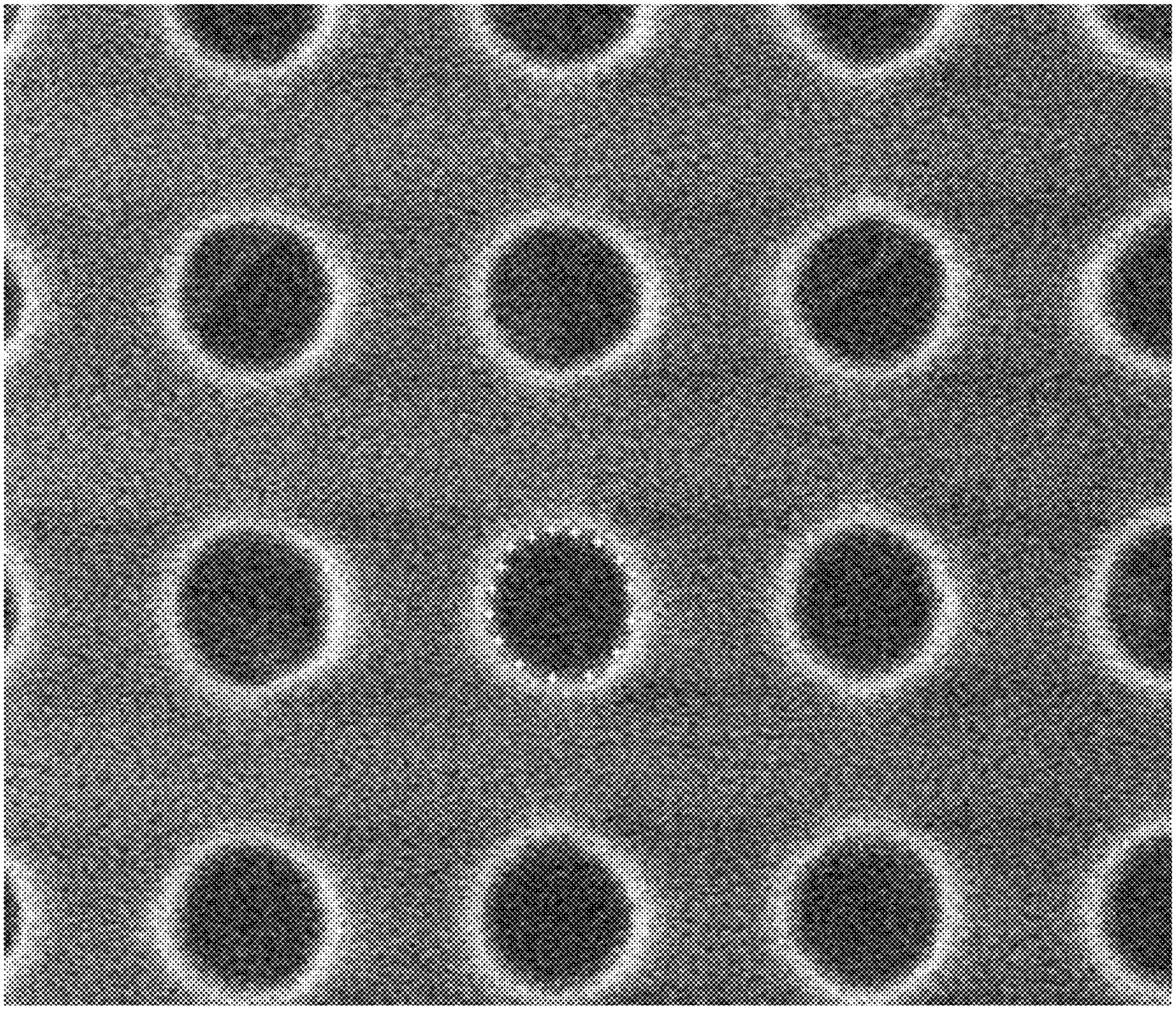


FIG. 5

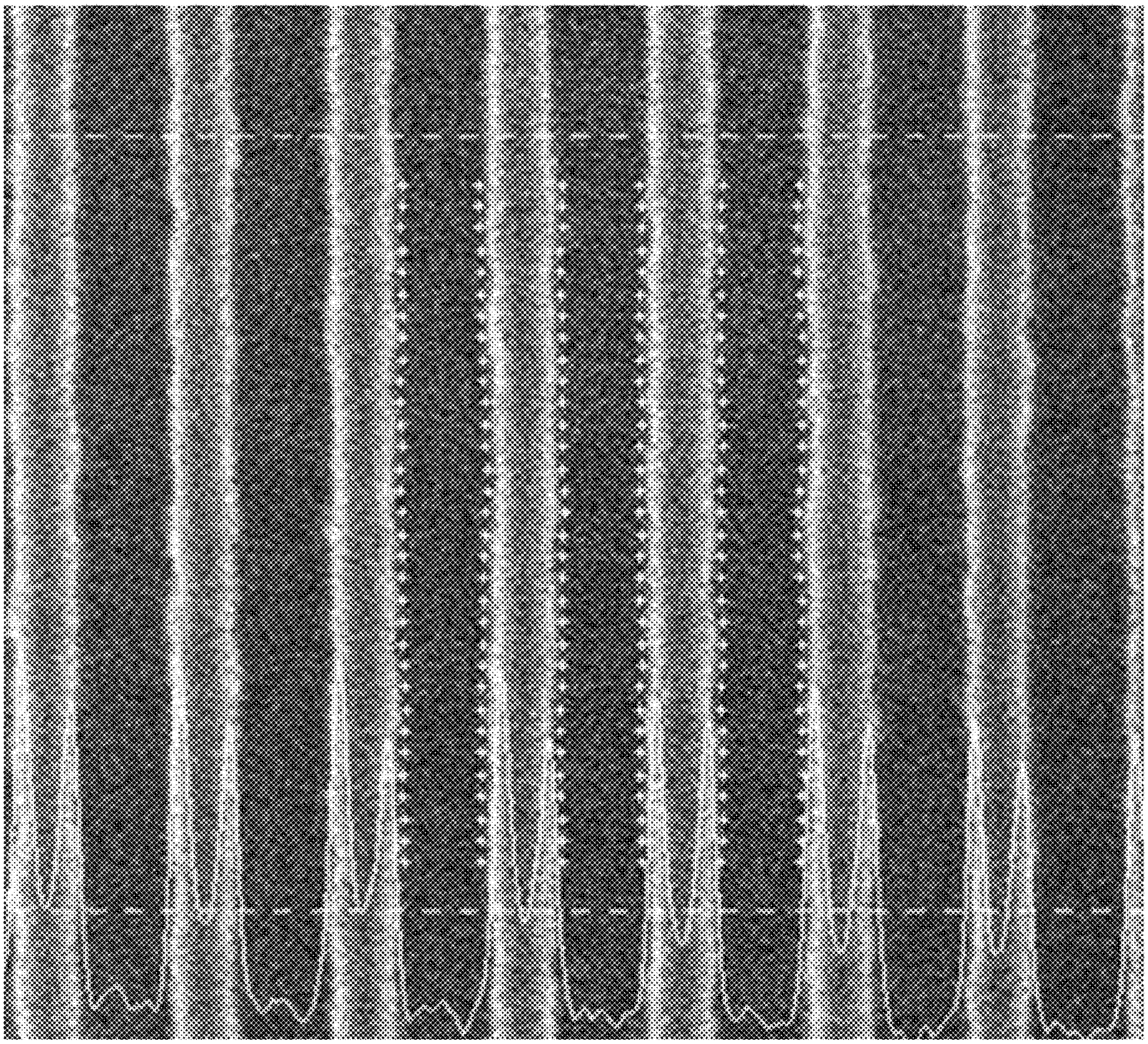


FIG. 6

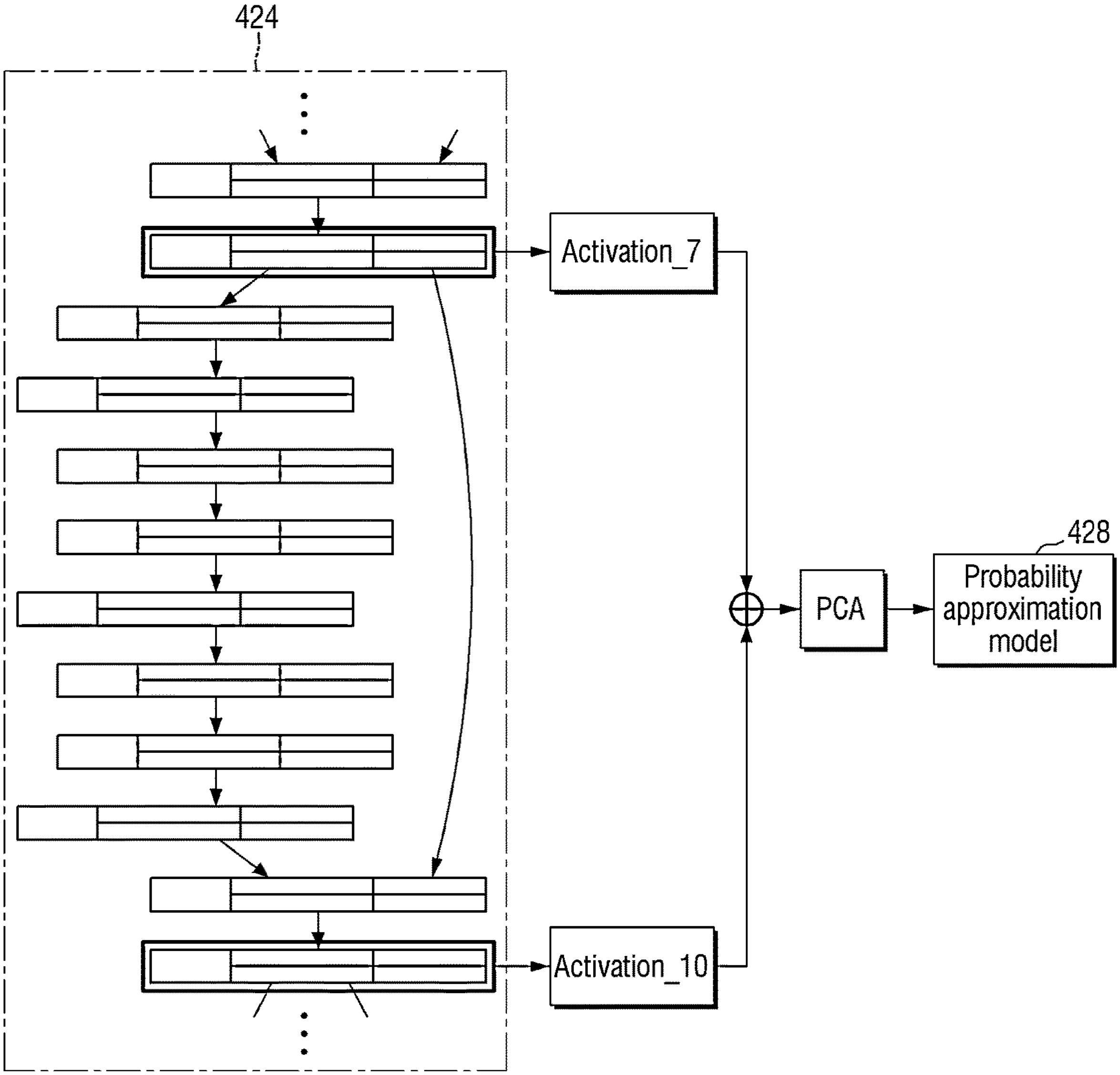
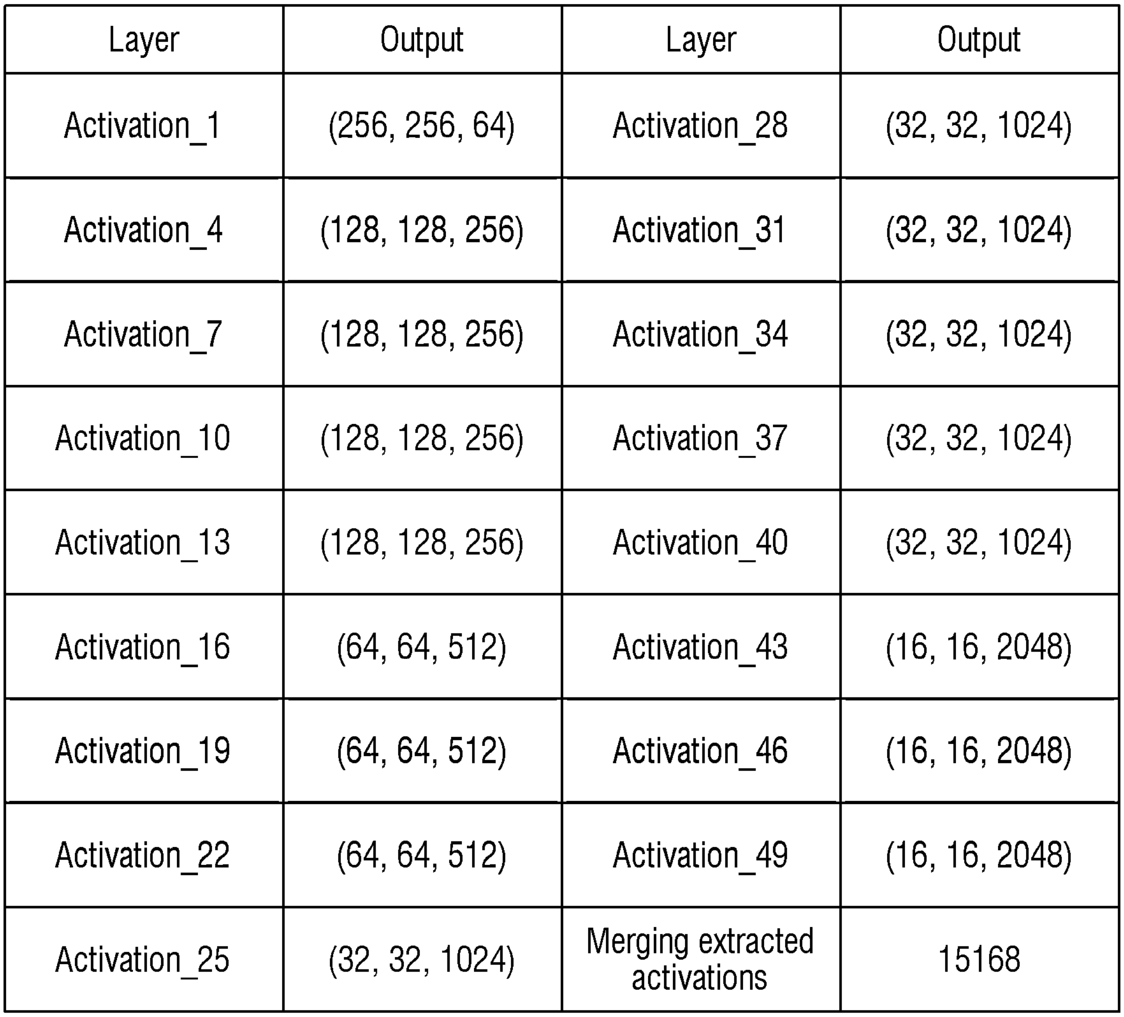

424
Activation_7
Activation_10
PCA
428
Probability approximation model

FIG. 7



Layer	Output	Layer	Output
Activation_1	(256, 256, 64)	Activation_28	(32, 32, 1024)
Activation_4	(128, 128, 256)	Activation_31	(32, 32, 1024)
Activation_7	(128, 128, 256)	Activation_34	(32, 32, 1024)
Activation_10	(128, 128, 256)	Activation_37	(32, 32, 1024)
Activation_13	(128, 128, 256)	Activation_40	(32, 32, 1024)
Activation_16	(64, 64, 512)	Activation_43	(16, 16, 2048)
Activation_19	(64, 64, 512)	Activation_46	(16, 16, 2048)
Activation_22	(64, 64, 512)	Activation_49	(16, 16, 2048)
