US 20250252299A1

(19) United States
(12) Patent Application Publication (10) Pub. No.: US 2025/0252299 A1
Teig et al. (43) Pub. Date: Aug. 7, 2025

(54) THREE DIMENSIONAL CIRCUIT IMPLEMENTING MACHINE TRAINED NETWORK

(71) Applicant: **Adeia Semiconductor Inc.**, San Jose, CA (US)

(72) Inventors: **Steven L. Teig**, Menlo Park, CA (US); **Kenneth Duong**, San Jose, CA (US)

(21) Appl. No.: **19/048,095**

(22) Filed: **Feb. 7, 2025**

Related U.S. Application Data

(63) Continuation of application No. 18/469,910, filed on Sep. 19, 2023, now Pat. No. 12,248,869, which is a (Continued)

Publication Classification

(51) **Int. Cl.**

G06N 3/065	(2023.01)
G06F 11/14	(2006.01)
G06F 11/20	(2006.01)
G06N 3/04	(2023.01)
G06N 3/048	(2023.01)
G06N 3/063	(2023.01)
G06N 3/08	(2023.01)
G06N 3/082	(2023.01)
G06N 3/084	(2023.01)
H01L 23/00	(2006.01)
H01L 23/31	(2006.01)
H01L 25/04	(2023.01)

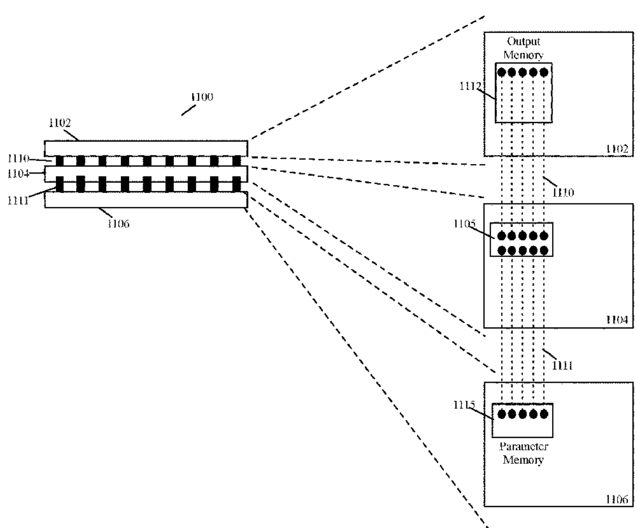
(Continued)

(52) **U.S. Cl.**

CPC ***G06N 3/065*** (2023.01); ***G06F 11/1423*** (2013.01); ***G06F 11/2007*** (2013.01); ***G06F 11/2028*** (2013.01); ***G06F 11/2041*** (2013.01); ***G06F 11/2051*** (2013.01); ***G06N 3/04*** (2013.01); ***G06N 3/048*** (2023.01); ***G06N 3/063*** (2013.01); ***G06N 3/08*** (2013.01); ***G06N 3/082*** (2013.01); ***G06N 3/084*** (2013.01); ***H01L 23/3128*** (2013.01); ***H01L 25/0657*** (2013.01); *G06F 2201/85* (2013.01); *H01L 24/16* (2013.01); *H01L 24/17* (2013.01); *H01L 25/043* (2013.01); *H01L 25/074* (2013.01); *H01L 25/0756* (2013.01); *H01L 25/117* (2013.01); *H01L 2224/16145* (2013.01); *H01L 2224/16225* (2013.01); *H01L 2224/16227* (2013.01); *H01L 2224/17181* (2013.01); *H01L 2225/06503* (2013.01); *H01L 2225/06513* (2013.01); *H01L 2225/06517* (2013.01); *H01L 2225/06524* (2013.01); *H01L 2225/06541* (2013.01); *H01L 2225/06565* (2013.01); *H01L 2225/06582* (2013.01); *H01L 2225/06586* (2013.01); *H01L 2924/16235* (2013.01); *H03K 19/21* (2013.01)

(57) **ABSTRACT**

Some embodiments provide a three-dimensional (3D) circuit structure that has two or more vertically stacked bonded layers with a machine-trained network on at least one bonded layer. As described above, each bonded layer can be an IC die or an IC wafer in some embodiments with different embodiments encompassing different combinations of wafers and dies for the different bonded layers. The machine-trained network in some embodiments includes several stages of machine-trained processing nodes with routing fabric that supplies the outputs of earlier stage nodes to drive the inputs of later stage nodes. In some embodiments, the machine-trained network is a neural network and the processing nodes are neurons of the neural network. In some embodiments, one or more parameters associated with each processing node (e.g., each neuron) is defined through machine-trained processes that define the values of these parameters in order to allow the machine-trained network (e.g., neural network) to perform particular operations (e.g., face recognition, voice recognition, etc.). For example, in some embodiments, the machine-trained parameters are weight values that are used to aggregate (e.g., to sum) several output values of several earlier stage processing nodes to produce an input value for a later stage processing node.



Related U.S. Application Data

continuation of application No. 17/500,374, filed on Oct. 13, 2021, now Pat. No. 11,790,219, which is a continuation of application No. 15/859,551, filed on Dec. 31, 2017, now Pat. No. 11,176,450.

(60) Provisional application No. 62/541,064, filed on Aug. 3, 2017.

Publication Classification

(51) **Int. Cl.**

H01L 25/065	(2023.01)
H01L 25/07	(2006.01)
H01L 25/075	(2006.01)
H01L 25/11	(2006.01)
H03K 19/21	(2006.01)

