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(54) **UNSUPERVISED MULTIVARIATE ANOMALY DETECTION THROUGH VARIATIONAL AUTO-ENCODING IN HVAC MACHINERY**

(71) Applicant: **Jonah Gluck**, Oyster Bay, NY (US)

(72) Inventor: **Jonah Gluck**, Oyster Bay, NY (US)

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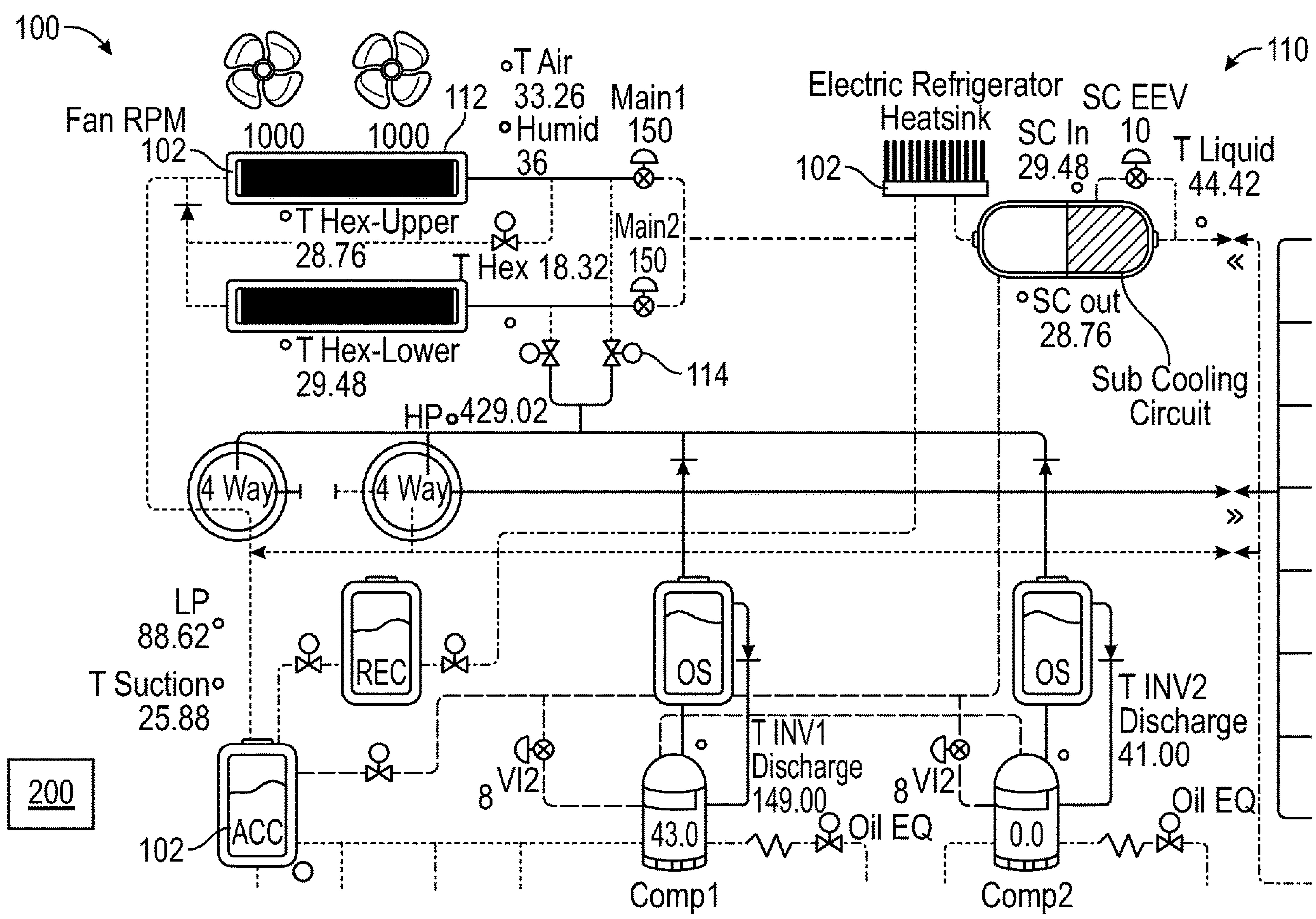
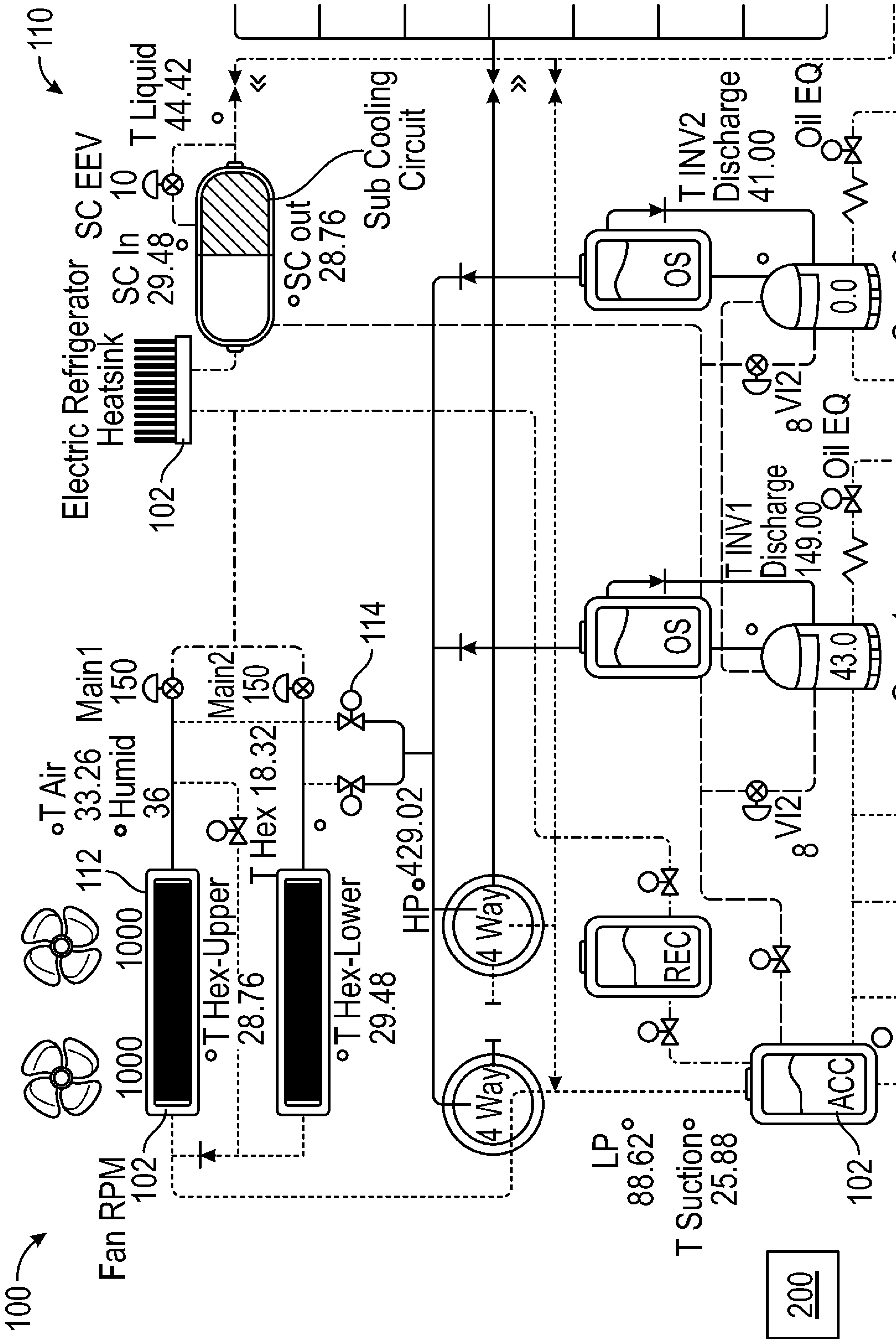
(57) **ABSTRACT**

