

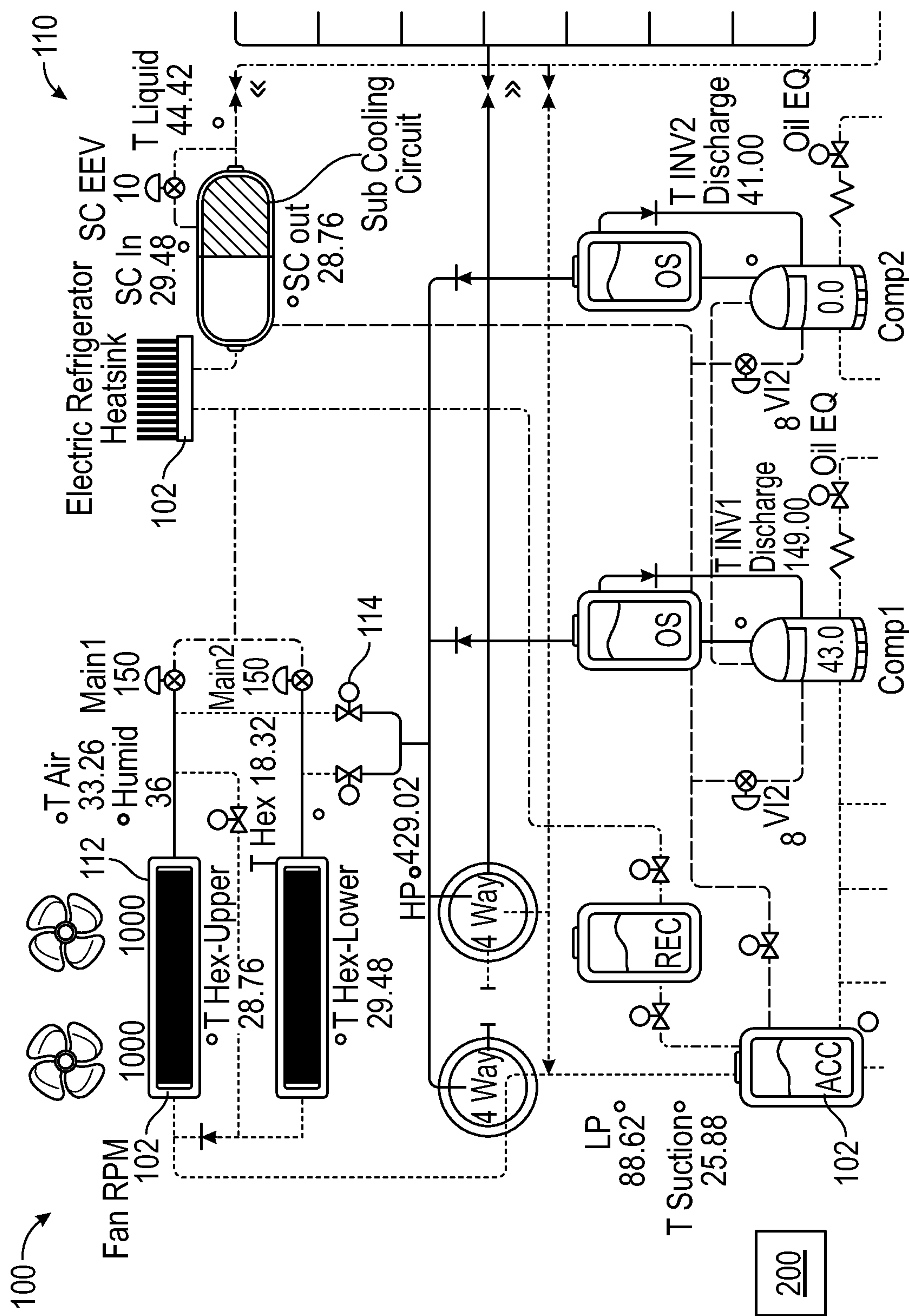


FIG. 1