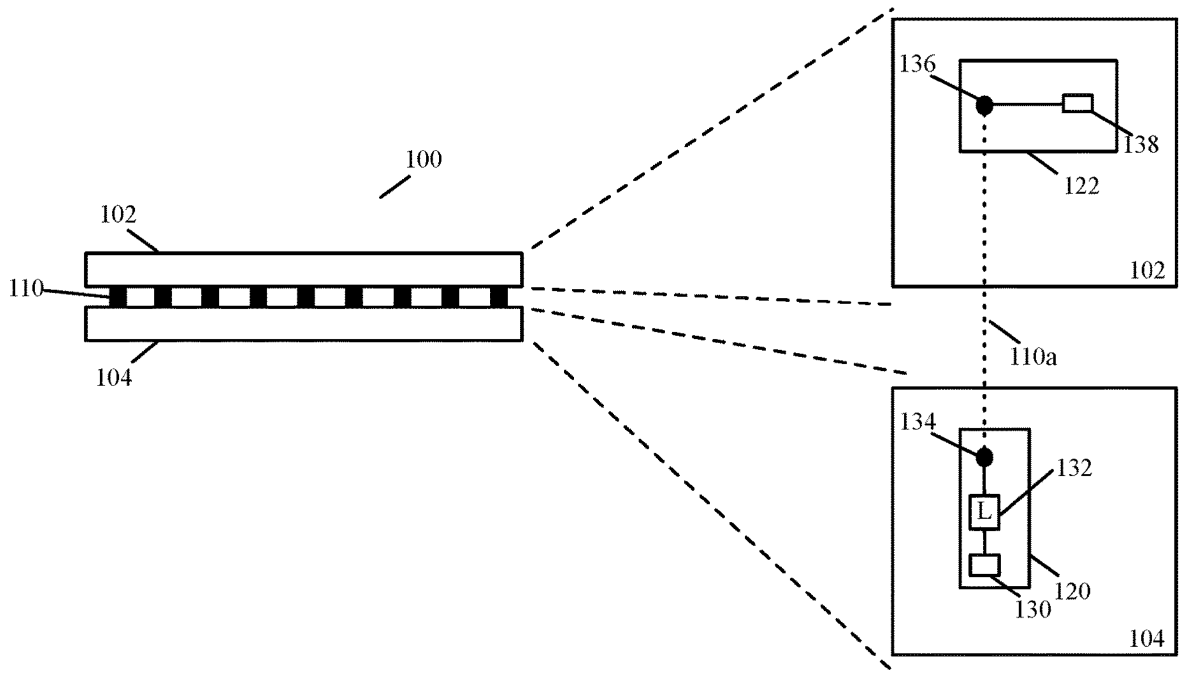


Figure 1

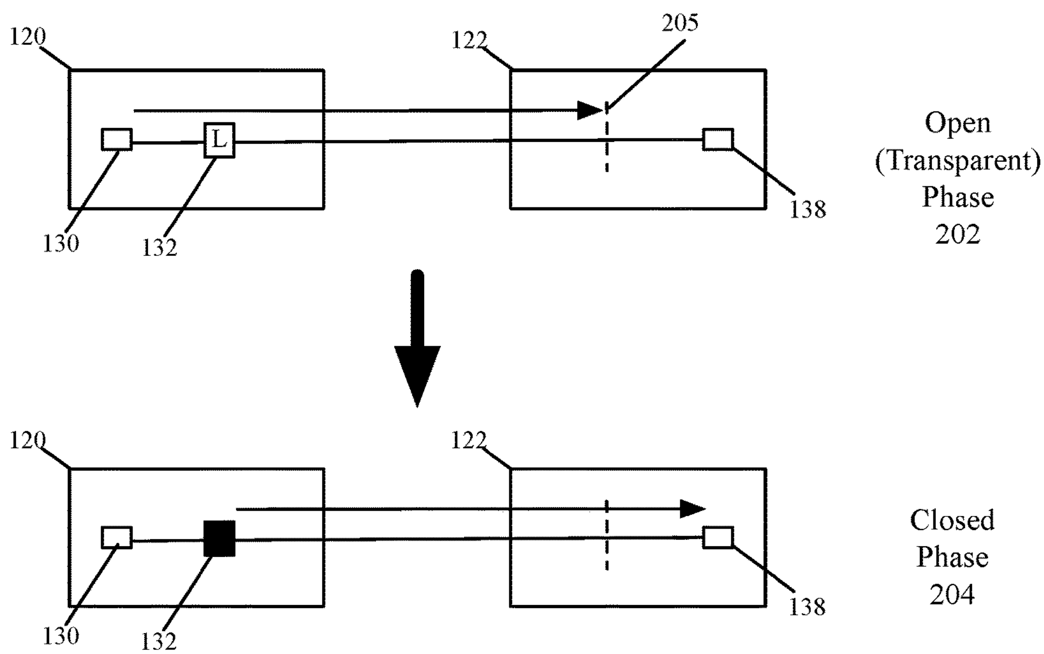


Figure 2

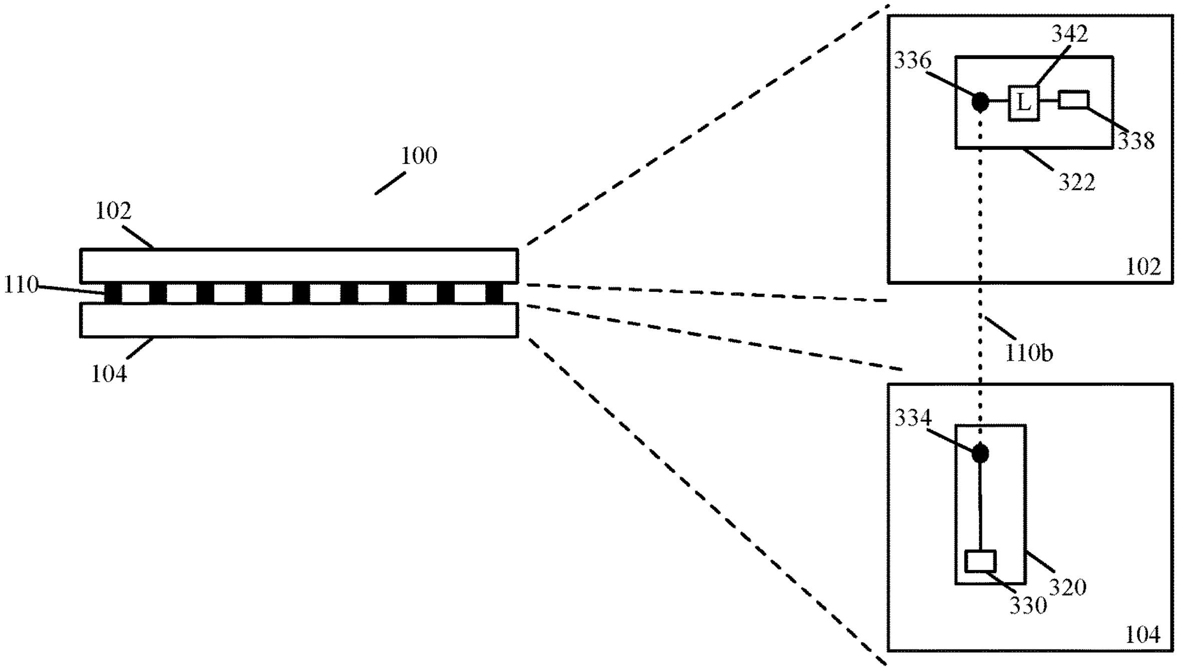


Figure 3

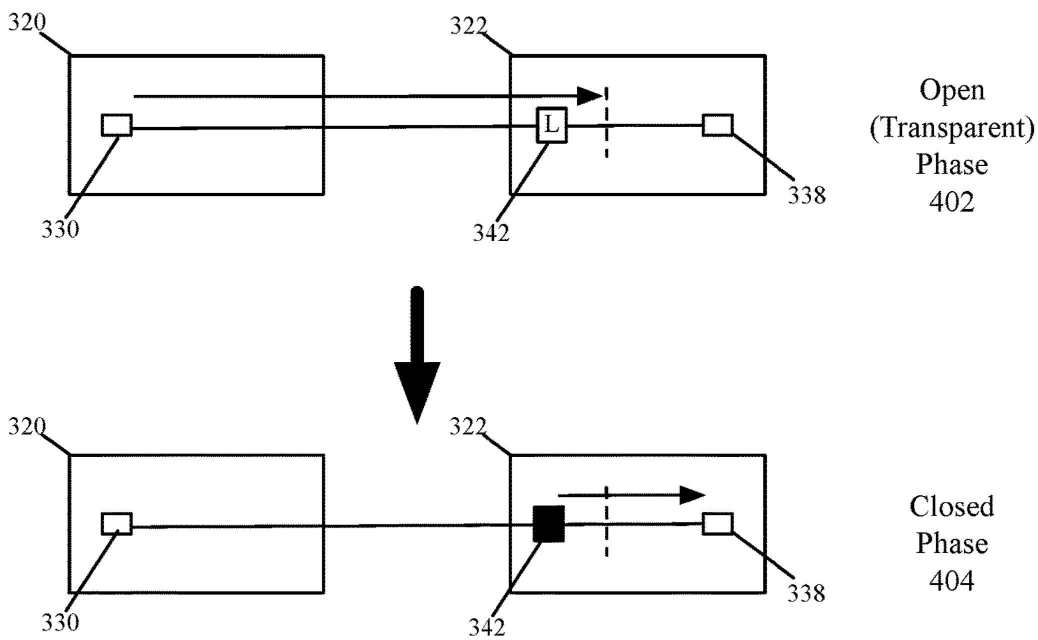
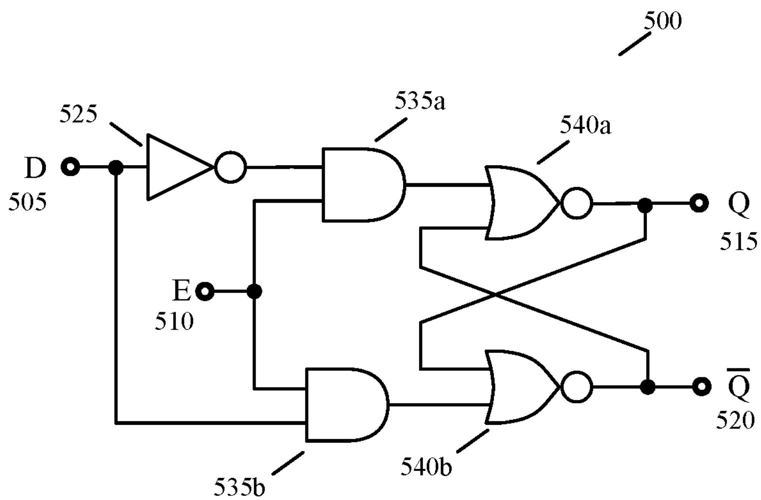


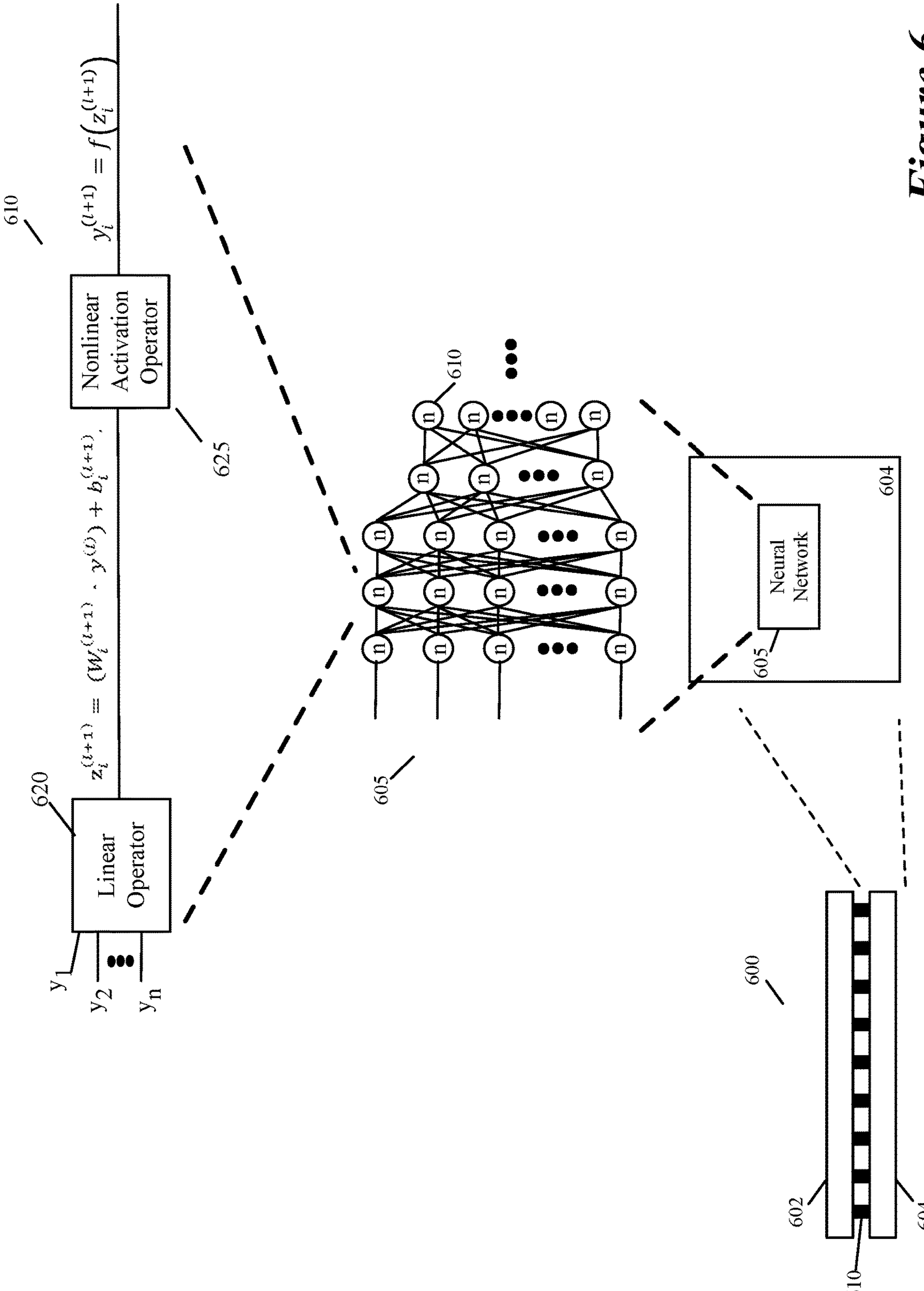
Figure 4



550

Enable	D	Q	$\overline{Q}$
0	0	Latched	
0	1	Latched	
1	0	0	1
1	1	1	0

Figure 5



610
$y_i^{(l+1)} = f\left(z_i^{(l+1)}\right)$
Nonlinear Activation Operator
625
$z_i^{(l+1)} = \left(W_i^{(l+1)} \cdot y^{(l)}\right) + b_i^{(l+1)}$
620
Linear Operator
y_1
y_2
y_n
610
605
Neural Network
605
604
600
602
604
610