A system for HVAC anomaly detection includes a sensor configured to capture temperature, pressure data, flow data, and/or current draw, a processor, and a memory. The memory includes instructions stored thereon, which, when executed cause the system to access the captured sensor data, provide the sensor data as an input to a machine learning network, and predicting one or more anomalies using the machine learning network,





100
110
Fan RPM
102
1000
1000
112
T Air
33.26
Humid
36
Main1
150
Main2
150
T Hex-Upper
28.76
T Hex-Lower
29.48
T Hex 18.32
114
HP
429.02
4 Way
4 Way
LP
88.62
T Suction
25.88
REC
ACC
102
200
Electric Refrigerator
Heatsink
102
SC In
29.48
SC EEV
10
T Liquid
44.42
SC out
28.76
Sub Cooling
Circuit
OS
OS
T INV1
Discharge
149.00
T INV2
Discharge
41.00
43.0
0.0
Comp1
Comp2
8
VI2I
8
VI2I
Oil EQ
Oil EQ

FIG. 1

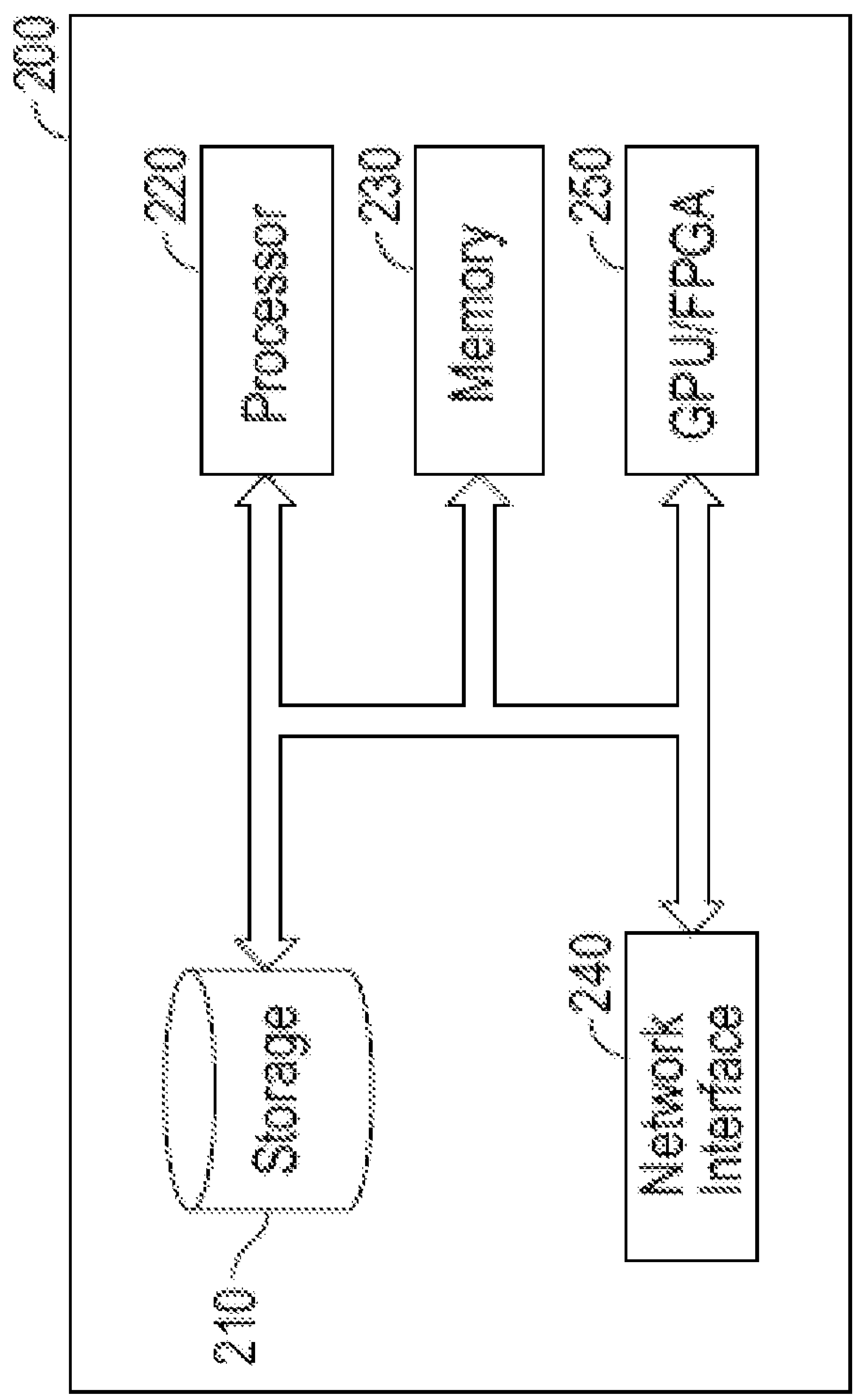

200
220
Processor
230
Memory
250
GPU/FPGA
210
Storage
240
Network
Interface

FIG. 2

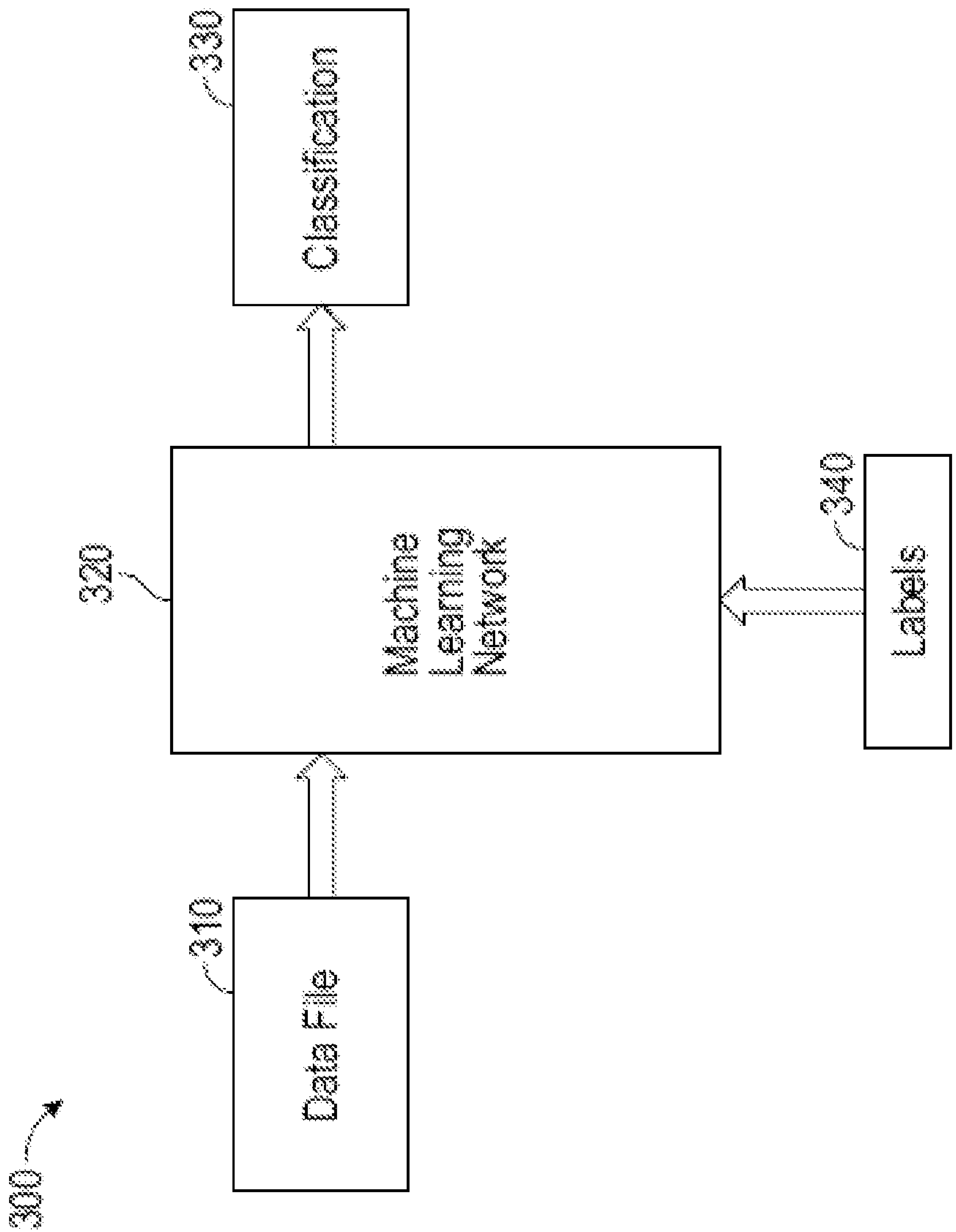

300
Data File
310
Machine Learning Network
320
Classification
330
Labels
340

FIG. 3

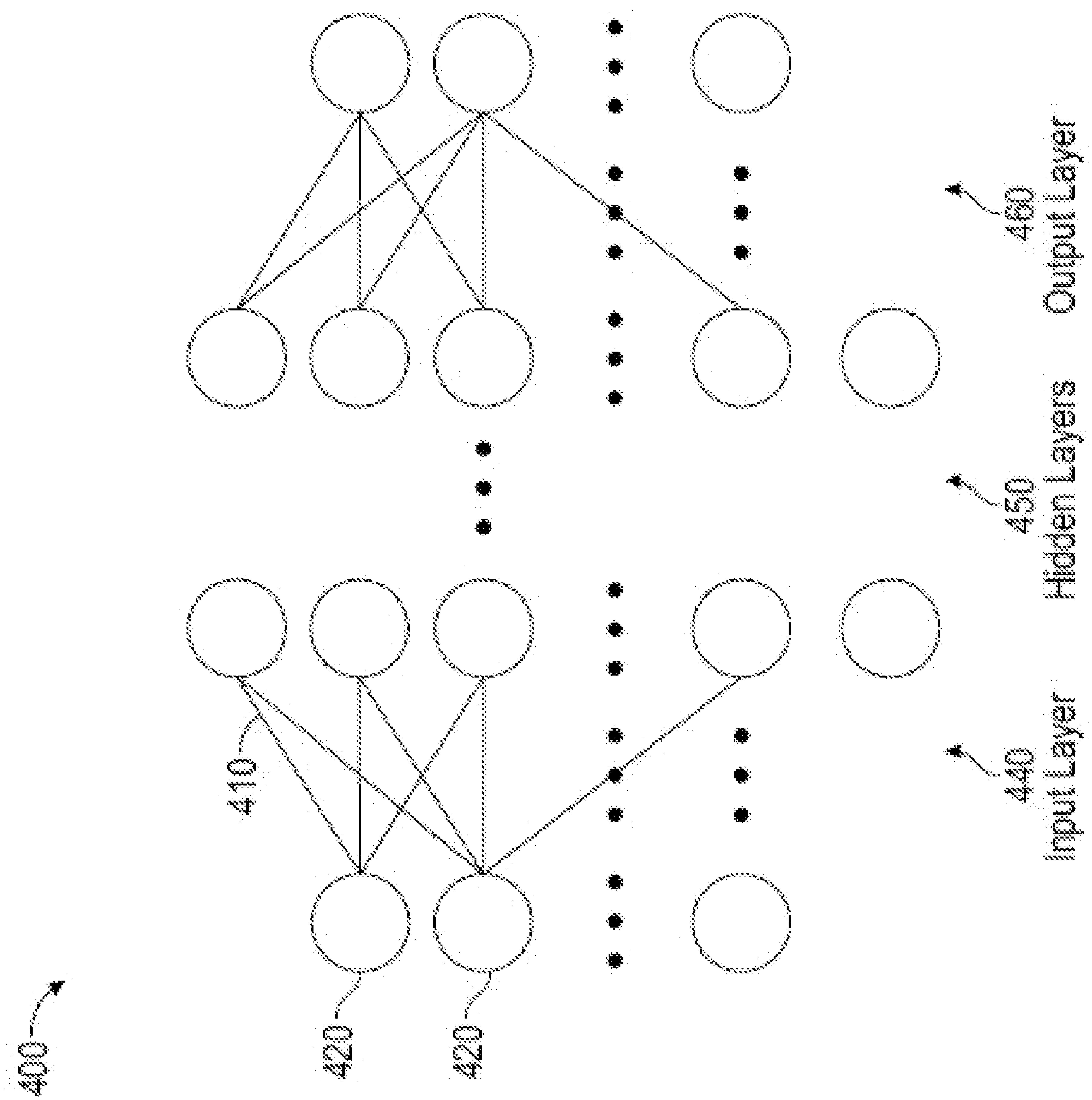

400
410
420
420
440
Input Layer
450
Hidden Layers
460
Output Layer

FIG. 4

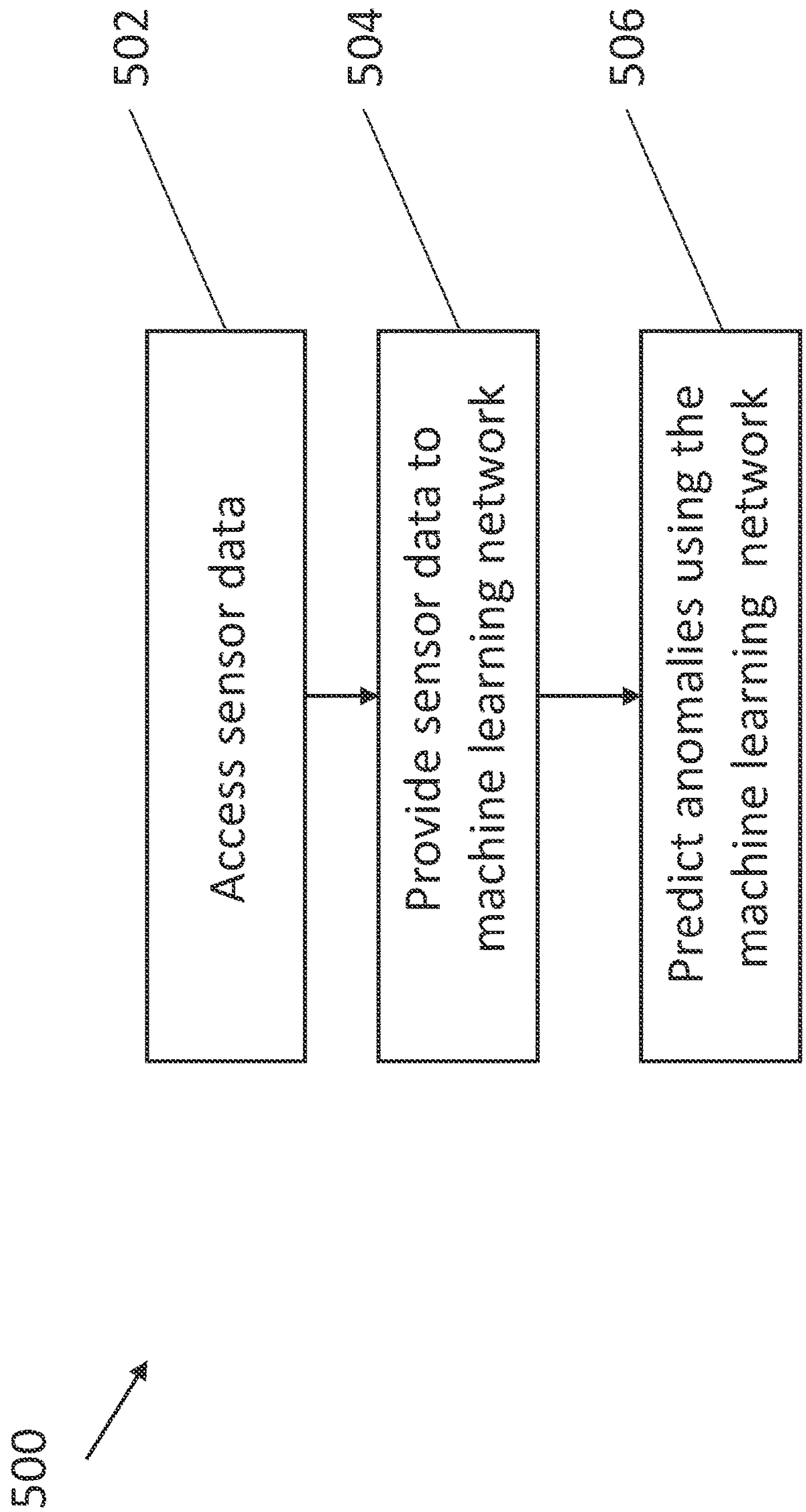

500
502
504
506
Access sensor data
Provide sensor data to machine learning network
Predict anomalies using the machine learning network

FIG. 5

UNSUPERVISED MULTIVARIATE ANOMALY DETECTION THROUGH VARIATIONAL AUTO-ENCODING IN HVAC MACHINERY

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims priority to and the benefit of the filing date of U.S. Provisional Application No. 63/326,372, filed on Apr. 1, 2022, which is hereby incorporated by reference herein in its entirety.

TECHNICAL FIELD

[0002] The present disclosure relates to unsupervised multivariate anomaly detection through variational auto-encoding in heating, ventilation, and air conditioning (HVAC) machinery.

BACKGROUND

[0003] Heating, ventilation, and air conditioning (HVAC) systems provide heating, ventilation, and/or cooling. HVAC systems have many components that may be susceptible to breakdown.

[0004] Accordingly, there is interest in improvements in monitoring for HVAC system failures.