Activation_25	(32, 32, 1024)	Merging extracted activations	15168

FIG. 8

PCA dimensions

GMM components

	10	11	12	13	14	15	16	17	18	19	20
10											
20											
30											
40											
50											
60											
70											
80	▨										
90											
100											
110											
120											
130											
140											
150											
160											
170											
180											
190											
200											
210											
220											
230											
240											

FIG. 9

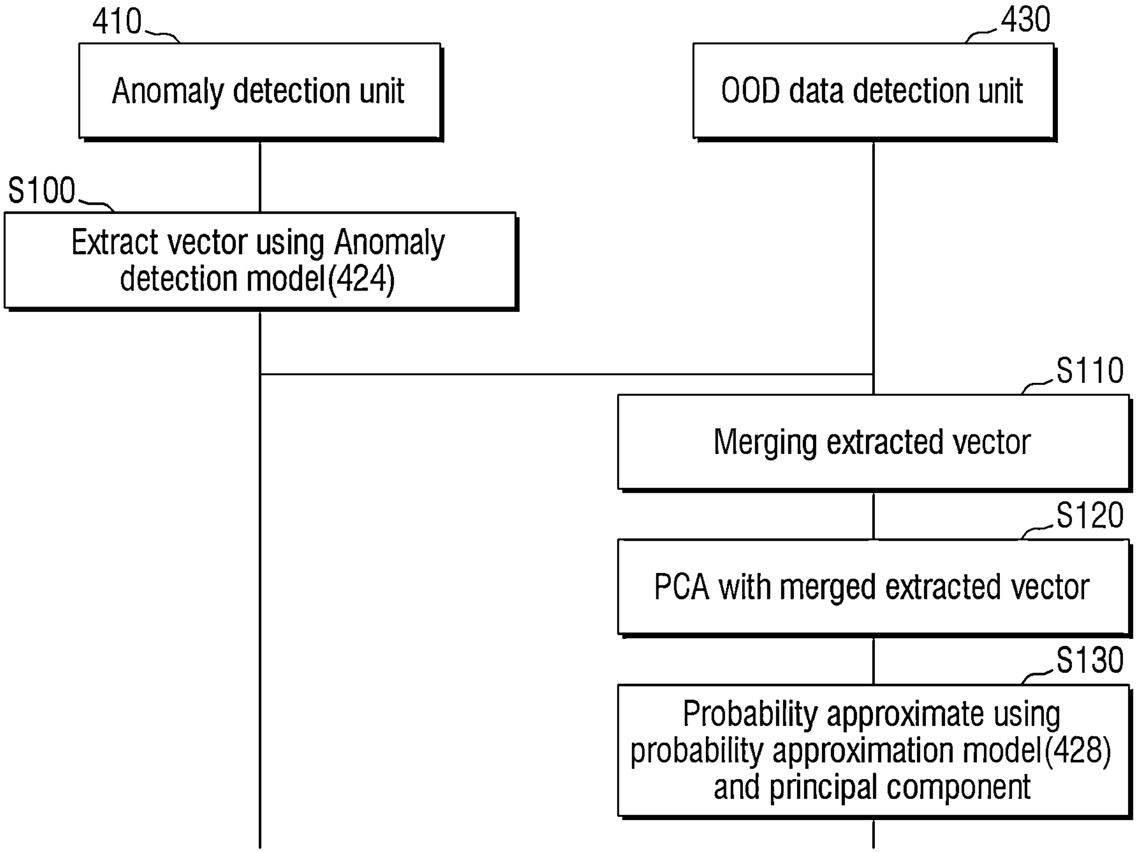

410
Anomaly detection unit
430
OOD data detection unit
S100
Extract vector using Anomaly detection model(424)
S110
Merging extracted vector
S120
PCA with merged extracted vector
S130
Probability approximate using probability approximation model(428) and principal component