Figure 6

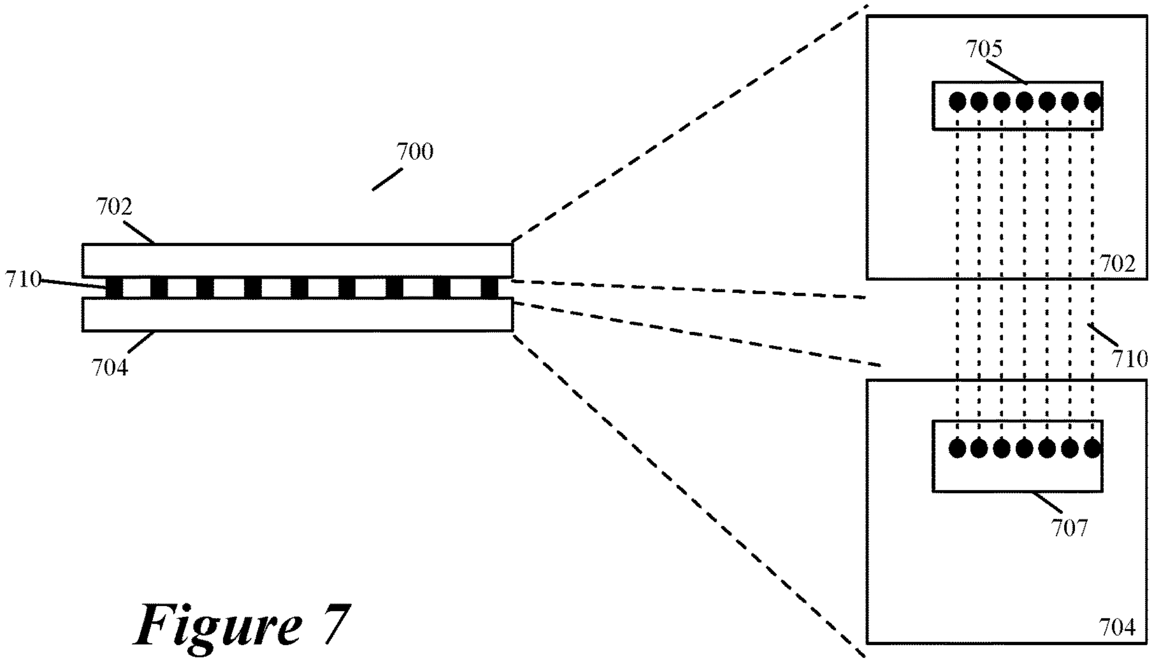


Figure 7

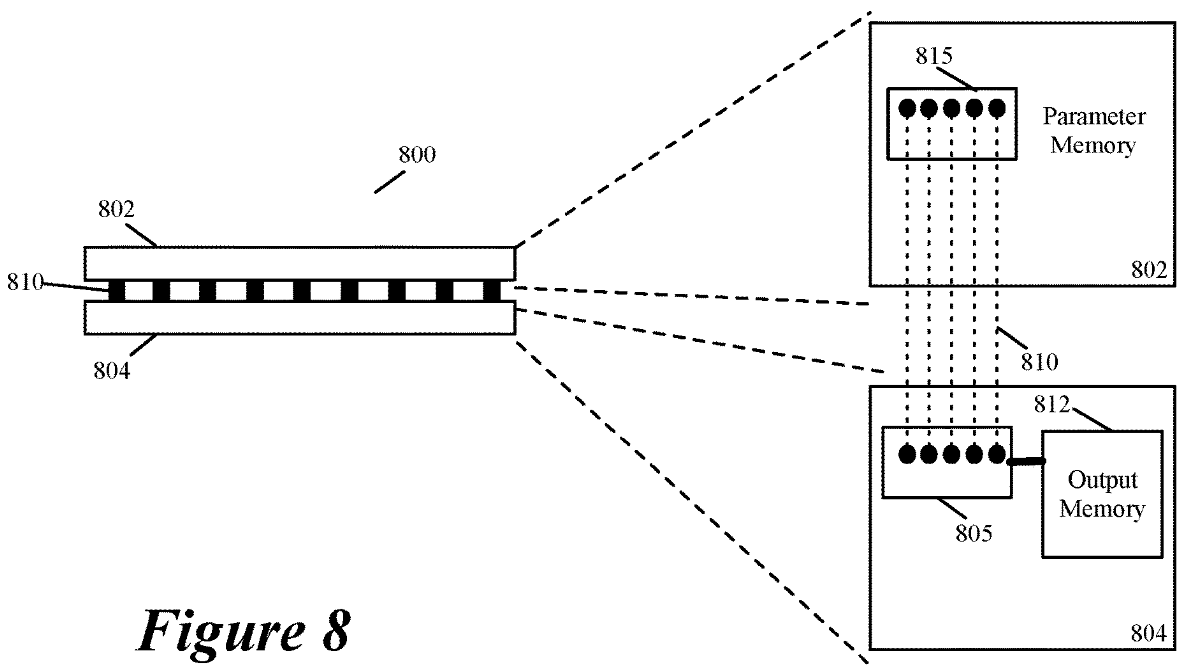


Figure 8

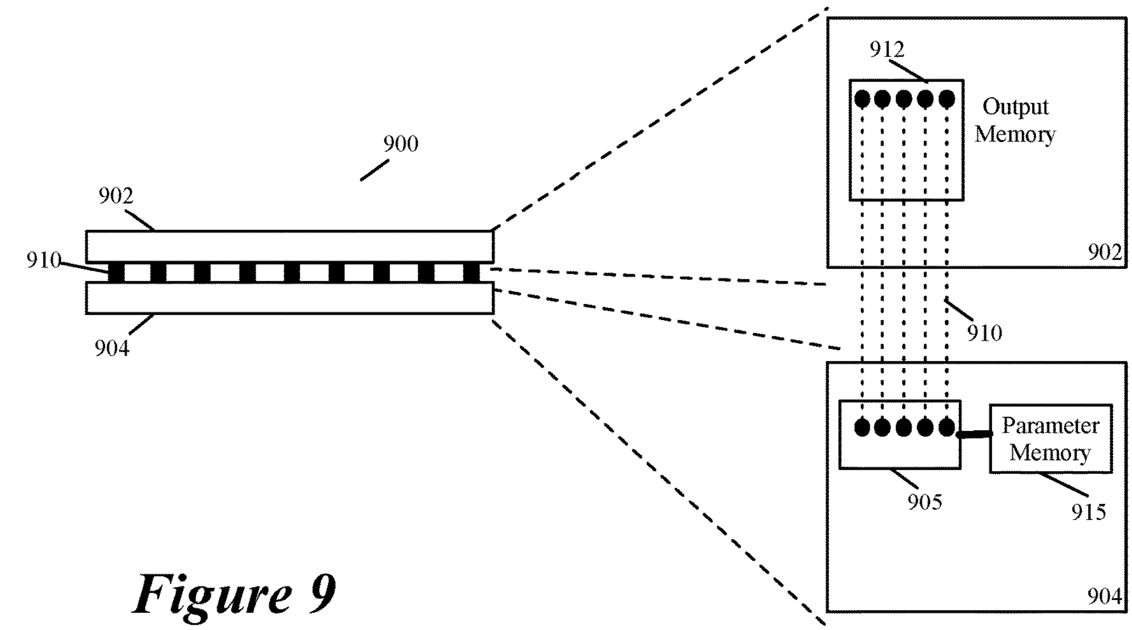


Figure 9

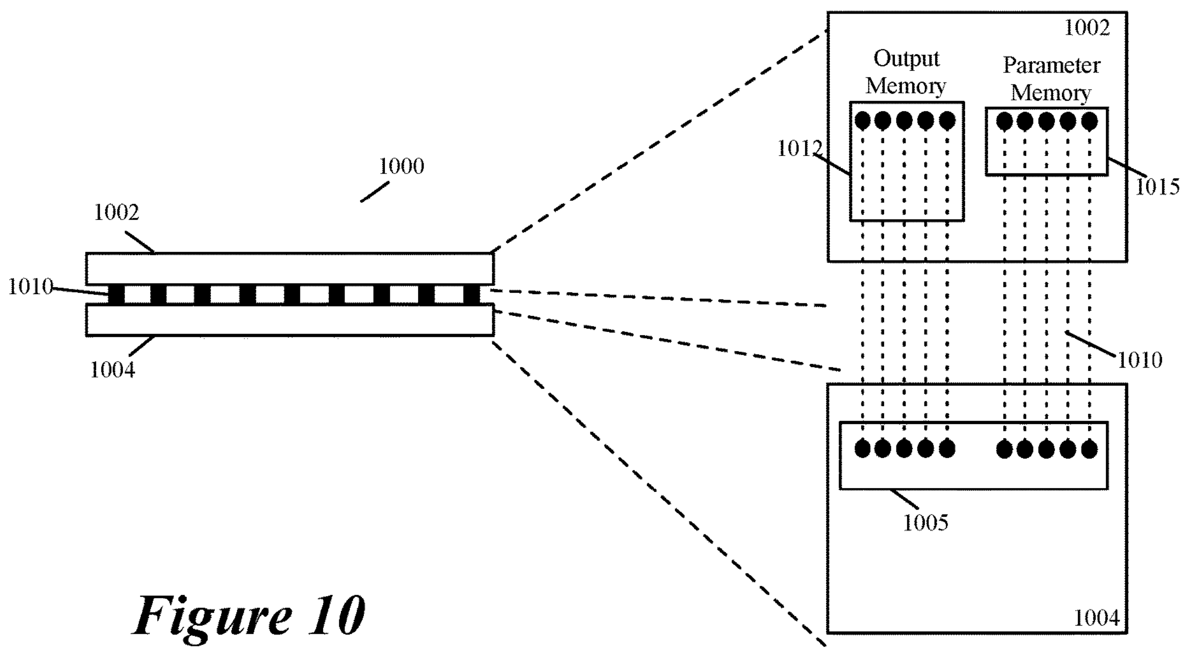
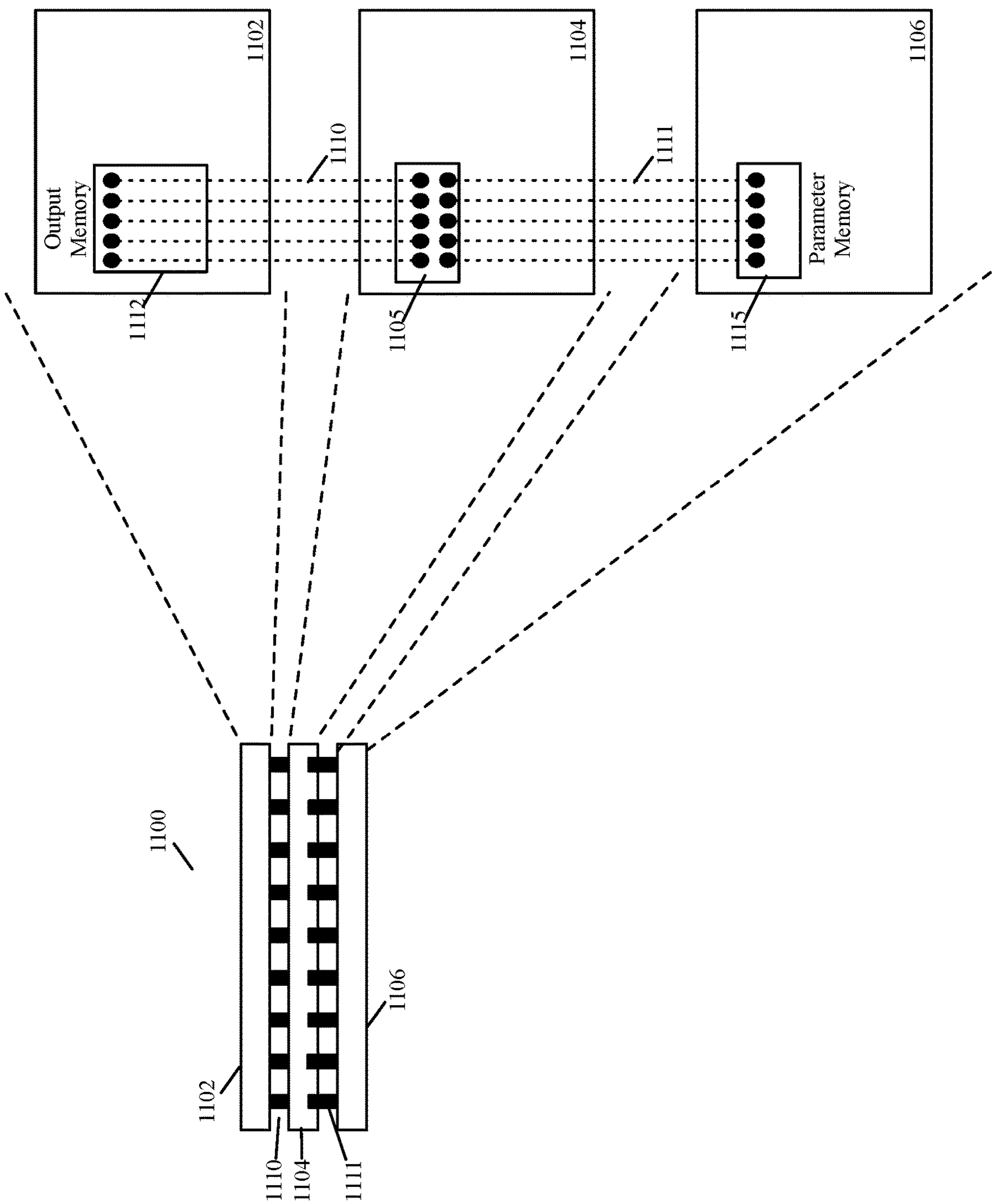


Figure 10



1102
1104
1106
Output Memory
Parameter Memory
1110
1111
1112
1105
1115
1100
1102
1110
1104
1111
1106