SUMMARY

[0005] An aspect of the present disclosure provides a system for heating, ventilation, and air conditioning (HVAC) anomaly detection. The system includes a sensor configured to capture temperature, pressure data, flow data, and/or current draw, a processor, and a memory. The memory includes instructions stored thereon, which, when executed by the processor, cause the system to: access the captured sensor data; provide the sensor data as an input to a machine learning network; and predict one or more anomalies using the machine learning network.

[0006] In accordance with aspects of the disclosure, the machine learning network may include variational auto-encoding, a transformer, other RNN based models (RNN, LSTM), Decision Trees (Isolation Forest), a Support Vector Machine (SVM), sequence-to-sequence model, K-means clustering, and/or an ensemble model.

[0007] In an aspect of the present disclosure, the instructions, when executed by the processor, may further cause the system to generate a report indicating the predicted one or more anomalies.

[0008] In another aspect of the present disclosure, the instructions, when executed by the processor, may further cause the system to transmit an indication to a user device about the predicted one or more anomalies.

[0009] In yet another aspect of the present disclosure, the instructions, when executed by the processor, may further cause the system to disable one or more components of the HVAC system based on the predicted one or more anomalies.

[0010] In accordance with aspects of the disclosure, a processor-implemented method for HVAC anomaly detection includes accessing captured sensor data from a sensor configured to capture temperature, pressure data, flow data, and/or current draw, providing the sensor data as an input to a machine learning network, and predicting one or more anomalies using the machine learning network.

[0011] In an aspect of the present disclosure, the machine learning network may include variational auto-encoding, a transformer, other RNN based models (RNN, LSTM), Decision Trees (Isolation Forest), a Support Vector Machine (SVM), sequence-to-sequence model, K-means clustering, and/or an ensemble model.

[0012] In another aspect of the present disclosure, the method may further include generating a report indicating the predicted one or more anomalies.

[0013] In yet another aspect of the present disclosure, the method may further include transmitting an indication to a user device about the predicted one or more anomalies.

[0014] In a further aspect of the present disclosure, the method may further include disabling one or more components of the HVAC system based on the predicted one or more anomalies.

[0015] In accordance with aspects of the disclosure, a non-transitory computer-readable medium, storing instructions, which, when executed by a processor, cause the performance of a processor-implemented method for HVAC anomaly detection, is presented. The method includes: accessing captured sensor data from a sensor configured to capture temperature, pressure data, flow data, and/or current draw; providing the sensor data as an input to a machine learning network; and predicting one or more anomalies using the machine learning network.

[0016] In an aspect of the present disclosure, the instructions, when executed by the processor, further cause the performance of a processor-implemented method for HVAC anomaly detection. The method may further include generating a report indicating the predicted one or more anomalies.

[0017] In another aspect of the present disclosure, the instructions, when executed by the processor, further cause the performance of a processor-implemented method for HVAC anomaly detection. The method may further include transmitting an indication to a user device about the predicted one or more anomalies.

[0018] In yet another aspect of the present disclosure, the instructions, when executed by the processor, further cause the performance of a processor-implemented method for HVAC anomaly detection. The method may further include disabling one or more components of the HVAC system based on the predicted one or more anomalies.

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] A better understanding of the features and advantages of the present disclosure will be obtained by reference to the following detailed description that sets forth illustrative aspects, in which the principles of the present disclosure are utilized, and the accompanying drawings of which:

[0020] FIG. **1** is a diagram of an exemplary system for HVAC anomaly detection, in accordance with examples of the present disclosure;

[0021] FIG. **2** is a block diagram of a controller configured for use with the system of FIG. **1**, in accordance with aspects of the disclosure;

[0022] FIG. **3** is a block diagram of a machine learning network with inputs and outputs of a deep learning neural network, in accordance with aspects of the present disclosure;

[0023] FIG. **4** is a diagram of layers of the machine learning network of FIG. **3**, in accordance with aspects of the present disclosure; and

[0024] FIG. **5** is a flow diagram of a computer-implemented method for HVAC anomaly detection, in accordance with aspects of the present disclosure.

DETAILED DESCRIPTION

[0025] Aspects of the present disclosure are described in detail with reference to the drawings wherein like reference numerals identify similar or identical elements.

[0026] The phrases "in an aspect," "in aspects," "in various aspects," "in some aspects," or "in other aspects" may each refer to one or more of the same or different aspects in accordance with the present disclosure.

[0027] Although the present disclosure will be described in terms of specific aspects, it will be readily apparent to those skilled in this art that various modifications, rearrangements, and substitutions may be made without departing from the spirit of the present disclosure. The scope of the present disclosure is defined by the claims appended hereto. For purposes of promoting an understanding of the principles of the present disclosure, reference will now be made to exemplary aspects illustrated in the drawings, and specific language will be used to describe the same.

[0028] The present disclosure includes systems and methods for predicting HVAC anomalies using data collected from sensors, using the collected data as inputs to a machine learning network, such as a variational auto-encoder, and predicting the anomalies using the machine learning network. For example, a multivariate analysis provides intuition for how a single sensor's decay will impact the entire system.