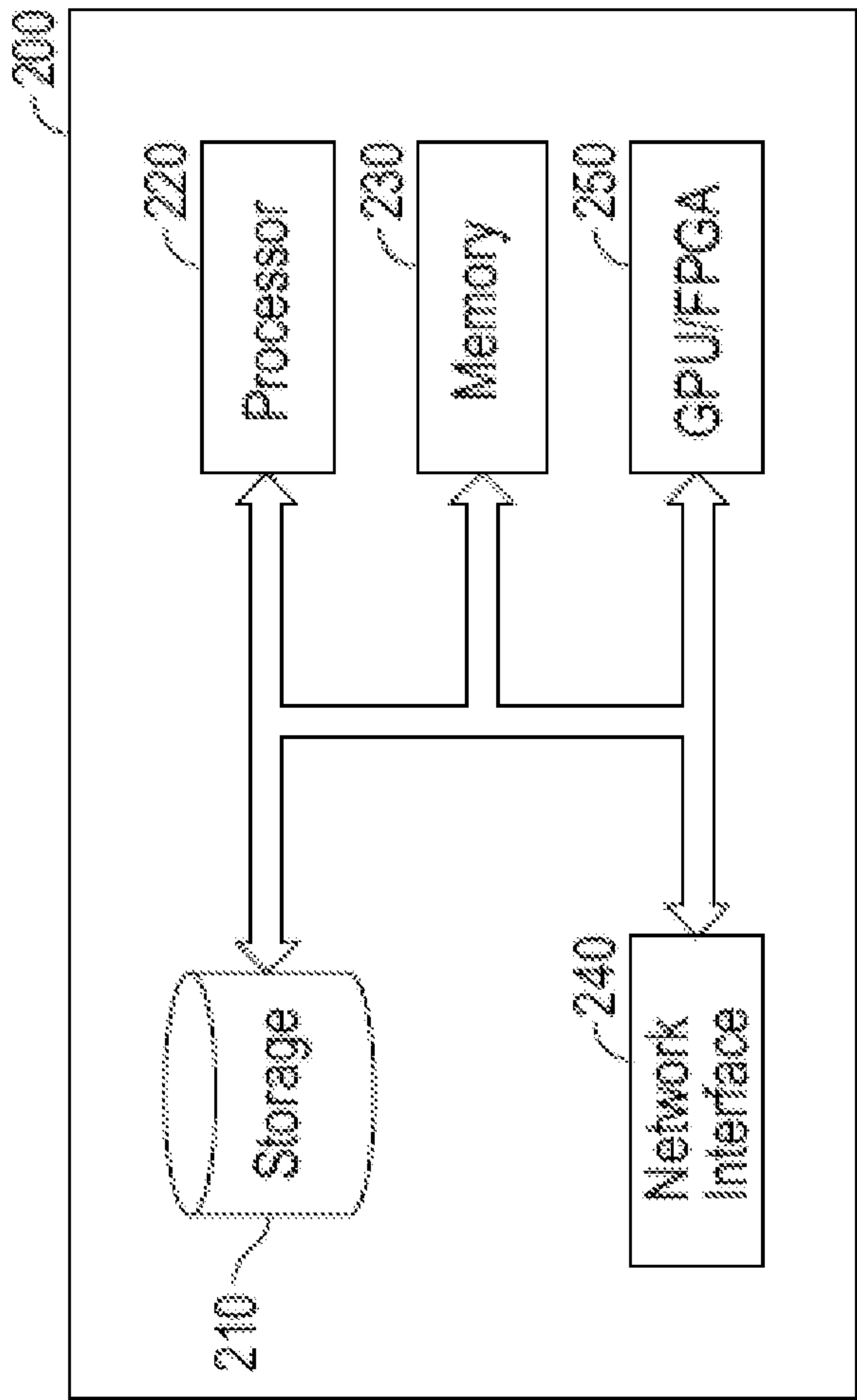


FIG. 2

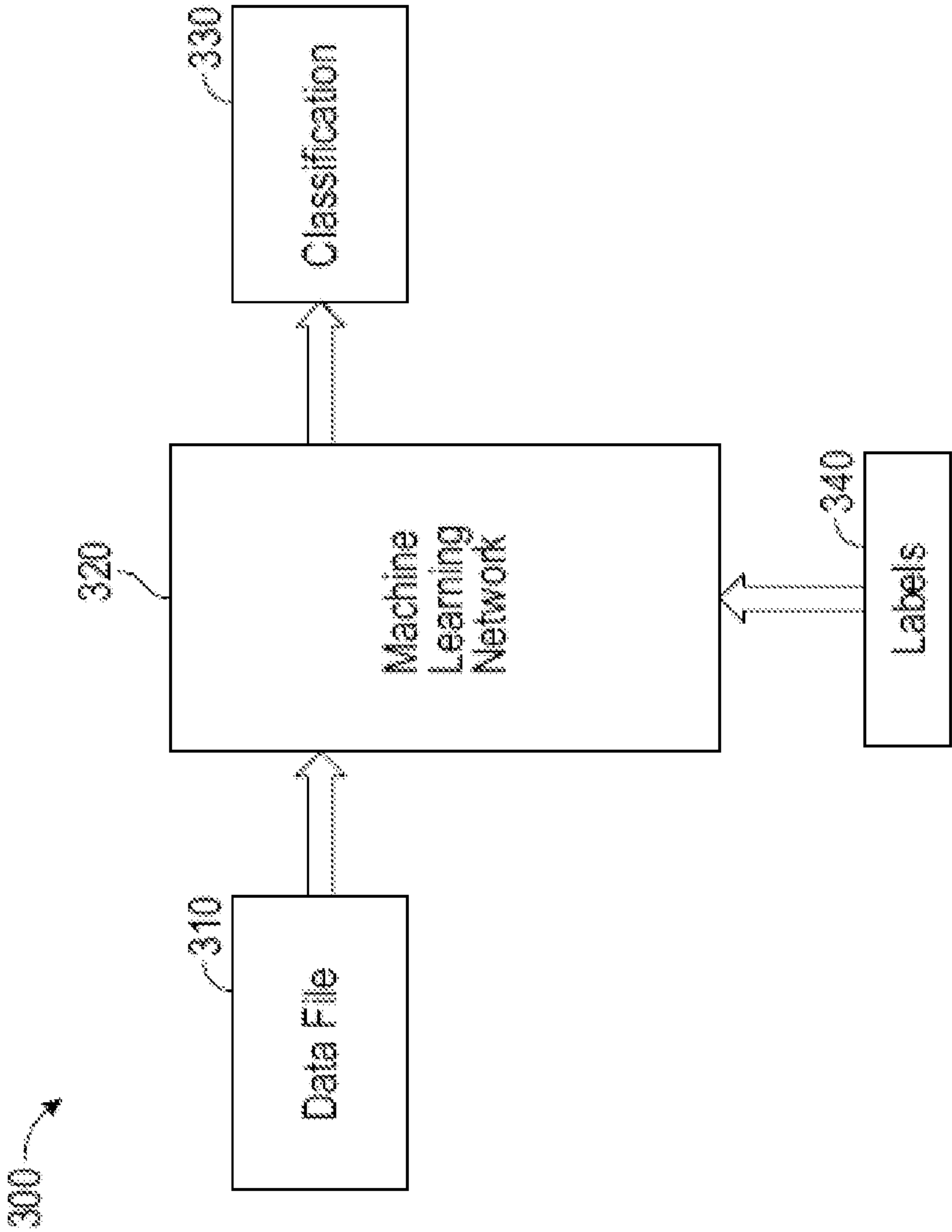