FIG. 10

	Determination of Anomaly	Probability value	Determination of OOD	likelihood
1	Y	79.1416		
2	N	79.5601		
3	⋮	⋮		
4				
5				
6				
7				
8			Y	
9			Y	
10	⋮	⋮		
11				
12				
13				
14				
15				
⋮				
X				

FIG. 11

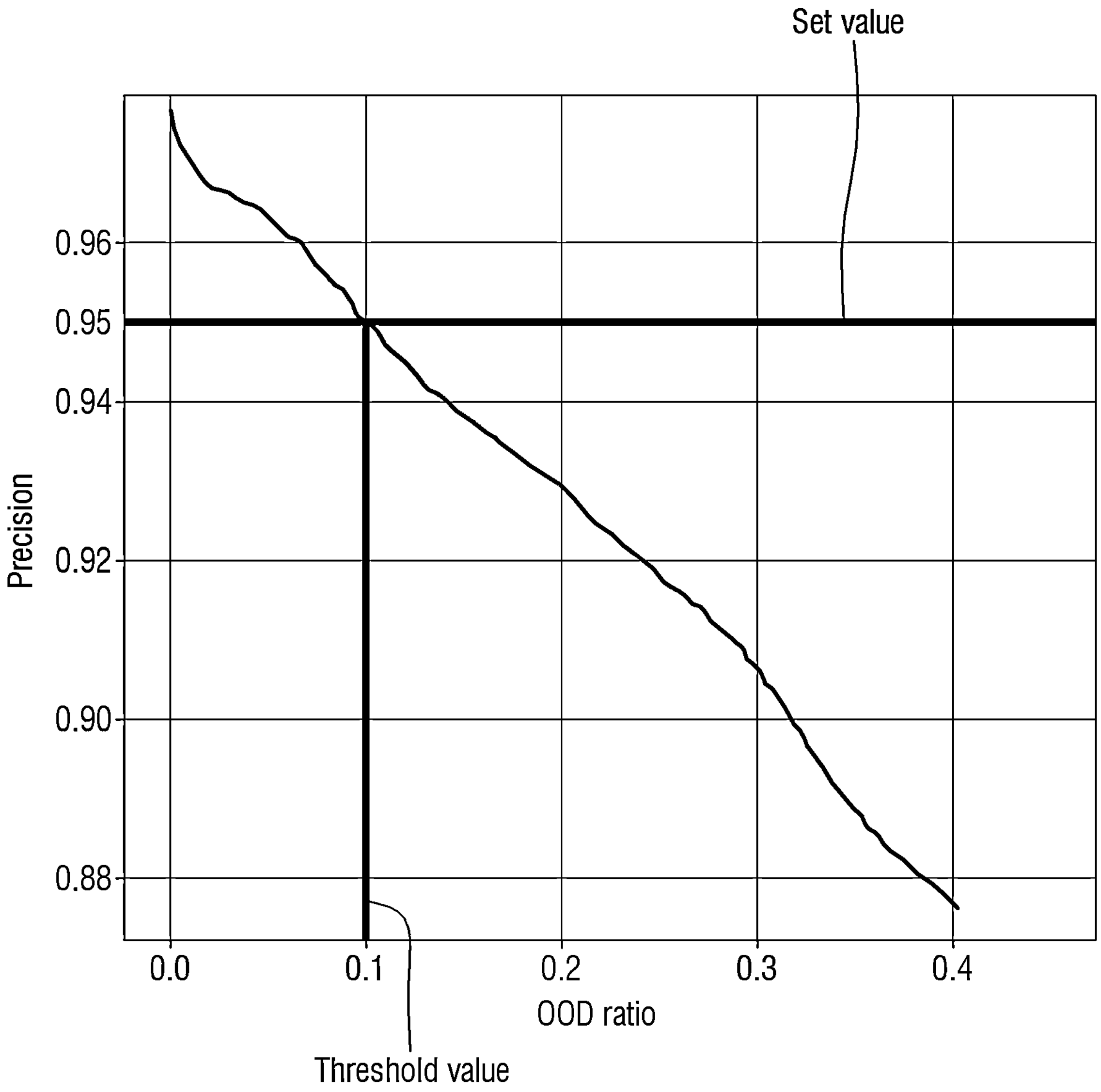

Set value
0.96
0.95
0.94
0.92
0.90
0.88
Precision
0.0
0.1
0.2
0.3
0.4
OOD ratio
Threshold value

FIG. 12

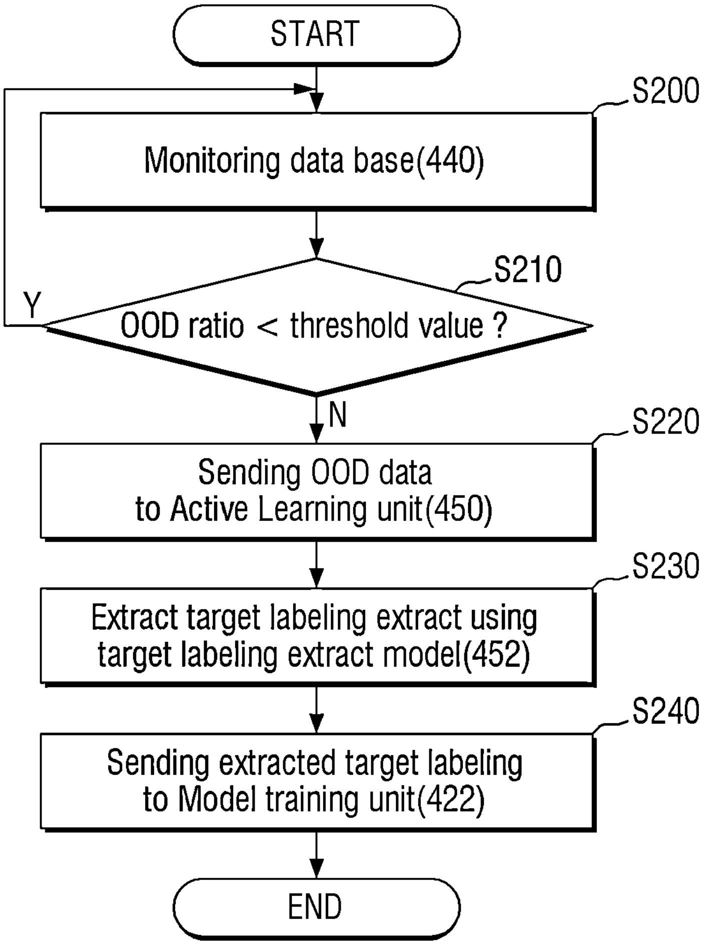

START
S200
Monitoring data base(440)
S210
OOD ratio < threshold value ?
Y
N
S220
Sending OOD data
to Active Learning unit(450)
S230
Extract target labeling extract using
target labeling extract model(452)
S240
Sending extracted target labeling
to Model training unit(422)
END