Figure 11

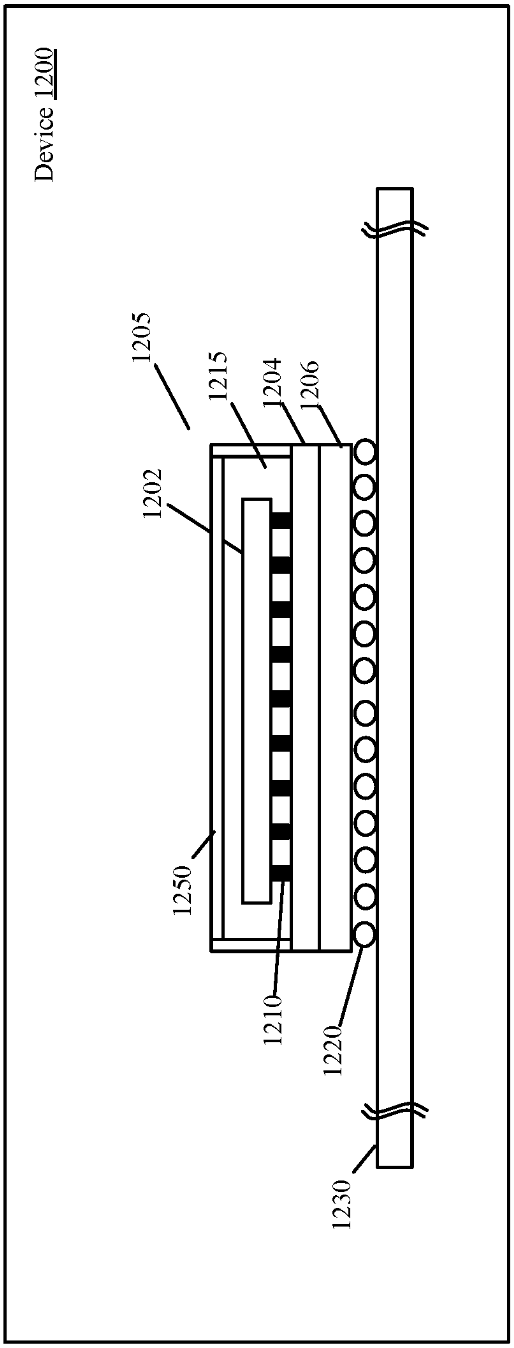


Figure 12

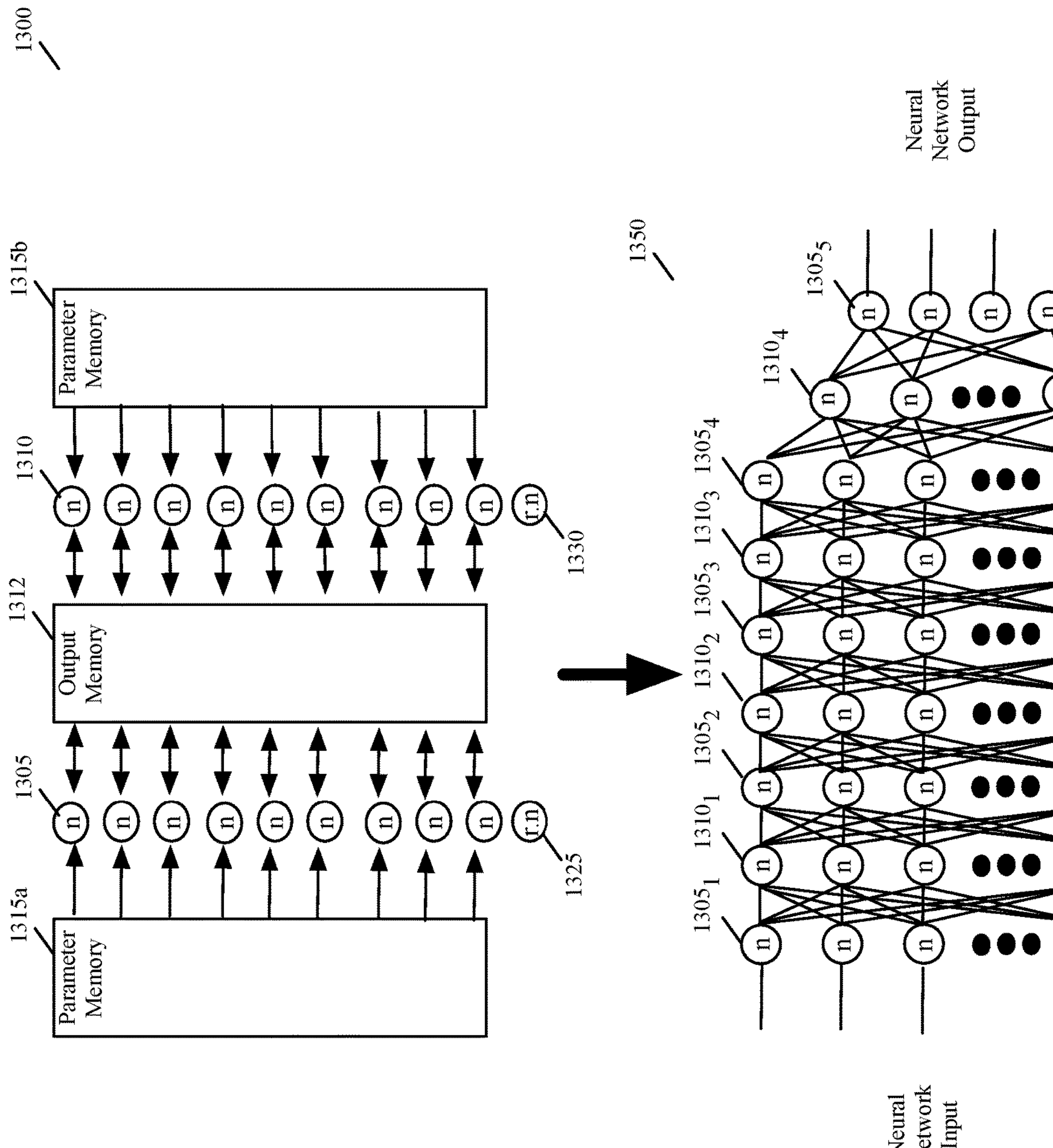

1300
1315a
Parameter Memory
1305
1325
r.n
1312
Output Memory
1310
1330
1315b
Parameter Memory
1350
1305_1
1310_1
1305_2
1310_2
1305_3
1310_3
1305_4
1310_4
1305_5
Neural Network Input
Neural Network Output

Figure 13

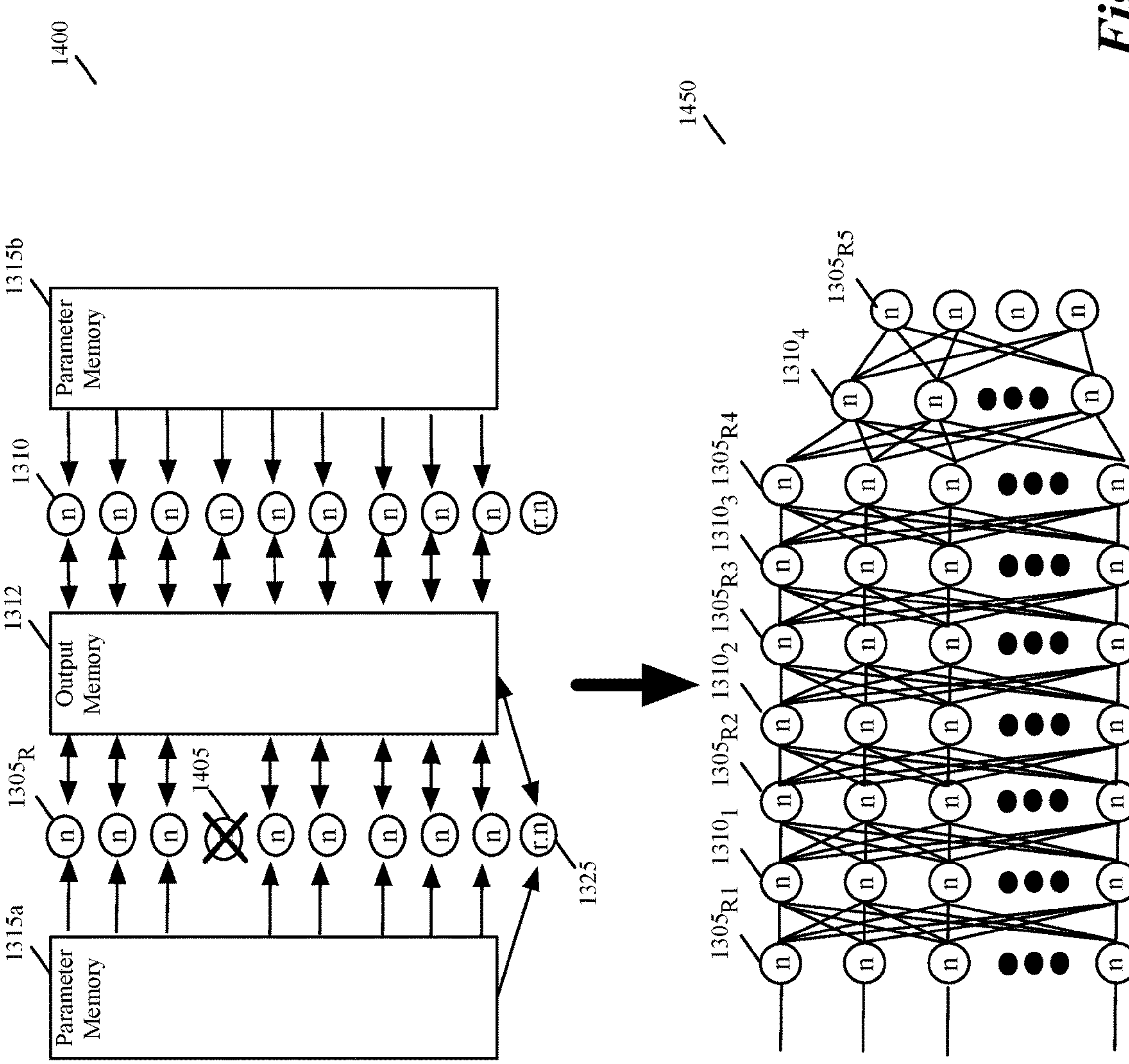

1400
1450
1315a
Parameter Memory
1305$_R$
1405
1325
r.n
1312
Output Memory
1310
1315b
Parameter Memory
n
1305$_{R1}$
1310$_1$
1305$_{R2}$
1310$_2$
1305$_{R3}$
1310$_3$
1305$_{R4}$
1310$_4$
1305$_{R5}$

Figure 14

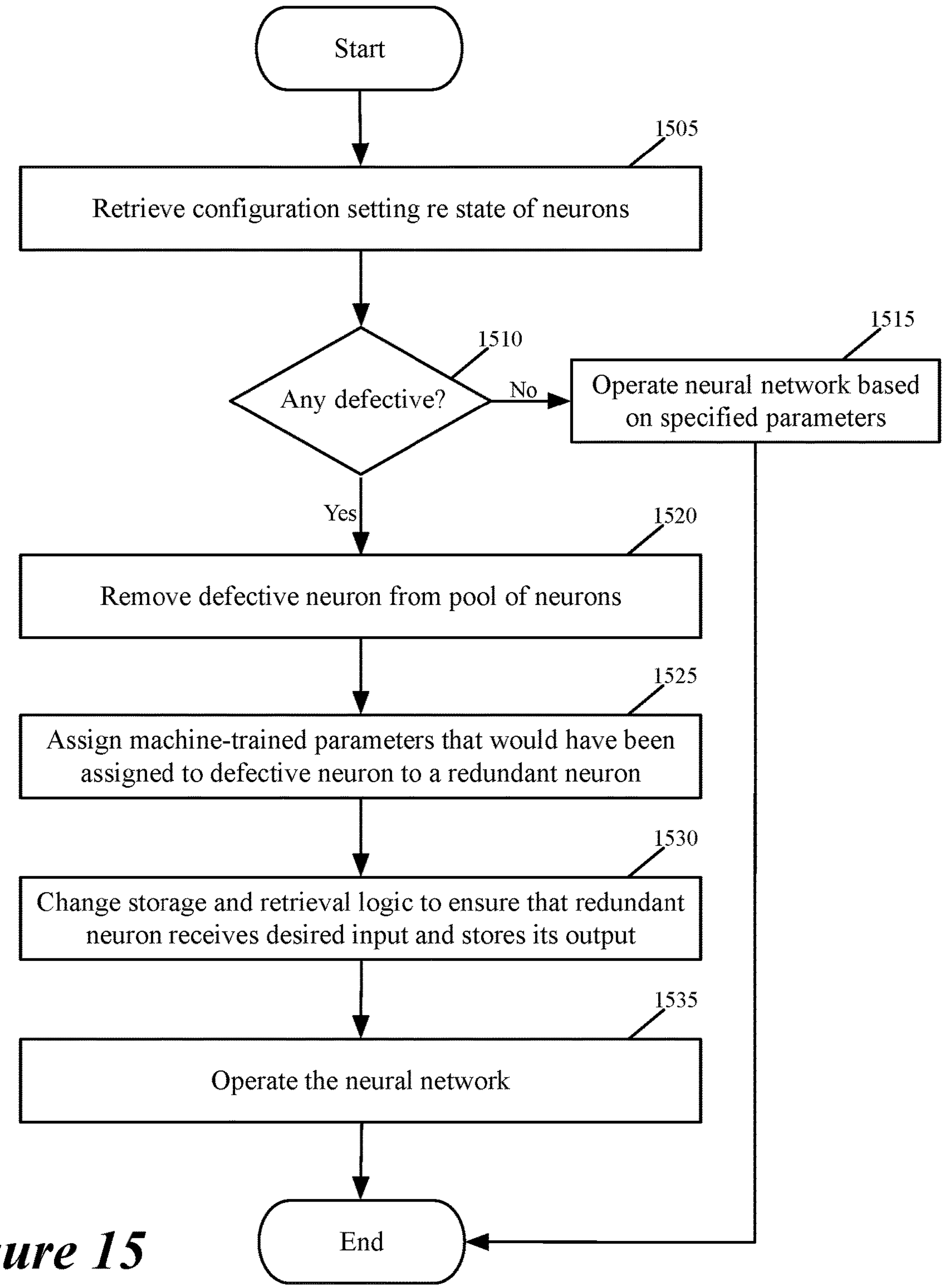

Start
1505
Retrieve configuration setting re state of neurons
1510
Any defective?
No
1515
Operate neural network based on specified parameters
Yes
1520
Remove defective neuron from pool of neurons
1525
Assign machine-trained parameters that would have been assigned to defective neuron to a redundant neuron
1530
Change storage and retrieval logic to ensure that redundant neuron receives desired input and stores its output
1535
Operate the neural network
End

Figure 15

THREE DIMENSIONAL CIRCUIT IMPLEMENTING MACHINE TRAINED NETWORK

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application is a continuation of U.S. patent application Ser. No. 18/469,910, filed on Sep. 19, 2023, which is a continuation of U.S. patent application Ser. No. 17/500,374, filed on Oct. 13, 2021, which is a continuation of U.S. patent application Ser. No. 15/859,551, filed on Dec. 31, 2017, which claims the benefit of the filing date of U.S. Provisional Patent Application No. 62/541,064, filed Aug. 3, 2017. The disclosure of each of the above applications is incorporated herein by reference in its entirety.