[0029] Referring to FIG. **1**, a system **100** for HVAC anomaly detection is shown. The system **100** for HVAC anomaly detection generally includes a sensor **102** and a controller **200**. The sensor **102** is configured to capture temperature, pressure data, flow data, and/or current draw from a component **112** of an HVAC system **110**. The HVAC system **110** may include one or more valves **114** configured to be actuated by the controller **200**.

[0030] FIG. **2** illustrates controller **200**, which includes a processor **220** connected to a computer-readable storage medium or a memory **230**. The controller **200** may be used to control and/or execute operations of the networked system **100**. The computer-readable storage medium or memory **230** may be a volatile type of memory, e.g., RAM, or a non-volatile type of memory, e.g., flash media, disk media, etc. In various aspects of the disclosure, the processor **220** may be another type of processor, such as a digital signal processor, a microprocessor, an ASIC, a graphics processing unit (GPU), a field-programmable gate array (FPGA), or a central processing unit (CPU). In certain aspects of the disclosure, network inference may also be accomplished in systems that have weights implemented as memristors, chemically, or other inference calculations, as opposed to processors.

[0031] In aspects of the disclosure, the memory **230** can be random access memory, read-only memory, magnetic disk memory, solid-state memory, optical disc memory, and/or another type of memory. In some aspects of the disclosure, the memory **230** can be separate from the controller **200** and can communicate with the processor **220** through communication buses of a circuit board and/or through communication cables such as serial ATA cables or other types of cables. The memory **230** includes computer-readable instructions that are executable by the processor **220** to operate the controller **200**. In other aspects of the disclosure, the controller **200** may include a network interface **240** to communicate with other computers or to a server. A storage device **210** may be used for storing data. The disclosed method may run on the controller **200** or on a user device, including, for example, on a mobile device, an IoT device, or a server system.

[0032] With reference to FIG. **3**, a block diagram for a machine learning network **320** for classifying data in accordance with some aspects of the disclosure is shown. In some systems, a machine learning network **320** may include, for example, a convolutional neural network (CNN) and/or a recurrent neural network. A deep learning neural network includes multiple hidden layers. As explained in more detail below, the machine learning network **320** may leverage one or more classification models (e.g., CNNs, decision trees, Naive Bayes, k-nearest neighbor) to classify data. The machine learning network **320** may be executed on the controller **200** (FIG. **2**). Persons of ordinary skill in the art will understand the machine learning network **320** and how to implement it.

[0033] In machine learning, a CNN is a class of artificial neural network (ANN). The convolutional aspect of a CNN relates to applying matrix processing operations to localized portions of the data, and the results of those operations (which can involve dozens of different parallel and serial calculations) are sets of many features that are delivered to the next layer. A CNN typically includes convolution layers, activation function layers, deconvolution layers (e.g., in segmentation networks), and/or pooling (typically max pooling) layers to reduce dimensionality without losing too many features. Additional information may be included in the operations that generate these features. Providing unique information that yields features that give the neural networks information can be used to provide an aggregate way to differentiate between different data input to the neural networks.

[0034] Referring to FIG. **4**, generally, a machine learning network **320** (e.g., a convolutional deep learning neural network) includes at least one input layer **440**, a plurality of hidden layers **450**, and at least one output layer **460**. The input layer **440**, the plurality of hidden layers **450**, and the output layer **460** all include neurons **420** (e.g., nodes). The neurons **420** between the various layers are interconnected via weights **410**. Each neuron **420** in the machine learning network **320** computes an output value by applying a specific function to the input values coming from the previous layer. The function that is applied to the input values is determined by a vector of weights **410** and a bias. Learning in the deep learning neural network progresses by making iterative adjustments to these biases and weights. The vector of weights **410** and the bias are called filters (e.g., kernels) and represent particular features of the input (e.g., a particular shape). The machine learning network **320** may output logits. Although CNNs are used as an example, other machine learning classifiers are contemplated.

[0035] The machine learning network **320** may be initially trained based on feeding a dataset into the machine learning network **320** that is known to be good and/or ground truth performance data. This enables the machine learning network **320** to learn what good performance looks like and detect deviations through unsupervised learning.

[0036] The machine learning network **320** may undergo supervised learning. The machine learning network **320** may be trained based on labeling training data to optimize weights. For example, samples of sensor feature data may be taken and labeled using other sensor feature data. In some methods in accordance with this disclosure, the training may include supervised learning or semi-supervised. Persons of ordinary skill in the art will understand training the machine learning network **320** and how to implement it.

[0037] Referring to FIG. **5**, a flow diagram for a method in accordance with the present disclosure for HVAC anomaly detection is shown as **500**. Although the steps of FIG. **5** are shown in a particular order, the steps need not all be performed in the specified order, and certain steps can be performed in another order. For example, FIG. **5** will be described below, with a controller **200** of FIG. **2** performing the operations. In aspects, the operations of FIG. **5** may be performed all or in part by another device, for example, a server and/or a computer system. These variations are contemplated to be within the scope of the present disclosure.

[0038] Initially, at step **502**, the controller **200** accesses sensor data captured by a sensor **102** configured to capture temperature, pressure data, flow data, and/or current draw of a component **112** of an HVAC system **110**. For example, the sensor **102** may be a thermocouple configured to sense the temperature of a heatsink that is connected to a refrigerator.