FIG. 13

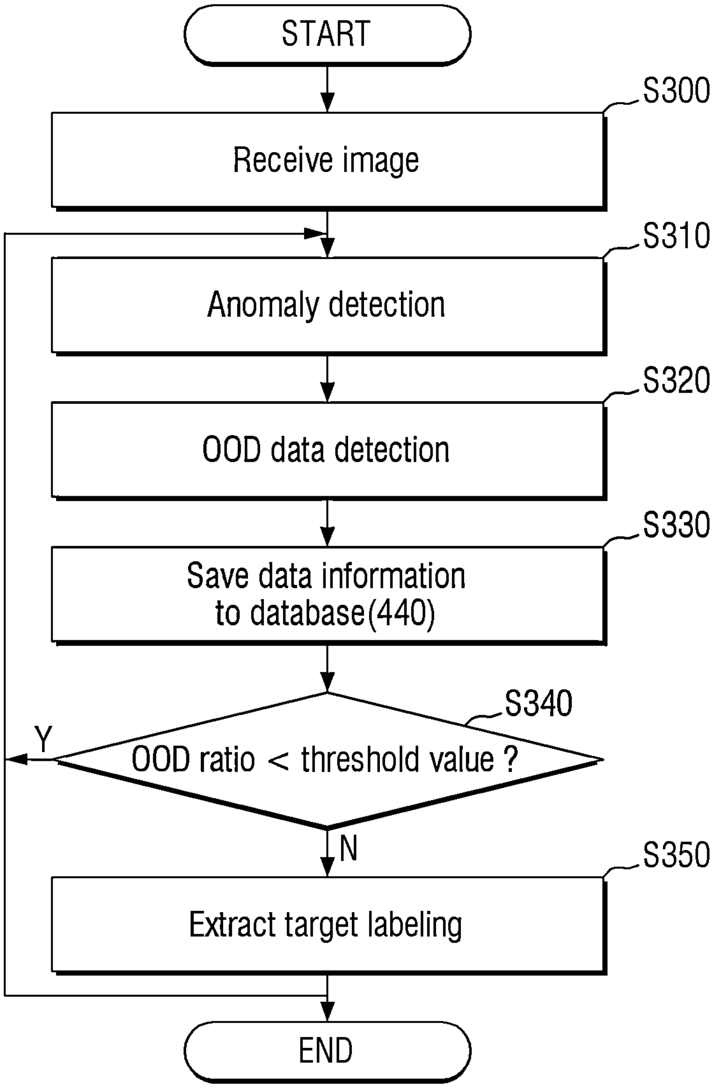
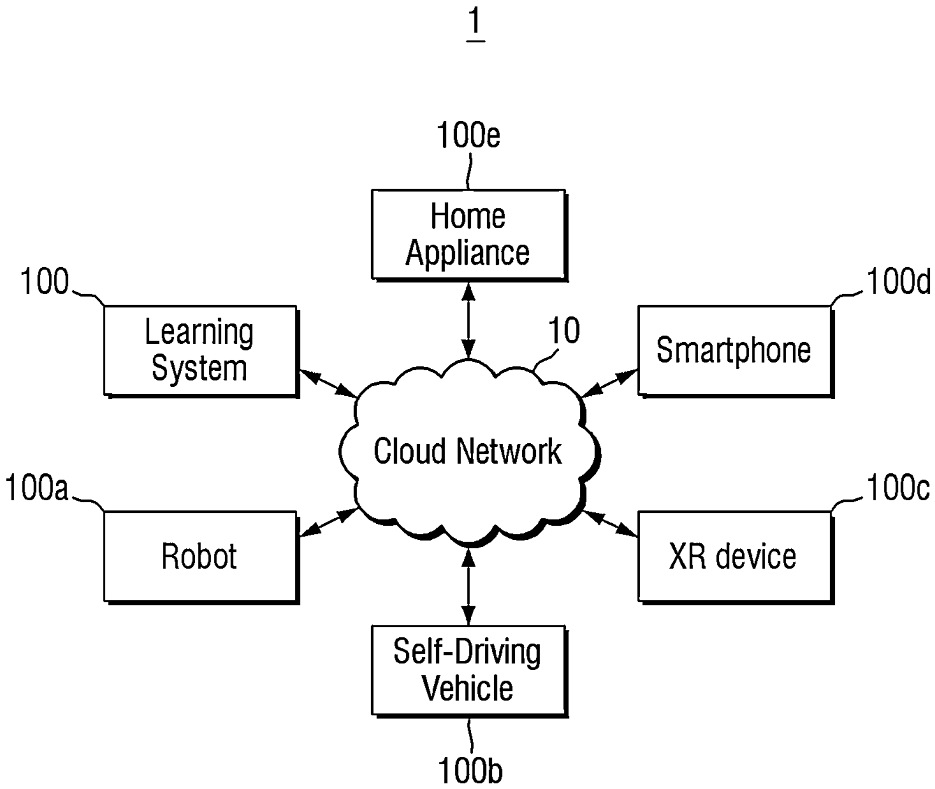

START
S300
Receive image
S310
Anomaly detection
S320
OOD data detection
S330
Save data information
to database(440)
S340
Y
OOD ratio < threshold value ?
N
S350
Extract target labeling
END

FIG. 14


1
100e
Home Appliance
100
Learning System
10
100d
Smartphone
Cloud Network
100a
Robot
100c
XR device
Self-Driving Vehicle
100b

DEEP LEARNING DEVICE AND SYSTEM INCLUDING THE SAME

CROSS-REFERENCE TO RELATED APPLICATIONS

This application claims priority from Korean Patent Application No. 10-2021-0065586 filed on May 21, 2021 in the Korean Intellectual Property Office and from Korean Patent Application No. 10-2021-0092932 filed on Jul. 15, 2021 in the Korean Intellectual Property Office, the disclosure of which is incorporated herein by reference in its entirety.

BACKGROUND

1. Technical Field

The present disclosure relates to a deep learning device and a system including the same.

2. Description of the Related Art

Recently, in semiconductor device manufacturing processes, an information technology (IT) system, big data, and/or artificial intelligence technology have been used to improve the quality and productivity of semiconductor devices and the quality of semiconductor devices have been predicted and/or analyzed using machine learning and/or deep learning for, e.g., quality control. For example, an image (e.g., a scanning electron microscopy (SEM) image) of a semiconductor device may be learned through deep learning and whether the semiconductor device is defective may be determined using a trained model.

In this case, the performance of deep learning may be degraded due to images that are out of distribution (OOD) of the learned images. Therefore, there is a growing need to detect OOD data and efficiently restore the performance of deep learning degraded due to the OOD data.

SUMMARY

Aspects of the present disclosure provide a deep learning device for efficiently detecting out-of-distribution (OOD) data to maintain the performance thereof.

Aspects of the present disclosure also provide a system including a deep learning device for efficiently detecting OOD data to maintain the performance thereof.

It should be noted that objects of the present invention are not limited to the above-described objects, and other objects of the present invention will be apparent to those skilled in the art from the following descriptions.

According to an aspect of the present inventive concepts, there is provided a deep learning device comprising processing circuitry configured to determine whether a received image is abnormal using an anomaly detection model, merge at least some vectors extracted from the anomaly detection model, perform a principal component analysis (PCA) on a result of the merging the at least some vectors, input, to a probability approximation model, principal components generated by the PCA to detect whether out of distribution (OOD) occurs in data of the received image, store, in a database, a result of the determination of whether the received image is abnormal and a result of determining whether the OOD occurs, and extract at least some the data in which the OOD occurs, as target labeling, using a target labeling extraction model when a rate of the data in which the OOD occurs is greater than or equal to a threshold value, wherein the anomaly detection model determines whether the received image is abnormal using the target labeling.

According to an aspect of the present inventive concepts, there is provided a deep learning system comprising an input unit configured to receive an image; a processor configured to control the input unit; and a deep learning device connected to the processor and configured to receive the image from the input unit, the deep learning device including processing circuitry and a database, the processing circuitry configured to determine whether an image received from the input unit is abnormal using an anomaly detection model, merge at least some vectors extracted from the anomaly detection model, perform a principle component analysis (PCA) on a result of the merging the at least some vectors, input, to a probability approximation model, principal components generated by the PCA to detect whether out of distribution (OOD) occurs in data of the image, store a result of the determination of whether the image is abnormal and a result of determining whether the OOD occurs, and extract at least some the data in which the OOD occurs, as target labeling, using a target labeling extraction model when a rate of the data in which the OOD occurs is greater than or equal to a threshold value, and the database is configured to store the result of the determination of whether the image is abnormal and the result of determining whether the OOD occurs, and wherein the anomaly detection model determines whether the image is abnormal using the target labeling.

According to an aspect of the present inventive concepts, there is provided a deep learning system comprising an input unit configured to receive an image; a processor configured to control the input unit; and a deep learning device connected to the processor and configured to receive the image from the input unit, the deep learning device including processing circuitry configured to determine whether an image received from the input unit is abnormal using an anomaly detection model, merge at least some vectors extracted from the anomaly detection model, perform a principle component analysis (PCA) on a result of the merging the at least some vectors, input, to a probability approximation model, principal components generated by the PCA to detect whether out of distribution (OOD) occurs in data of the image, store, in a database, a result of the determining whether the image is abnormal and the result of determining whether the OOD occurs, and extract at least some pieces of data in which the OOD occurs using a target labeling extraction model when a rate of data in which the OOD occurs with respect to the image stored in the database is greater than or equal to a threshold value, wherein the anomaly detection model determines whether the image is abnormal using the target labeling.

BRIEF DESCRIPTION OF THE DRAWINGS

The above and other aspects and features of the present disclosure will become more apparent by describing exemplary embodiments thereof in detail with reference to the attached drawings, in which:

FIG. **1** is a block diagram for describing a system including a deep learning device according to some embodiments.

FIG. **2** is a block diagram for describing the memory **600** of FIG. **1**.

FIG. **3** is a block diagram for describing a deep learning device according to some embodiments.

FIGS. **4** and **5** are diagrams for explaining examples of an input image.

FIG. **6** is a block diagram for describing operations of a deep learning device according to some embodiments.

FIG. **7** is a table for describing an operation of merging at least some of vectors extracted from an anomaly detection model according to some embodiments.

FIG. **8** is a table for describing an operation of an OOD data detection unit according to some embodiments.