BACKGROUND

[0002] In recent years, there have been great advances in the field of machine learning. Much of these advances have been in machine trained networks (e.g., deep neural networks) and algorithms for training such networks. However, there has not been as much advances in circuits for implementing machine-trained networks. This has been primarily due to an over reliance on implementing machine trained networks in datacenters as opposed to in devices in the real world. Therefore, there is a need in the art for innovative circuits for implementing machine trained networks as well as other types of designs.

BRIEF SUMMARY

[0003] Some embodiments of the invention provide a three-dimensional (3D) circuit structure that uses latches to transfer signals between two bonded circuit layers. In some embodiments, this structure includes a first circuit partition on a first bonded layer and a second circuit partition on a second bonded layer. It also includes at least one latch to transfer signals between the first circuit partition on the first bonded layer and the second circuit partition on the second bonded layer. In some embodiments, the latch operates in (1) an open first mode that allows a signal to pass from the first circuit partition to the second circuit partition and (2) a closed second mode that maintains the signal passed through during the prior open first mode.

[0004] Unlike a flip-flop that releases in one clock cycle a signal that it stores in a prior clock cycle, a transparent latch does not introduce such a setup time delay in the design. In fact, by allowing the signal to pass through the first circuit partition to the second circuit partition during its open mode, the latch allows the signal to borrow time from a first portion of a clock cycle of the second circuit partition for a second portion of the clock cycle of the second circuit partition. This borrowing of time is referred to below as time borrowing. Also, this time borrowing allows the signal to be available at the destination node in the second circuit partition early so that the second circuit can act on it in the clock cycle that this signal is needed. Compared to flip-flops, latches also reduce the clock load because, while flip-flops require at least two different clock transitions to store and then release a value, transparent latches only require one signal transition to latch a value that they previously passed through.

[0005] In some embodiments, the 3D circuit has several such latches at several boundary nodes between different circuit partitions on different bonded layers. Each latch in some embodiments iteratively operates in two sequential modes, an open first mode to let a signal pass from one circuit partition (e.g., a first partition or a second partition) to the other circuit partition (e.g., the second partition or the first partition), and a closed second mode to hold the signal passed during the prior open first mode.

[0006] Each latch in some embodiments is associated with one pair of boundary nodes, with one node in the first bonded layer and another node in the second bonded layer. Each pair of nodes is electrically interconnected through a conductive interface, such as a through-silicon via (TSV) or a direct bond interface (DBI) connection (also called hybrid bonding). Each latch in some embodiments is defined on just one of the two bonded layers. In some embodiments, each latch on one bonded layer has its output carried to the other bonded layer by interconnect (e.g., wires) and the conductive interface (e.g., TSV or DBI connection) that connects the latch's associated pair of nodes. In other embodiments, each latch on one bonded layer has its input supplied from the other bonded layer by interconnect and the conductive interface that connects the latch's associated pair of nodes. In still other embodiments, a conductive-interface connection can have two latches on the two bonded layers that it connects, and either latch can be used to facilitate time borrowing as a signal travels between the two circuit partitions on the two bonded layers.

[0007] The first and second bonded layers are different in different embodiments. In some embodiments, both bonded layers are integrated circuit (IC) dies. In other embodiments, both bonded layers are IC wafers. In still other embodiments, one of these bonded layers is an IC die, while the other bonded layer is an IC wafer. The first and second bonded layers are vertically stacked on top of each other with no other intervening bonded layers in some embodiments, while these two bonded layers have one or more intervening bonded layers between them in other embodiments.

[0008] In some embodiments, one bonded layer fully overlaps the other bonded layer (e.g., the two bonded layers have the same size and are aligned such that they overlap each other's bounding shape), or one bonded layer is smaller than the other bonded layer and is completely subsumed by the footprint of the other bonded layer (i.e., has its bounding shape completely overlapped by the bounding shape of the other bonded layer). In other embodiments, the two bonded layers partially overlap. Also, in some embodiments, the first and second circuit partitions on the first and second bonded layers fully overlap (e.g., the two partition have the same size and are aligned such that they overlap each other's bounding shape), or one partition is smaller than the other partition and is completely subsumed by the footprint of the other partition). In other embodiments, the two circuit partitions partially overlap.

[0009] Some embodiments provide a three-dimensional (3D) circuit structure that has two or more vertically stacked bonded layers with a machine-trained network on at least one bonded layer. As described above, each bonded layer can be an IC die or an IC wafer in some embodiments with different embodiments encompassing different combinations of wafers and dies for the different bonded layers. The machine-trained network in some embodiments includes several stages of machine-trained processing nodes with routing fabric that supplies the outputs of earlier stage nodes to drive the inputs of later stage nodes. In some embodiments, the machine-trained network is a neural network and the processing nodes are neurons of the neural network.

[0010] In some embodiments, one or more parameters associated with each processing node (e.g., each neuron) is defined through machine-trained processes that define the values of these parameters in order to allow the machine-trained network (e.g., neural network) to perform particular operations (e.g., face recognition, voice recognition, etc.). For example, in some embodiments, the machine-trained parameters are weight values that are used to aggregate (e.g., to sum) several output values of several earlier stage processing nodes to produce an input value for a later stage processing node.

[0011] In some embodiments, the machine-trained network includes a first sub-network on one bonded layer and a second sub-network on another bonded layer, with these two sub-networks partially or fully overlapping. Alternatively, or conjunctively, the machine-trained network or sub-network on one bonded layer partially or fully overlaps a memory (e.g., formed by one or more memory arrays) on another bonded layer in some embodiments. This memory in some embodiments is a memory that stores machine-trained parameters for configuring the processing nodes of the machine-trained network or sub-network to perform a particular operation. In other embodiments, this memory is a memory that stores the outputs of the processing nodes (e.g., outputs of earlier stage processing node for later stage processing node).

[0012] While being vertically aligned with one memory, the machine-trained network's processing nodes in some embodiments are on the same bonded layer with another memory. For instance, in some embodiments, a first bonded layer in a 3D circuit includes the processing nodes of a machine-trained network and a first memory to store machine-trained parameters for configuring the processing nodes, while a second bonded layer in the 3D circuit includes a second memory to store values produced by the processing nodes. In other embodiments, the first bonded layer in the 3D circuit includes the processing nodes of a machine-trained network and a first memory to store values produced by the processing nodes, while the second bonded layer in the 3D circuit includes a second memory to store machine-trained parameters for configuring the processing nodes.

[0013] In still other embodiments, the first bonded layer in the 3D circuit includes the processing nodes of a machine-trained network, while the second bonded layer in the 3D circuit includes a first memory to store values produced by the processing nodes and a second memory to store machine-trained parameters for configuring the processing nodes. In yet other embodiments, the processing nodes on one bonded layer partially or fully overlap two memories on two different layers, with one memory storing machine-trained parameters and the other memory storing processing node output values. The 3D circuit of other embodiments has processing nodes on two or more bonded layers with parameter and/or output memories on the same or different bonded layers. In this document, parameter memory is a memory that stores machine-trained parameters for configuring the machine-trained network (e.g., for configuring the processing nodes of the network) to perform one or more tasks, while output memory is a memory that stores the outputs of the processing nodes of the machine-trained network.

[0014] Again, in the above-described embodiments, the bonded layers (two or more) that contain a machine-trained network's processing nodes and memories do not have any intervening bonded layer in some embodiments, while they have one or more intervening bonded layers between or among them in other embodiments. Also, in some embodiments, the machine-trained network's processing nodes and memories on different bonded layers are connected to each other through conductive interfaces, such as TSV or DBI connections.

[0015] In some embodiments, the IC die on which a neural network is defined is an ASIC (Application Specific IC) and each neuron in this network is a computational unit that is custom-defined to operate as a neuron. Some embodiments implement a neural network by re-purposing (i.e., reconfiguring) one or more neurons used for earlier neural network stages to implement one or more neurons in later neural network stages. This allows fewer custom-defined neurons to be used to implement the neural network. In such embodiments, the routing fabric between the neurons is at least partially defined by one or more output memories that are used to store the outputs of earlier used neurons to feed the inputs of later staged neurons.

[0016] In some embodiments, the output and parameter memories of the neural network have different memory structures (i.e., are different types of memories). For instance, in some embodiments, the output memory has a different type of output interface (e.g., one that allows for random access of the output memory's storage locations) than the parameter memory (e.g., the parameter memory's output interface only provides sequential access of its storage locations). Alternatively, or conjunctively, the parameter memory of the neural network is a read-only memory (ROM), while the output memory of the neural network is a read-write memory in some embodiments. The parameter memory in some embodiments is a sequential ROM that sequentially reads out locations in the ROM to output the parameters that configure the neural network to perform certain machine-trained task(s).