FIG. 3

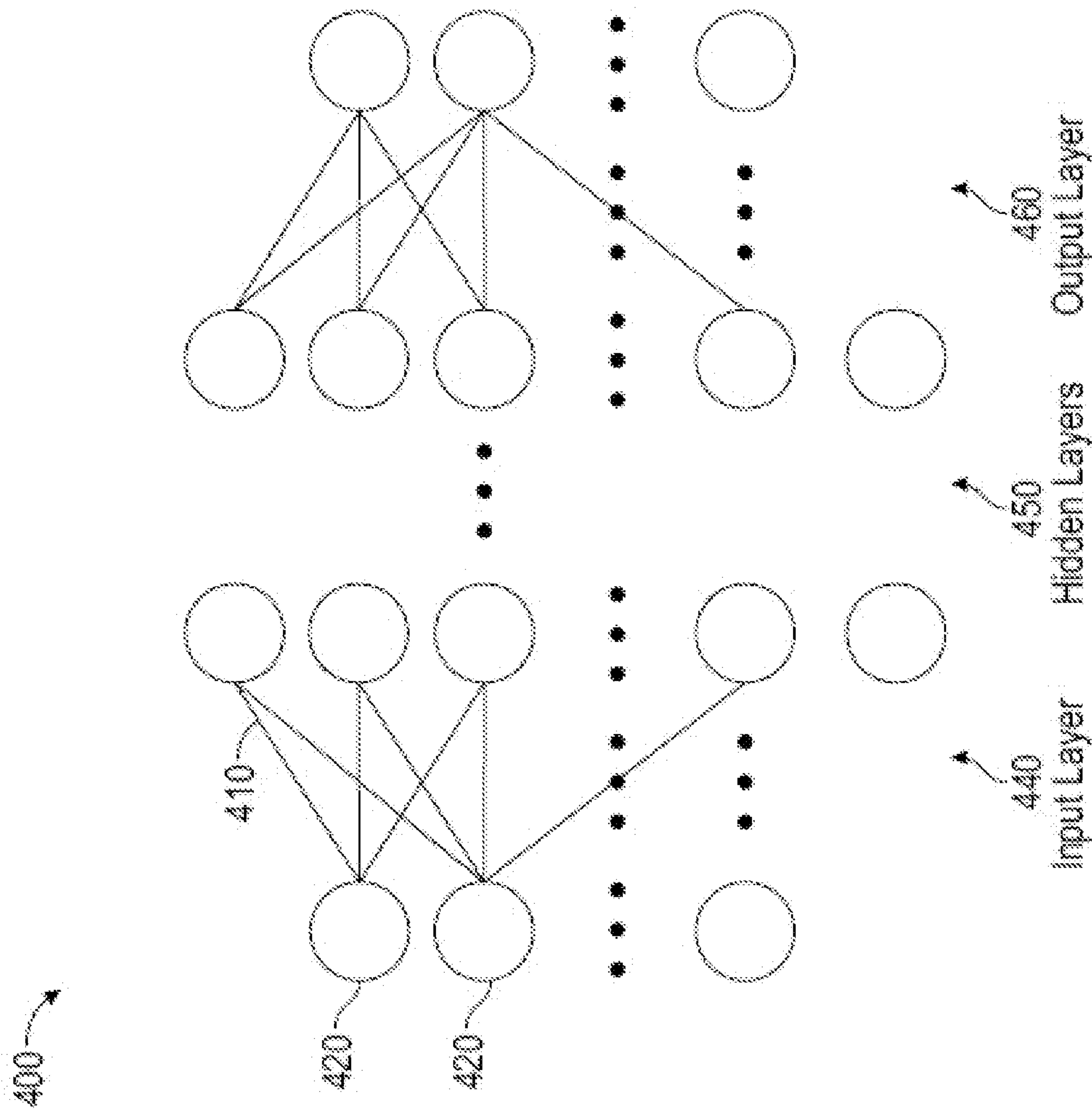


FIG. 4