FIG. **9** is a ladder diagram for describing detecting anomaly and detecting OOD data according to some embodiments.

FIG. **10** is a table for describing data stored in a database according to some embodiments.

FIG. **11** is a graph for describing a process of determining a threshold value.

FIG. **12** is a flowchart of operations of a deep learning device according to some embodiments.

FIG. **13** is a flowchart of operations of a deep learning device according to some embodiments.

FIG. **14** is a block diagram for describing a deep learning system network environment **1** according to some embodiments.

DETAILED DESCRIPTION OF THE EMBODIMENTS

FIG. **1** is a block diagram for describing a system including a deep learning device according to some embodiments.

Referring to FIG. **1**, a deep learning system **100** according to some embodiments may be embodied in and/or as, for example, a fixed or movable device such as a TV, a projector, a cellular phone, a smart phone, a desktop computer, a notebook computer, a digital broadcasting terminal, a personal digital assistant (PDA), a portable multimedia player (PMP), a navigation device, a tablet personal computer (PCf), a wearable device, a set-top box (STB), a digital multimedia broadcasting (DMB) receiver, a radio, a robot, a vehicle, and/or the like.

The deep learning system **100** includes a communication unit **200**, an input unit **300**, a deep learning device **400** a processor **500**, a memory **600**, an output unit **700**, and a sensing unit **800**. A configuration of the deep learning system **100** is not limited thereto. For example, though illustrated as separate components, some of the components of the deep learning system **100** may be combined and/or other components may be further included.

The communication unit **200** may transmit data to and/or receive data from other external electronic devices (e.g., electronic devices **100***a* to **100***e* of FIG. **16**) using a wired/wireless communication technique. For example, the communication unit **200** may exchange at least one of sensor information, a user input, a learning model, a control signal, etc. with the external devices.

Some examples of communication technology that may be employed by the communication unit **200** may include, but are not limited to, Global System for Mobile (GSM) communication, Code Division Multi Access (CDMA), Long-Term Evolution (LTE), 5G, Wireless LAN (WLAN), Wireless-Fidelity (Wi-Fi), Bluetooth, Radio Frequency Identification (RFID), Infrared Data Association (IrDA), ZigBee, Near Field Communication (NFC), and/or the like.

The input unit **300** may obtain various types of data. In this case, the input unit **300** may include a camera for receiving image signals, a microphone for receiving audio signals, a user input unit for receiving information from a user, and/or the like. Here, the camera and/or the microphone may be regarded as a sensor and a signal obtained from the camera and/or the microphone may be referred to as sensing data and/or sensor information. In some embodiments, the input unit **300** may obtain and/or process signals from an external device (e.g., through the communication unit **200**).

The input unit **300** may obtain training data for training a deep learning model by the deep learning device **400** and/or input data to be used to obtain an output using a deep learning model. The input unit **300** may obtain input raw data, and in this case, the deep learning device **400** may extract input feature points by preprocessing the input raw data received from the input unit **300**.

For example, the input unit **300** may obtain images (e.g., scanning electron microscopy (SEM) images) of a semiconductor device and/or a semiconductor device manufacturing process and transmit the images to the deep learning device **400**.

The deep learning device **400** may train a model configured as an artificial neural network with data (e.g., images) received from the input unit **300**. Here, the trained artificial neural network may also be referred to as a learning model. The learning model may be used to infer a result value with respect to new input data other than training data, and the inferred result value may be used as a basis of judgment for performing an operation.

In this case, the deep learning device **400** may perform deep learning processing through a learning processor **460** (as in FIG. **3**) included therein.

In some embodiments, the deep learning device **400** may be implemented using an external memory connected directly to the memory **600** and/or a memory included in an external device.

The sensing unit **800** may obtain at least one among information stored in the deep learning device **400**, information about surroundings of the deep learning device **400**, and user information using various types of sensors.

In this case, sensors included in the sensing unit **800** may include a proximity sensor, an illumination sensor, an acceleration sensor, a magnetic sensor, a gyro sensor, an inertial sensor, an RGB sensor, an IR sensor, a fingerprint sensor, an ultrasonic sensor, an optical sensor, a microphone, a light detection and ranging (LiDAR) sensor, a radar device, and/or the like. As noted above, in some embodiments, the input unit **300** and the sensing unit **800**, though illustrated as separate components, may be combined and/or share sensors and/or inputs (e.g., camera(s) and/or microphone(s)).

The output unit **700** may generate an output associated with a sense of vision, hearing, or touch. For example, the output unit **700** may include a display unit for outputting video information, a speaker for outputting audio information, a haptic module for outputting tactile information, and/or the like.

The memory **600** may store data that supports various functions of the deep learning device **400**. For example, the memory **600** may store input data, training data, a learning model, learning history, etc. obtained, e.g., by the deep learning device **400**, the input unit **300** and/or the communication unit **200**.

The learning model may be used to infer a result value with respect to new input data other than training data, and the inferred result value may be used as a basis of judgment for performing an operation.

The processor **500** may control overall operations of the deep learning system **100**. The processor **500** may obtain information about an intention with respect to a user input and identify a user's requirements on the basis of the obtained information. The processor **500** may control at least some of the components of the deep learning device **400** to execute and/or to drive an application program stored in the memory **600**. Furthermore, the processor **500** may combine and operate two or more of the components of the deep learning device **400** to drive the application program.

FIG. **2** is a block diagram for describing the memory **600** of FIG. **1**.

Referring to FIGS. **1** and **2**, the memory **600** may include a model storage unit **610**. The model storage unit **610** may store a model (and/or artificial neural network) **620** that is being trained or is trained through the deep learning device **400**.

Referring to FIGS. **1** and **2**, the deep learning device **400** learns a representation (e.g., an SEM image) of a semiconductor device, which is provided through the input unit **300**, and determines whether the semiconductor device is defective using a trained model. For example, if the deep learning device **400** determines a semiconductor device is defective, the deep learning device **400** may, based on the type of defect and/or configuration of the deep learning device **400** (and/or deep learning system **100**), produce a notice of the defect (e.g., an alert), may indicate the semiconductor device should be reprocessed and/or discarded, indicate the semiconductor device production apparatus requires maintenance and/or adjustment, and/or the like.

However, in some cases, the performance of the deep learning device **400** may be degraded due to images that are out of distribution (OOD) of the images on which learning of the deep learning device **400** is performed. Therefore, there is a growing need for the deep learning device **400** to detect OOD data and efficiently restore deep learning performance degraded due to the OOD data.

The deep learning device **400** of some embodiments that automatically detects OOD data, including e.g. images serving as a basis for the deep learning, and efficiently restores deep learning performance degraded due to the OOD data will be described in detail below.

FIG. **3** is a block diagram for describing a deep learning device according to some embodiments.

Referring to FIGS. **1** and **3**, the deep learning device **400** may include an anomaly detection unit **410**, an OOD data detection unit **430**, a database **440**, an active learning unit **450**, a model training unit **420**, and the learning processor **460**.

The deep learning device **400** and/or the components included therein (e.g., the anomaly detection unit **410**, the OOD data detection unit **430**, the active learning unit **450**, the model training unit **420**, and the learning processor **460**) may include and/or be included in processing circuitry such as hardware including logic circuits; a hardware/software combination such as a processor executing software; or a combination thereof. For example, the processing circuity may include, but is not limited to, a central processing unit (CPU), a memory controller, an arithmetic logic unit (ALU), a digital signal processor, a microcomputer, a field programmable gate array (FPGA), and programmable logic unit, a microprocessor, application-specific integrated circuit (ASIC), etc. The database **440** may be and/or may be included in a storage media. For example, in some embodiments, the memory **600** of FIGS. **1** and **2** may include the database **440**.

The anomaly detection unit **410** may determine whether a semiconductor process image received from the input unit **300** is abnormal or not. Examples of the semiconductor process image received from the input unit **300** may be as shown in FIGS. **4** and **5**.

FIGS. **4** and **5** are diagrams for explaining examples of an input image.

Referring to FIG. **4**, a semiconductor process image received from the input unit **300** may be, for example, an image of a channel hole.

Referring to FIG. **5**, a semiconductor process image received from the input unit **300** may be, for example, an image of a word line cut.

However, the images received from the input unit **300** are not limited to the semiconductor process images of FIGS. **4** and **5** and may be, for example, various semiconductor process images.

Referring back to FIGS. **1** and **3**, the anomaly detection unit **410** may determine whether a semiconductor process image is abnormal using a model trained through an anomaly detection model **424**.

For example, the anomaly detection model **424** may be a learning model included in an anomaly detection model training unit **422** of the model training unit **420**.

The anomaly detection model **424** may perform learning, for example, on the basis of semiconductor process images labeled as normal and semiconductor process images labeled as abnormal.

A learning model used by the anomaly detection model **424** may be, for example, a convolutional neural network (CNN). However, the learning model used by the anomaly detection model **424** is not limited thereto and may be various network learning models based on a CNN. For example, the learning model used by the anomaly detection model **424** may be and/or include deep convolutional neural networks (e.g., AlexNet and/or GoogleNet), artificial neural networks (ANN) (e.g., residual neural networks ("ResNet")), dense convolutional networks ("DenseNet"), and/or scaled CNNs (e.g., EfficientNet). Alternatively and/or additionally, the learning model may include other types of machine learning models, for example, linear and/or logistic regression, statistics clustering, Bayesian classification, determination trees, dimensional reduction such as main component analyses, expert systems, and/or random forests, and/or a combination thereof.