[0039] Next, at step **504**, the controller **200** provides the sensor data as an input to a machine learning network **320**. The machine learning network may include variational auto-encoding, a transformer, other RNN based models (RNN, LSTM), Decision Trees (Isolation Forest), a Support Vector Machine (SVM), sequence to sequence model, K-means clustering, and/or an ensemble model. other machine learning models are contemplated. One or more machine learning models may be paired. For example, a variational auto-encoder is an unsupervised model, and, when paired with the gated recurrent unit, proves to be capable of detecting anomalies throughout sequences of data.

[0040] Next, at step **504**, the controller **200** predicts one or more anomalies using the machine learning network. The machine learning network may extract patterns in time-series data.

[0041] The predicted anomaly may be reported to a user in the form of a report, an alert, or may shut off one or more components of the HVAC system, such as by actuating a valve. In aspects, the controller **200** may generate a report indicating the predicted one or more anomalies. In aspects, the controller **200** may transmit an indication to a user device about the predicted one or more anomalies. In aspects, the controller **200** may disable one or more components **112** of the HVAC system **110** based on the predicted one or more anomalies.

[0042] Although HVAC systems are used as an example, other large-scale systems are contemplated to be within the scope of this disclosure.

[0043] It should be understood that the foregoing description is only illustrative of the present disclosure. Various alternatives, modifications, and variances can be devised by those skilled in the art without departing from the disclosure. For instance, although certain aspects herein are described as separate aspects, each of the aspects herein may be combined with one or more of the other aspects herein. Specific structural and functional details disclosed herein are not to be interpreted as limiting but as a basis for the claims and as a representative basis for teaching one skilled in the art to variously employ the present disclosure in any appropriately detailed structure. The aspects described with reference to the attached drawing figures are presented only to demonstrate certain examples of the disclosure. Other elements, steps, methods, and techniques that are insubstantially different from those described above and/or in the appended claims are also intended to be within the scope of the disclosure.

What is claimed is:

1. A system for heating, ventilation, and air conditioning (HVAC) anomaly detection comprising:
- a sensor configured to capture temperature, pressure data, flow data, and/or current draw;
- a processor; and
- a memory, including instructions stored thereon, which, when executed by the processor, cause the system to:
  - access the captured sensor data;
  - provide the sensor data as an input to a machine learning network; and
  - predict one or more anomalies using the machine learning network.

2. The system of claim **1**, wherein the machine learning network includes variational auto-encoding, a transformer, other RNN based models (RNN, LSTM), Decision Trees (Isolation Forest), a Support Vector Machine (SVM), sequence to sequence model, K-means clustering, and/or an ensemble model.

3. The system of claim **1**, wherein the instructions, when executed by the processor, further cause the system to generate a report indicating the predicted one or more anomalies.

4. The system of claim **1**, wherein the instructions, when executed by the processor, further cause the system to transmit an indication to a user device about the predicted one or more anomalies.

5. The system of claim **1**, wherein the instructions, when executed by the processor, further cause the system to disable one or more components of the HVAC system based on the predicted one or more anomalies.

6. A processor-implemented method for HVAC anomaly detection comprising:
- accessing captured sensor data from a sensor configured to capture temperature, pressure data, flow data, and/or current draw;
- providing the sensor data as an input to a machine learning network; and
- predicting one or more anomalies using the machine learning network.

7. The method of claim **6**, wherein the machine learning network includes variational auto-encoding, a transformer, other RNN based models (RNN, LSTM), Decision Trees (Isolation Forest), a Support Vector Machine (SVM), sequence-to-sequence model, K-means clustering, and/or an ensemble model.

8. The method of claim **6**, further comprising generating a report indicating the predicted one or more anomalies.

9. The method of claim **6**, further comprising transmitting an indication to a user device about the predicted one or more anomalies.

10. The method of claim **6**, further comprising disabling one or more components of the HVAC system based on the predicted one or more anomalies.

11. A non-transitory computer-readable medium, storing instructions, which when executed by a processor, cause performance of a processor-implemented method for HVAC anomaly detection, the method comprising:

accessing captured sensor data from a sensor configured to capture temperature, pressure data, flow data, and/or current draw;

providing the sensor data as an input to a machine learning network; and

predicting one or more anomalies using the machine learning network.

12. The non-transitory computer-readable medium of claim **11**, wherein the machine learning network includes variational auto-encoding, a transformer, other RNN based models (RNN, LSTM), Decision Trees (Isolation Forest), a Support Vector Machine (SVM), sequence to sequence model, K-means clustering, and/or an ensemble model.

13. The non-transitory computer-readable medium of claim **11**, wherein the instructions, when executed by the processor, further cause the performance of a processor-implemented method for HVAC anomaly detection, the method further comprising generating a report indicating the predicted one or more anomalies.

14. The method of claim **11**, wherein the instructions, when executed by the processor, further cause the performance of a processor-implemented method for HVAC anomaly detection, the method further comprises transmitting an indication to a user device about the predicted one or more anomalies.

15. The method of claim **11**, wherein the instructions, when executed by the processor, further cause the performance of a processor-implemented method for HVAC anomaly detection, the method further comprising disabling one or more components of an HVAC system based on the predicted one or more anomalies.

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