[0017] The output memory in some embodiments is a dynamic random access memory (DRAM). In other embodiments, the output memory is an ephemeral RAM (ERAM) that has one or more arrays of storage cells (e.g., capacitive cells) and pass transistors like traditional DRAMs, but does not use read-independent refresh cycles to charge the storage cells unlike traditional DRAMs. This is because the values in the ERAM memory are written and read at such rates that these values do not need to be refreshed with separate refresh cycles. In other words, because intermediate output values of the neural network only need to be used as input into the next layer (or few layers) of the neural network, they are temporary in nature. Thus, the output memory can be implemented with a memory architecture that is compact like a DRAM memory architecture without the need for read-independent refresh cycles.

[0018] Some embodiments of the invention provide an integrated circuit (IC) with a defect-tolerant neural network. The neural network has one or more redundant neurons in some embodiments. After the IC is manufactured, a defective neuron in the neural network can be detected through a test procedure and then replaced by a redundant neuron (i.e., the redundant neuron can be assigned the operation of the defective neuron). The routing fabric of the neural network can be reconfigured so that it re-routes signals around the discarded, defective neuron. In some embodiments, the reconfigured routing fabric does not provide any signal to or forward any signal from the discarded, defective neuron, and instead provides signals to and forwards signals from the redundant neuron that takes the defective neuron's position in the neural network.

[0019] In the embodiments that implement a neural network by re-purposing (i.e., reconfiguring) one or more individual neurons to implement neurons of multiple stages of the neural network, the IC discards a defective neuron by removing it from the pool of neurons that it configures to perform the operation(s) of neurons in one or more stages of neurons, and assigning this defective neuron's configuration (s) (i.e., its machine-trained parameter set(s)) to a redundant neuron. In some of these embodiments, the IC would re-route around the defective neuron and route to the redundant neuron, by (1) supplying machine-trained parameters and input signals (e.g., previous stage neuron outputs) to the redundant neuron instead of supplying these parameters and signals to the defective neuron, and (2) storing the output(s) of the redundant neuron instead of storing the output(s) of the defective neuron.

[0020] One of ordinary skill will understand that while several embodiments of the invention have been described above by reference to machine-trained neural networks with neurons, other embodiments of the invention are implemented on other machine-trained networks with other kinds of machine-trained processing nodes.

[0021] The preceding Summary is intended to serve as a brief introduction to some embodiments of the invention. It is not meant to be an introduction or overview of all inventive subject matter disclosed in this document. The Detailed Description that follows and the Drawings that are referred to in the Detailed Description will further describe the embodiments described in the Summary as well as other embodiments. Accordingly, to understand all the embodiments described by this document, a full review of the Summary, Detailed Description, the Drawings, and the Claims is needed. Moreover, the claimed subject matters are not to be limited by the illustrative details in the Summary, Detailed Description, and the Drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0022] The novel features of the invention are set forth in the appended claims. However, for the purpose of explanation, several embodiments of the invention are set forth in the following figures.

[0023] FIG. **1** illustrates an example of a three-dimensional (3D) circuit structure that has several latches at several boundary nodes between the two bonded layers.

[0024] FIG. **2** illustrates how the latch of FIG. **1** allows the signal traversing the two dies to time borrow.

[0025] FIG. **3** illustrates another example of a 3D circuit structure with a latch being placed on the IC die layer on which a signal terminates.

[0026] FIG. **4** illustrates how the latch of FIG. **3** allows the signal traversing the two dies to time borrow.

[0027] FIG. **5** illustrates an example of a transparent latch.

[0028] FIG. **6** illustrates a 3D circuit structure that has two or more vertically stacked bonded layers with a neural network on at least one bonded layer.

[0029] FIG. **7** illustrates an example of a neural network that includes a first sub-network on one bonded layer and a second sub-network on another bonded layer.

[0030] FIG. **8** illustrates an example of a neural network that has its neurons aligned with one memory while being on the same bonded layer with another memory.

[0031] FIGS. **9** and **10** illustrate different examples of a 3D IC with different components of a neural network on different IC dies.

[0032] FIG. **11** illustrates an example of a 3D IC with the neuron on one bonded layer partially or fully overlapping two memories on two different layers.

[0033] FIG. **12** illustrates a device that uses a 3D IC of some embodiments.

[0034] FIGS. **13** and **14** illustrate examples of the implementation of a neural network by repurposing (i.e., reconfiguring) one or more individual neurons to implement neurons of multiple stages of the neural network.

[0035] FIG. **15** conceptually illustrates a defect-curing process.

DETAILED DESCRIPTION

[0036] In the following detailed description of the invention, numerous details, examples, and embodiments of the invention are set forth and described. However, it will be clear and apparent to one skilled in the art that the invention is not limited to the embodiments set forth and that the invention may be practiced without some of the specific details and examples discussed.

[0037] Some embodiments of the invention provide a three-dimensional (3D) circuit structure that uses latches to transfer signals between two bonded circuit layers. In some embodiments, this structure includes a first circuit partition on a first bonded layer and a second circuit partition on a second bonded layer. It also includes at least one latch to transfer signals between the first circuit partition on the first bonded layer and the second circuit partition on the second bonded layer. In some embodiments, the latch operates in (1) an open first mode (also called a transparent mode) that allows a signal to pass from the first circuit partition to the second circuit partition and (2) a closed second mode that maintains the signal passed through during the prior open first mode.

[0038] Unlike a flip-flop that releases in one clock cycle a signal that it stores in a prior clock cycle, a transparent latch does not introduce such a setup time delay in the design. In fact, by allowing the signal to pass through the first circuit partition to the second circuit partition during its open mode, the latch allows the signal to borrow time from a first portion of a clock cycle of the second circuit partition for a second portion of the clock cycle of the second circuit partition. This borrowing of time is referred to below as time borrowing. Also, this time borrowing allows the signal to be available at the destination node in the second circuit partition early so that the second circuit can act on it in the clock cycle that this signal is needed. Compared to flip-flops, latches also reduce the clock load because, while flip-flops require at least two different clock transitions to store and then release a value, transparent latches only require one signal transition to latch a value that they previously passed through.

[0039] The first and second bonded layers are different in different embodiments. In some embodiments, both bonded layers are integrated circuit (IC) dies. In other embodiments, both bonded layers are IC wafers. In still other embodiments, one of these bonded layers is an IC die, while the other bonded layer is an IC wafer. The first and second bonded layers are vertically stacked on top of each other with no other intervening bonded layers in some embodiments, while these two bonded layers have one or more intervening bonded layers between them in other embodiments.

[0040] In some embodiments, the 3D circuit has several such latches at several boundary nodes between different circuit partitions on different bonded layers. Each latch in some embodiments is associated with one pair of boundary nodes, with one node in the first bonded layer and another node in the second bonded layer. Each pair of nodes is electrically interconnected through a conductive interface, such as a through-silicon via (TSV) or a direct bond interface (DBI) connection. Each latch in some embodiments is defined on just one of the two bonded layers.

[0041] FIG. **1** illustrates an example of a 3D circuit structure that has several latches at several boundary nodes between the two bonded layers. This structure is a 3D IC **100** that is formed by vertically stacking two IC dies **102** and **104**. In this example, the two dies **102** and **104** have the same size and are aligned so that their bounding shapes overlap each other. This does not have to be the case, as in some embodiments, the different dies have different sizes and are vertically aligned differently.

[0042] In FIG. **1**, the 3D circuit structure **100** has several conductive vertical connections **110** that connect circuits on the two IC dies **102** and **104**. Examples of such connections include TSV s and DBI connections. DBI provides area-efficient, dense interconnect between two blocks. In two dimensions, the number of interconnects between two blocks is limited to the perimeter facing each other. Fine pitch 3D interface, on the other hand, is only limited by the area of the block overlap. For example, a 1×1 mm block with 100 nm wire pitch and 2 um DBI pitch can fit **10,000** wires through one side in a 2D format versus **250,000** wires spread across the entire block through DBI in a 3D format. DBI is further described in U.S. Pat. Nos. 6,962,835 and 7,485,968, both of which are incorporated herein by reference.

[0043] For each of several conductive vertical connections between two adjacent dies, one or both of the dies has a latch that electrically connects (through interconnect) to the conductive-interface connection. In some embodiments, each such latch iteratively operates in two sequential modes, an open first mode (also called a transparent mode) to let a signal pass from one circuit partition on one IC die to a circuit partition on the other IC die, and a closed second mode to hold the signal passed during the prior open first mode.

[0044] FIG. **1** illustrates one such latch **132**. This latch facilitates signal flow between a first node **130** in a first circuit block **120** on the IC die **104** to a second node **138** in a second circuit block **122** on the IC die **102**. This signal flow traverses along a conductive vertical connection **110***a* (e.g., one DBI connection) between the IC dies **102** and **104**. As shown, this conductive vertical connection **110***a* connects two nodes on the two dies, a node **134** on die **104** and a node **136** on die **102**. In this example, the latch **132** on the IC dies **104** has its output carried to the IC die **102** by interconnect (e.g., wires) and the conductive vertical connection **110***a*.

[0045] FIG. **2** illustrates how the latch **132** allows the signal traversing the two dies **102** and **104** to time borrow. Specifically, it shows the latch **132** operating in an open first phase **202**. During this phase, the latch is open and transparent. Thus, it allows a signal to pass from the first circuit partition **120** to location **205** in the second circuit partition **122**. FIG. **2** also shows the latch **132** operating in a closed second phase **204**. During this phase, the latch has closed. When the latch closes, it maintains the signal that passed through it during the prior open first phase. As shown, the signal reaches the node **138** during the second phase.