For example, the learning model may additionally and/or alternatively include artificial neural network organizations and processing models, such as, a repeated neural network (RNN) selectively including a deconvolution neural network, a long short-term memory (LSTM) unit, and/or a gated recurrent unit (GRU), a stacked neural network (SNN), a state-space dynamic neural network (SSDNN), a deep faith network (DBN), a generative adversarial network (GAN), and/or a restricted Boltzmann machine (RBM).

In some embodiments, the anomaly detection unit **410** may determine whether semiconductor process images are abnormal through the anomaly detection model **424** on the basis of images input from the input unit **300**.

In this case, OOD may occur in the images learned by the anomaly detection model training unit **422**. Therefore, whether OOD data is generated may be detected through the OOD data detection unit **430**.

For example, the OOD data detection unit **430** may detect, through a probability approximation model **428**, whether OOD data is generated in the images learned by the anomaly detection model training unit **422**.

In some embodiments, the probability approximation model **428** may be a model included in a probability approximation model training unit **426** in the model training unit **420**.

The probability approximation model **428** may use data learned through the anomaly detection model **424**, for example, as described in detail with reference to FIG. **6** below.

FIG. **6** is a block diagram for describing operations of a deep learning device according to some embodiments.

Referring to FIGS. **1**, **3**, and **6**, the probability approximation model **428** may use data learned through the anomaly detection model **424**. In FIG. **6**, it is assumed that a learning model used by the anomaly detection model **424** is ResNet50.

The probability approximation model training unit **426** may merge at least some of vectors extracted from the anomaly detection model **424**.

For example, the probability approximation model training unit **426** may merge a plurality (e.g., seventeen) of activation layers among vectors extracted from the anomaly detection model **424**. The number of activation layers merged by the probability approximation model training unit **426** is, however, not limited to seventeen.

Thereafter, the probability approximation model training unit **426** may perform a principal component analysis (PCA) on the merged activation layers to generate a principal component.

The probability approximation model training unit **426** may use the principal component as an input of the probability approximation model **428**. The probability approximation model **428** may be and/or include, for example, a Gaussian Mixture Model (GMM). However, the probability approximation model **428** is not limited thereto and may be and/or include at least one of a histogram-based model, a Kernel density estimation model, a Parzen window estimation model, a k-nearest neighbor estimation model, a k-means clustering model, and/or the like.

An operation of the probability approximation model training unit **426** will be described with reference to FIG. **7** below.

FIG. **7** is a table for describing an operation of merging at least some of vectors extracted from an anomaly detection model according to some embodiments.

The probability approximation model training unit **426** may merge, for example, seventeen activation layers among vectors extracted from the anomaly detection model **424**. The number of activation layers merged by the probability approximation model training unit **426** is, however, not limited to seventeen.

For example, the probability approximation model training unit **426** may merge a first activation layer Activation_1, a fourth activation layer Activation_4, a seventh activation layer Activation_7, a tenth activation layer Activation_10, a thirteenth activation layer Activation_13, a sixteenth activation layer Activation_16, a nineteenth activation layer Activation_19, a twenty-second activation layer Activation_22, a twenty-fifth activation layer Activation_25, a twenty-eighth activation layer Activation_28, a thirty-first activation layer Activation_31, a thirty-fourth activation layer Activation_34, a thirty-seventh activation layer Activation_37, a fortieth activation layer Activation_40, a forty-third activation layer Activation_43, a forty-sixth activation layer Activation_46, and a forty-ninth activation layer Activation_49.

An example output of each of these activation layers may be as shown in FIG. **7**. For example, an output of the first activation layer Activation_1 may be (256, 256, 64), an output of the fourth activation layer Activation_4 may be (128, 128, 256), an output of the seventh activation layer Activation_7 may be (128, 128, 256), an output of the tenth activation layer Activation_10 may be (128, 128, 256), an output of the thirteenth activation layer Activation_13 may be (64, 64, 512), an output of the sixteenth activation layer Activation_16 may be (64, 64, 512), an output of the nineteenth activation layer Activation_19 may be (64, 64, 512), an output of the twenty-second activation layer Activation_22 may be (64, 64, 512), an output of the twenty-fifth activation layer Activation_25 may be (32, 32, 1024), an output of the twenty-eighth activation layer Activation_28 may be (32, 32, 1024), an output of the thirty-first activation layer Activation_31 may be (32, 32, 1024), an output of the thirty-fourth activation layer Activation_34 may be (32, 32, 1024), an output of the thirty-seventh activation layer Activation_37 may be (32, 32, 1024), the fortieth activation layer Activation_40 may be (32, 32, 1024), an output of the forty-third activation layer Activation_43 may be (16, 16, 2048), an output of the forty-sixth activation layer Activation_46 may be (16, 16, 2048), and an output of the forty-ninth activation layer Activation_49 may be (16, 16, 2048). The outputs of these activation layers are merely examples and are not limited thereto.

An output may be obtained by merging the plurality of activation layers, For example, the output obtained through the probability approximation model training unit **426** by merging the first activation layer Activation_1, the fourth activation layer Activation_4, the seventh activation layer Activation_7, the tenth activation layer Activation_10, the thirteenth activation layer Activation_13, the sixteenth activation layer Activation_16, the nineteenth activation layer Activation_19, the twenty-second activation layer Activation_22, the twenty-fifth activation layer Activation_25, the twenty-eighth activation layer Activation_28, the thirty-first activation layer Activation_31, the thirty-fourth activation layer Activation_34, the thirty-seventh activation layer Activation_37, the fortieth activation layer Activation_40, the forty-third activation layer Activation_43, the forty-sixth activation layer Activation_46, and the forty-ninth activation layer Activation_49 may be 15168. The output of the anomaly detection model **424** illustrated in FIG. **7** is merely an example, and the output of the anomaly detection model **424** is not limited thereto.

Referring to FIGS. **1**, **3**, and **6**, the probability approximation model training unit **426** may use output data of the anomaly detection model **424** as an input of the probability approximation model **428**.

Referring to FIGS. **1** and **3**, the OOD data detection unit **430** may use the probability approximation model **428** to detect whether OOD data of an image, which is to be learned by the anomaly detection model **424**, is generated.

The OOD data detection unit **430** may detect an optimal value, for clustering, by setting dimensions of outputs (PCA dimensions) of a principal component, which are generated through the PCA performed by the probability approximation model training unit **426**, and the number of probability approximation models **428** as hyper parameters, for example, as will be described with reference to FIG. **8** below.

FIG. **8** is a table for describing an operation of an OOD data detection unit according to some embodiments.

Referring to FIGS. **1**, **3**, and **8**, an example in which the probability approximation model **428** is a GMM will be described.

The OOD data detection unit **430** may detect an optimal value, for clustering, by setting, as hyper parameters PCT, dimensions of a principal component generated through the PCA performed by the probability approximation model training unit **426** and the number of probability approximation models **428**.

The OOD data detection unit **430** may detect an optimal value using, e.g., a Bayesian information criterion (BIC) and by setting, as hyper parameters, the PCA dimensions of a principal component generated through the PCA performed by the probability approximation model training unit **426** and the number of probability approximation models **428**. However, embodiments are not limited thereto, and the OOD data detection unit **430** may detect an optimal value by using an Dunn index, a silhouette score, an Akaike information criterion (AIC), and/or the like; and setting the PCA dimensions of a principal component generated through the PCA performed by the probability approximation model training unit **426** and the number of probability approximation models **428** as hyper parameters. For ease of description, in this drawing, an example in which the OOD data detection unit **430** uses the BIC will be described.

For example, the OOD data detection unit **430** increases the PCA dimensions of the principal component by 1 from 10 to 20. In addition, the OOD data detection unit **430** increases the number of GMMs (and/or GMM components) by 10 from 10 to 240. Accordingly, a BIC for PCA dimensions of each principal component and the number of GMMS (and/or GMM components) may be calculated, and PCA dimensions of the principal component and the number of GMMS (and/or GMM components) corresponding to a lowest BIC may be determined as optimal values.

In this drawing, it may be determined that an optical value is obtained when the PCA dimensions of the principal component are 10 and the number of GMMS (and/or GMM components) is 80, but examples embodiments are not so limited.

Therefore, the OOD data detection unit **430** may detect OOD data using the probability approximation model **428** by setting the PCA dimensions of the principal component to 10 and the number of GMMs (and/or GMM components) to 80.

The operations of the anomaly detection unit **410** and the OOD data detection unit **430** will be described using a ladder diagram of FIG. **9** below.

FIG. **9** is a ladder diagram for describing detecting anomaly and detecting OOD data according to some embodiments.

Referring to FIGS. **1**, **3** and **9**, first, the anomaly detection unit **410** determines, e.g., by using the anomaly detection model **424**, whether an image received through the input unit **300** is abnormal. In this case, features (e.g., vectors) of the image may be extracted through the anomaly detection model **424** (S**100**).

Next, the OOD data detection unit **430** may extract and merge some vectors of data output through the anomaly detection model **424** (S**110**).

Next, the OOD data detection unit **430** may perform the PCA on a result of merging the extracted vectors (S**120**).