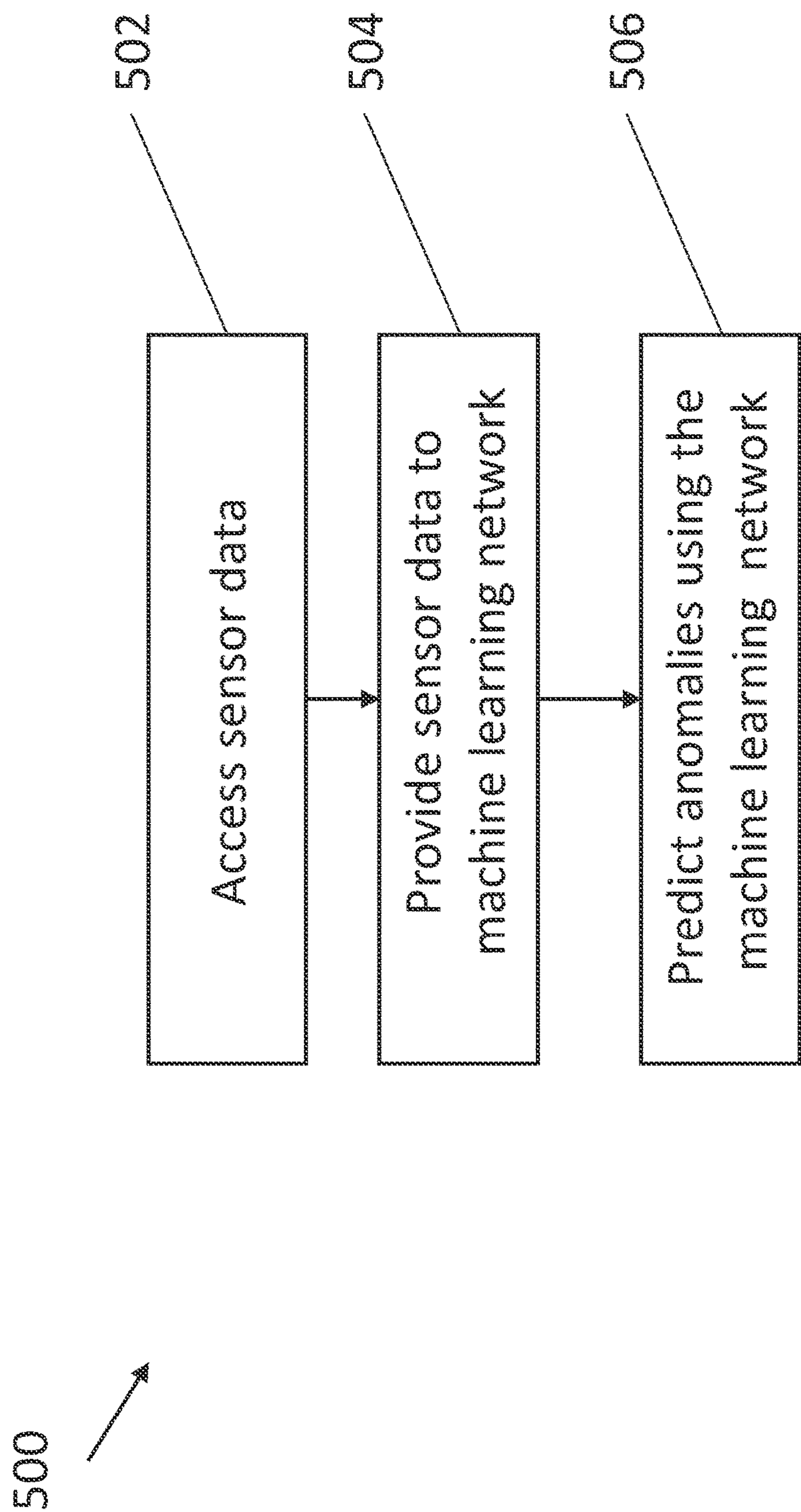


FIG. 5

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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