Thereafter, the OOD data detection unit **430** may perform probability approximation using a condition for detecting an optimal value between PCA dimensions of principal components and the number of probability approximation models **428** to detect whether OOD occurs in the image received through the input unit **300** (S**130**).

Referring back to FIGS. **1** and **3**, a result of detecting whether an image is abnormal (e.g., by the anomaly detection unit **410**) and a result of detecting whether OOD occurs (e.g., by the OOD data detection unit **430**) may be stored in the database **440**. Data stored in the database **440** is not limited thereto. The data stored in the database **440** will be described in detail with reference to FIG. **10** below.

FIG. **10** is a table for describing data stored in a database according to some embodiments.

Referring to FIGS. **1**, **3**, and **10**, information about X pieces of data (e.g., a semiconductor process image) (wherein X is and/or represents a natural number) received from the input unit **300** may be stored in the database **440**.

The X pieces of the data stored in the database **440** may indicate a determination of anomaly, a probability value, a determination of OOD, a likelihood, and/or the like.

More specifically, the determination of anomaly may indicate a result of detecting whether the image is abnormal (e.g., by the anomaly detection unit **410**). For example, when the anomaly detection unit **410** detects anomaly in first data 1, an indication (e.g., "Y" indicating the anomaly) may be stored. When the anomaly detection unit **410** does not detect anomaly in second data 2, "N" may be stored.

The probability value indicates a probability that a result of detecting whether an image is abnormal by the anomaly detection unit **410** is correct. For example, when a probability that a result of detecting whether the first data 1 is abnormal by the anomaly detection unit **410** is correct and is 79.1416%, 79.1416 may be recorded. For example, when a probability that a result of detecting whether the first data 2 is abnormal by the anomaly detection unit **410** is correct and is 79.5601%, 79.5601 may be recorded.

For convenience of description, a description of remaining data (third data to Xth data) will be omitted herein.

The determination of OOD may indicate a result of determining (e.g., by the OOD data detection unit **430**) whether the image received from the input unit **300** is OOD data. For example, when the OOD data detection unit **430** determines that eighth data 8 and ninth data 9 are OOD data, the determination of OOD, with respect to the eighth data and the ninth data, may be recorded as Y.

The likelihood may be a likelihood of each piece of the data calculated by the probability approximation model **428**.

The deep learning processor **460** may determine at least one executable operation of the deep learning device **400** on the basis of information determined and/or generated by a data analysis algorithm and/or a machine learning algorithm. In addition, the learning processor **460** may control the components of the deep learning device **400** to perform the determined operation.

To this end, the learning processor **460** may request, retrieve, receive, and/or use the data stored in the memory **600**, and control the components of the deep learning device **400** to perform an expected operation and/or otherwise desirable operation among the at least one executable operation.

In this case, when it is necessary and/or otherwise desirable to connect to an external device in order to perform the determined operation, the learning processor **460** may generate a control signal for controlling the external device and transmit the control signal to the external device.

In addition, the learning processor **460** may collect history information including data about the operation of the deep learning device **400** or a user's feedback on the operation of the deep learning device **400** and store the history information in the memory **600** or transmit the history information to the external device. The collected history information may be used to update a learning model.

As a ratio of the number of pieces of data in which OOD occurs to the total number X of pieces of data stored in the database **440** increases, the performance of the deep learning device **400** according to some embodiments may decrease, e.g., as will be described in detail with reference to FIG. **11** below.

FIG. **11** is a graph for describing a process of determining a threshold value.

Referring to FIGS. **1**, **3**, **10**, and **11**, as a ratio of the number of pieces of data in which OOD occurs compared to the total number X of pieces of data stored in the database **440** increases from 0 to 1, the performance of the deep learning device **400** decreases. The graph of FIG. **11** is only an example and various types of graphs may be used provided that, as a ratio of the number of pieces of data in which OOD occurs to the total number X of pieces of data stored in the database **440** increases from 0 to 1, the performance of the deep learning device **400** decreases.

The performance of the deep learning device **400** may be, for example, the performance accuracy of the anomaly detection unit **410**. For example, the performance of the deep learning device **400** may refer to the precision of a result of detecting, e.g., by the anomaly detection unit **410**, whether an image received from the input unit **300** is abnormal and/or includes OOD.

In some embodiments, a user of the deep learning device **400** may set a set value serving as a reference value for determining whether the performance of the deep learning device **400** is available. For example, when a user sets that the deep learning device **400** is not reliable when the performance of the deep learning device **400** is less than or equal to 0.95, the set value may be 0.95.

The learning processor **460** may continuously check a ratio of the number of pieces of data in which OOD occurs to the total number X of pieces of data stored in the database **440**. In this case, the learning processor **460** may continuously monitor whether an OOD ratio (e.g., a ratio of the number of pieces of data in which OOD occurs to the total number X of pieces of data stored in the database **440**) is equal to a threshold value.

For example, when the set value set by a user is 0.95, the OOD ratio is 0.1 and thus the learning processor **460** monitors whether an OOD ratio of the database **440** is 0.1.

In this case, when it is determined that the OOD ratio of the database **440** reaches the threshold value, the learning processor **460** may inform a user of this fact and/or control the active learning unit **450** to extract, as target labeling, at least part of data in which OOD occurs. For example, the learning processor **460**, to inform the user, may initiate and/or generate a notification for the user.

According to some embodiments, the deep learning device **400** may monitor an OOD ratio satisfying a predetermined (and/or otherwise determined) allowable value of the performance of the deep learning device **400**, and automatically enhance degraded performance of the deep learning device **400** when it is determined that the OOD ratio falls below the allowable value (e.g., reaches a threshold value). Therefore, the performance of the deep learning device **400** may be efficiently maintained.

In addition, because the performance of the deep learning device **400** is improved by extracting, as target labeling, at least part of data in which OOD occurs, degraded performance of the deep learning device **400** may be restored without having to use all the data in which OOD occurs, thereby efficiently maintaining the performance of the deep learning device **400**.

Next, an operation of the active learning unit **450** will be described. The active learning unit **450** may extract target labeling to be transmitted to the model training unit **420** among data in which OOD occurs. In this case, the active learning unit **450** may extract target labeling on the basis of at least some of vectors of data output through the anomaly detection model **424** and a likelihood calculated by the OOD data detection unit **430**.

For example, the active learning unit **450** may extract at least part of data in which OOD occurs as target labeling through a target labeling extraction model **452**. The target labeling extraction model **452** may be, for example, k-center greedy and/or gradient embedding (e.g., Deep Batch Active Learning by Diverse and/or Uncertain Gradient Lower Bounds) using at least some of vectors of data output through the anomaly detection model **424** and a likelihood calculated by the OOD data detection unit **430**.

For example, the active learning unit **450** may extract, as target labeling, a percentage (e.g., 10%) of the data in which OOD occurs.

According to some embodiments, the deep learning device **400** may restore the performance of the deep learning device **400**, which is degraded, using only some of the data in which OOD occurs. Therefore, the performance of the deep learning device **400** may be efficiently managed.

Example operations of the deep learning device **400** described above will be described with reference to the flow of FIG. **12** below.

FIG. **12** is a flowchart of operations of a deep learning device according to some embodiments.

Referring to FIGS. **1**, **3**, and **12**, the database **440** is monitored through the learning processor **460** (S**200**). Thereafter, whether an OOD ratio is less than a threshold value is determined (e.g., by the learning processor **460**) (S**210**). For example, when it is determined that the OOD ratio is less than the threshold value (Y), the learning processor **460** may continue to (and/or continuously) monitor the performance of the deep learning device **400**.

However, when it is determined by the learning processor **460** that the OOD ratio is greater than (and/or equal) to the threshold value (N), data in which OOD occurs among data stored in the database **440** may be transmitted to the active learning unit **450** (S**220**).

Thereafter, the active learning unit **450** extracts target labeling through the target labeling extraction model **452** (S**230**). The active learning unit **450** transmits the extracted target labeling to the model training unit **420** (S**240**).

An example process of detecting, by the deep learning device **400**, the occurrence of OOD and restoring the graded performance of the deep learning device **400**, e.g., according to some embodiments, will be described with reference to FIG. **13**.

FIG. **13** is a flowchart of operations of a deep learning device according to some embodiments.

Referring to FIGS. **1**, **3**, and **13**, the deep learning device **400** receives an image (e.g., through the input unit **300**) (S**300**). Next, whether the image is abnormal is determined (e.g., by the anomaly detection unit **410**) (S**310**). For example, the anomaly detection unit **410** may use the anomaly detection model **424** of the model training unit **420**.

Thereafter, whether OOD occurs in the received image may be determined (e.g., by the OOD data detection unit **430**) (S**320**). For example, the OOD data detection unit **430** may use the probability approximation model **428** of the model training unit **420**.

Thereafter, a result of determining whether the image is abnormal (e.g., by the anomaly detection unit **410**), and a result of determining whether OOD data occurs in the image (e.g., by the OOD data detection unit **430**) may be stored (e.g., in the database **440**) (S**330**).

An OOD ratio (e.g., with respect to data stored in the database **440**) is monitored by the learning processor **460**. For example, when it is determined (e.g., by the learning processor **460**) that the OOD ratio (e.g. with respect to the data stored in the database **440**) is less than a threshold value (Y), operation S**310** may performed (e.g., by the anomaly detection unit **410**). When it is determined (e.g., by the learning processor **460**) that the OOD ratio (e.g., with respect to the data stored in the database **440**) is greater than (and/or equal) to the threshold value (N), a user may be informed of this fact and/or data (e.g., in which OOD occurs and which is stored in the database **440**) is transmitted to the active learning unit **450** (e.g., by the learning processor **460**). In some embodiments, the active learning unit **450** extracts data to be target labeled from among the data in which OOD occurs and which is transmitted thereto (S**350**).

FIG. **14** is a block diagram for describing a deep learning system network environment **1** according to some embodiments.

Referring to FIG. **14**, the deep learning system network environment **1**, according to some embodiments, may be connected to at least one of a robot **100***a*, a self-driving vehicle **100***b*, an XR device **100***c*, a smart phone **100***d*, and/or a home appliance **100***e* through a cloud network **10**. Here, the robot **100***a*, the self-driving vehicle **100***b*, the XR device **100***c*, the smart phone **100***d*, and/or the home appliance **100***e* to which deep learning technology is applied may be referred to as external deep learning devices **100***a* to **100***e*.

The cloud network **10** may be part of a cloud computing infrastructure and/or may be a network included in the cloud computing infrastructure. In some embodiments, the cloud network **10** may be configured to use a 3G network, a 4G network, a Long-Term Evolution (LTE) network, a 5G network, and/or the like.

For example, the devices **100***a* to **100***e* and **100** (e.g., constituting the deep learning system network environment **1**) may be connected to one another through the cloud network **10**; and/or the devices **100***a* to **100***e* and **100** may communicate with one another via a base station and/or communicate with one another without the base station.

The deep learning system **100** may be connected to at least one of the robot **100***a*, the self-driving vehicle **100***b*, the XR device **100***c*, the smart phone **100***d*, and/or the home appliance **100***e* via the cloud network **10** to help a deep learning processing of the at least one deep learning device **100***a*, **100***b*, **100***c*, **100***d*, and/or **100***e* connected thereto.

For example, referring to FIGS. **1**, **3**, and **14**, when it is detected and/or determined (e.g., by the learning processor **460** of the deep learning system **100**) that an OOD ratio is equal to or greater than a threshold value, a notification informing of this fact may be transmitted to at least one of the robot **100***a*, the self-driving vehicle **100***b*, the XR device **100***c*, the smart phone **100***d* and/or the home appliance **100***e* through the communication unit **200**.

The deep learning system **100** may receive input data from each of the deep learning devices **100***a* to **100***e*, infer a result value with respect to the received input data using a learning model, generate a response or a control command on the basis of the inferred result value, and transmit the response or the control command to each of the external deep learning devices **100***a* to **100***e*.

Alternatively, the external deep learning devices **100***a* to **100***e* may infer a result value with respect to the input data using the learning model and generate a response or a control command on the basis of the inferred result value.

Although embodiments of the present disclosure have been described above with reference to the accompanying drawings, it will be understood by those of ordinary skill in the art that the present disclosure is not limited thereto and may be implemented in many different forms without departing from the technical idea or essential features thereof. Therefore, it should be understood that the embodiments set forth herein are merely examples in all respects and not restrictive.

What is claimed is:

1. A deep learning device comprising:

processing circuitry configured to:

determine whether a received image is abnormal using an anomaly detection model,

merge at least some vectors extracted from the anomaly detection model,

perform a principal component analysis (PCA) on a result of the merging the at least some vectors,

input, to a probability approximation model, principal components generated by the PCA to detect whether out of distribution (OOD) occurs in data of the received image,

store, in a database, a result of the determination of whether the received image is abnormal and a result of determining whether the OOD occurs, and

extract at least some of the data in which the OOD occurs, as target labeling, using a target labeling extraction model when a rate of the data in which the OOD occurs is greater than or equal to a threshold value,

wherein the anomaly detection model determines whether the received image is abnormal using the target labeling.

2. The deep learning device of claim **1**, wherein the anomaly detection model includes at least one of a convolutional neural network (CNN), an artificial neural network (ANN), a dense convolutional network (DenseNet), or a scaled CNN.

3. The deep learning device of claim **1**, wherein the probability approximation model includes at least one of a Gaussian Mixture Model (GMM), a histogram-based model, a kernel density estimation model, a Parzen window estimation model, a k-nearest neighbor estimation model, or a k-means clustering model.

4. The deep learning device of claim **1**, wherein the processing circuitry is further configured to check, in real time, whether the rate of the data in which the OOD occurs is greater than or equal to the threshold value.

5. The deep learning device of claim **1**, wherein the processing circuitry is further configured to:

detect an optimal value for clustering between the principal components and the probability approximation model; and

detect whether the OOD occurs using at least some of the principal components which satisfy the optimal value and at least part of the probability approximation model which satisfy the optimal value.

6. The deep learning device of claim **5**, wherein the optimal value is calculated according to at least one of a Bayesian information criterion (BIC), a Dunn index, a silhouette score, or an Akaike information criterion (AIC).

7. The deep learning device of claim **1**, wherein the threshold value comprises a rate of the data in which the OOD occurs with respect to the image stored in the database when performance precision is a set value.

8. A deep learning system comprising:

an input unit configured to receive an image;

a processor configured to control the input unit; and

a deep learning device connected to the processor and configured to receive the image from the input unit, the deep learning device including processing circuitry and a database, the processing circuitry configured to

determine whether an image received from the input unit is abnormal using an anomaly detection model,

merge at least some vectors extracted from the anomaly detection model, perform a principal component analysis (PCA) on a result of the merging the at least some vectors,

input, to a probability approximation model, principal components generated by the PCA to detect whether out of distribution (OOD) occurs in data of the image,

store a result of the determination of whether the image is abnormal and a result of determining whether the OOD occurs, and

extract at least some of the data in which the OOD occurs, as target labeling, using a target labeling extraction model when a rate of the data in which the OOD occurs is greater than or equal to a threshold value, and

the database is configured to store the result of the determination of whether the image is abnormal and the result of determining whether the OOD occurs,

wherein the anomaly detection model determines whether the image is abnormal using the target labeling.

9. The deep learning system of claim **8**, wherein the anomaly detection model includes at least one of a convolutional neural network (CNN), an artificial neural network (ANN), a dense convolutional network (DenseNet), or scaled CNN.

10. The deep learning system of claim **8**, wherein the probability approximation model includes at least one of a Gaussian Mixture Model (GMM), a histogram-based model, a kernel density estimation model, a Parzen window estimation model, a k-nearest neighbor estimation model or a k-means clustering model.

11. The deep learning system of claim **8**, wherein the processing circuitry is further configured to check, in real time, whether the rate of the data in which the OOD occurs is greater than or equal to the threshold value.

12. The deep learning system of claim **8**, wherein the processing circuitry is configured to:

detect an optimal value for clustering between the principal components and the probability approximation model; and

detect whether the OOD occurs using at least some of the principal components which satisfy an optical value and at least part of the probability approximation model which satisfy the optimal value.

13. The deep learning system of claim **12**, wherein the optimal value is calculated according to at least one of a Bayesian information criterion (BIC), a Dunn index, a silhouette score, or an Akaike information criterion (AIC).

14. The deep learning system of claim **8**, wherein the threshold value comprises a rate of the data in which the OOD occurs with respect to the image stored in the database when performance precision is a set value.

15. A deep learning system comprising:

an input unit configured to receive an image;

a processor configured to control the input unit; and

a deep learning device connected to the processor and configured to receive the image from the input unit, the deep learning device including processing circuitry configured to:

determine whether an image received from the input unit is abnormal using an anomaly detection model,

merge at least some vectors extracted from the anomaly detection model,

perform a principal component analysis (PCA) on a result of the merging the at least some vectors,

input, to a probability approximation model, principal components generated by the PCA to detect whether out of distribution (OOD) occurs in data of the image,

store, in a database, a result of the determining whether the image is abnormal and the result of detecting whether the OOD occurs, and

extract at least some pieces of data in which the OOD occurs using a target labeling extraction model when a rate of data in which the OOD occurs with respect to the image stored in the database is greater than or equal to a threshold value,

wherein the anomaly detection model determines whether the image is abnormal using the target labeling extraction model.

16. The deep learning system of claim **15**, wherein the anomaly detection model includes at least one of a convolutional neural network (CNN), an artificial neural network (ANN), a dense convolutional network (DenseNet), or scaled CNN.

17. The deep learning system of claim **15**, wherein the probability approximation model includes at least one of a Gaussian Mixture Model (GMM), a histogram-based model, a kernel density estimation model, a Parzen window estimation model, a k-nearest neighbor estimation model or a k-means clustering model.

18. The deep learning system of claim **15**, wherein the processing circuitry is further configured to check, in real time, whether the rate of the data in which the OOD occurs is greater than or equal to the threshold value.

19. The deep learning system of claim **15**, wherein the processing circuitry is configured to:

detect an optimal value for clustering between the principal components and the probability approximation model, and

detect whether the OOD occurs using at least some of the principal components which satisfy an optical value and at least part of the probability approximation model which satisfy the optimal value.

20. The deep learning system of claim **15**, wherein the threshold value comprises a rate of the data in which the OOD occurs with respect to the image stored in the database when performance precision is a set value.

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