[0046] Because the latch was open during its first phase, the signal was allowed to pass through from the first circuit block **120** to the second circuit block in this phase, which, in tum, allowed the signal to reach its destination **138** in the second circuit block **120** sooner in the closed second phase **204** of the latch **132**. In this manner, the latch allows the signal to time borrow (e.g., borrow time from the first phase to speed up the operation of the second circuit block during the second phase).

[0047] Instead of placing a latch on the IC die layer from which the signal originates, some embodiments place the latch on the IC die layer on which the signal terminates. FIGS. **3** and **4** illustrate one such example. The example in this figure is similar to the example in FIGS. **1** and **2**, except that the latch **132** on the IC die **104** has been replaced with a latch **342** on the IC die **102**. This latch is used when a signal traverses from a node **330** on a circuit block **320** on the first die **104** along a vertical connection **110***b* to node **338** on a circuit block **322** on the second die **102**. The vertical connection **110***b* connects two nodes **334** and **336** on the two dies **105** and **102**.

[0048] As shown in FIG. **4**, the latch **342** operates in an open first phase **402**. During this phase, the signal from a node **330** passes from the first circuit partition **320** to location **405** in the second circuit partition **322**. When the latch **342** closes (i.e., operates in the closed second phase **404**), the latch maintains the signal that passed through it during the prior open first phase to allow the signal to reach the node **338** during the second phase.

[0049] In other embodiments, a conductive vertical connection can be associated with two latches on the two bonded layers that it connects, and either latch can be used to facilitate time borrowing as a signal travels between the two circuit partitions on the two bonded layers through the conductive vertical connection. Thus, for the examples illustrated in FIGS. **1-4**, the 3D IC has both latches **132** and **142** respectively in circuit partitions **120** and **122**, and either of these latches can be selectively enabled to facilitate time borrowing across the two layers.

[0050] FIG. **5** illustrates an example of a transparent latch **500**. This latch is a D-latch that is formed by an inverter **525**, two AND gates **535***a* and **535***b*, and two XOR gates **540***a* and **540***b*. The inverter receives the input signal at its D terminal **505** and provides its output to an input of AND gate **535***a*. The input signal is also fed to one of the inputs of the AND gate **535***b*. The AND gates **535***a* and **535***b* also get a latch enable signal Eat the latch's enable terminal **510**. This enable signal can be a signal generated by another user-design circuit or a signal supplied by a clock or by a storage location driven by the clock or a user-design circuit.

[0051] The outputs of the AND gates **535***a* and **535***b* are supplied respectively to XOR gates **540***a* and **540***b*. These XOR gates are cross-coupled such that their outputs are fed back to the inputs of each other. The outputs of the XOR gates **540***a* and **540***b* represent the output of the latch. When only one latch output is needed, the output of XOR gate **540***a* presented at the Q terminal **515** of the latch serves as the output of the latch **500**. As shown by the truth table **550**

in FIG. 5, the latch operates in its open/transparent mode (to pass through a signal) when the enable signal is 1, while it operates in a close/latch mode (to maintain the signal previously passed) when the enable signal is 0.

[0052] Some embodiments provide a three-dimensional (3D) circuit structure that has two or more vertically stacked bonded layers with a machine-trained network on at least one bonded layer. For instance, each bonded layer can be an IC die or an IC wafer in some embodiments with different embodiments encompassing different combination of wafers and dies for the different bonded layers. Also, the machine-trained network includes an arrangement of processing nodes in some embodiments. In several examples described below, the processing nodes are neurons and the machine-trained network is a neural network. However, one of ordinary skill will realize that other embodiments are implemented with other machine-trained networks that have other kinds of machine-trained processing nodes.

[0053] FIG. **6** illustrates an example of a 3D circuit structure with a neural network on at least one of its bonded layers. In this example, the 3D circuit structure is a 3D IC **600** that has two vertically stacked dies **602** and **604**, with IC die **604** having a neural network **605**. In this example, the IC dies **602** and **604** have the same size and are aligned so that their bounding shapes overlap. This does not have to be the case, as in some embodiments, the different dies have different sizes and are vertically aligned differently. As shown in FIG. **6**, the IC dies **602** and **604** have several vertical connections, which in some embodiments are DBI connections. In other embodiments, these connections are other types of direct bonding connections or TSV connections.

[0054] As further shown, the neural network **605** in some embodiments includes several stages of neurons **610** with routing fabric that supplies the outputs of earlier stage neurons to drive the inputs of later stage neurons. In some embodiments, one or more parameters associated with each neuron is defined through machine-trained processes that define the values of these parameters in order to allow the neural network to perform particular operations (e.g., face recognition, voice recognition, etc.).

[0055] FIG. **6** illustrates an example of such machine-trained parameters for some embodiments. These parameters are the weight values Wi that are used to sum several output values Yi of several earlier stage neurons to produce an input value z_i for an activation function **625** of a later stage neuron. In this example, the neural network is a feed-forward neural network that has multiple neurons arranged in multiple layers (multiple stages), with each neuron having a linear component **620** and a non-linear component **625**, called an activation function. In other embodiments, the neural network is not a feed forward network (e.g., is a recurrent network, etc.).

[0056] In all but the last layer of the feed-forward neural network **605**, each neuron **610** receives two or more outputs of neurons from earlier neuron layers (earlier neuron stages) and provides its output to one or more neurons in subsequent neuron layers (subsequent neuron stages). The outputs of the neurons in the last layer represent the output of the network **605**. In some embodiments, each output dimension of the network **600** is rounded to a quantized value.

[0057] The linear component (linear operator) **620** of each interior or output neuron computes a dot product of a vector of weight coefficients and a vector of output values of prior nodes, plus an offset. In other words, an interior or output neuron's linear operator computes a weighted sum of its inputs (which are outputs of the previous stage neurons that the linear operator receives) plus an offset. Similarly, the linear component **620** of each input stage neuron computes a dot product of a vector of weight coefficients and a vector of input values, plus an offset. Each neuron's nonlinear component (nonlinear activation operator) **625** computes a function based on the output of the neuron's linear component **620**. This function is commonly referred to as the activation function.

[0058] The notation of FIG. **6** can be described as follows. Consider a neural network with L hidden layers (i.e., L layers that are not the input layer or the output layer). Hidden layers are also referred to as intermediate layers. The variable l can be any of the L hidden layers (i.e., $l \in \{1, \ldots, L\}$ index the hidden layers of the network). The variable $Z_i^{(l+1)}$ represents the output of the linear component of an interior neuron i in layer l+1. As indicated by the following Equation (A), the variable $Z^{(l+1)}$ in some embodiments is computed as the dot product of a vector of weight values $W^{(l)}$ and a vector of outputs $y^{(l)}$ from layer l plus an offset bi, typically referred to as a bias.

$$Z_i^{(l+1)} = \left(W_i^{(l+1)} \cdot y^{(l)}\right) + b_i^{(l+1)} \tag{A}$$

[0059] The symbol • is the dot product. The weight coefficients $W^{(l)}$ are weight values that can be adjusted during the network's training in order to configure this network to solve a particular problem. Other embodiments use other formulations than Equation (A) to compute the output $Z^{(l+1)}$ of the linear operator **620**.

[0060] The output $y^{(l+1)}$ of the nonlinear component **625** of a neuron in layer l+1 is a function of the neuron's linear component, and can be expressed as by Equation (B) below.

$$y_i^{(l+1)} = f\left(z_i^{(l+1)}\right), \tag{B}$$

[0061] In this equation, f is the nonlinear activation function for node i. Examples of such activation functions include a sigmoid function ($f(x)=1/(1+e^{-x})$), a tanh function, a ReLU (rectified linear unit) function or a leaky ReLU function.

[0062] Traditionally, the sigmoid function and the tanh function have been the activation functions of choice. More recently, the ReLU function has been proposed for the activation function in order to make it easier to compute the activation function. See Nair, Vinod and Hinton, Geoffrey E., "Rectified linear units improve restricted Boltzmann machines," ICML, pp. 807-814, 2010. Even more recently, the leaky ReLU has been proposed in order to simplify the training of the processing nodes by replacing the flat section of the ReLU function with a section that has a slight slope. See He, Kaiming, Zhang, Xiangyu, Ren, Shaoqing, and Sun, Jian, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," arXiv preprint arXiv: **1502.01852**, **2015**. In some embodiments, the activation functions can be other types of functions, like cup functions and periodic functions.

[0063] Before the neural network **605** can be used to solve a particular problem (e.g., to perform face recognition), the network in some embodiments is put through a supervised training process that adjusts (i.e., trains) the network's configurable parameters (e.g., the weight coefficients of its linear components). The training process iteratively selects different input value sets with known output value sets. For each selected input value set, the training process in some embodiments forward propagates the input value set through the network's nodes to produce a computed output value set. For a batch of input value sets with known output value sets, the training process back propagates an error value that expresses the error (e.g., the difference) between the output value sets that the network **605** produces for the input value sets in the training batch and the known output value sets of these input value sets. This process of adjusting the configurable parameters of the machine-trained network **605** is referred to as supervised, machine training (or machine learning) of the neurons of the network **605**.

[0064] In some embodiments, the IC die on which the neural network is defined is an ASIC (Application Specific IC) and each neuron in this network is a computational unit that is custom-defined to operate as a neuron. Some embodiments implement a neural network by re-purposing (i.e., reconfiguring) one or more neurons used for earlier neural network stages to implement one or more neurons in later neural network stages. This allows fewer custom-defined neurons to be needed to implement the neural network. In such embodiments, the routing fabric between the neurons is at least partially defined by one or more output memories that are used to store the outputs of earlier stage neurons to feed the inputs of later stage neurons.

[0065] In some embodiments, the neural network includes a first sub-network on one bonded layer and a second sub-network on another bonded layer, with these two sub-networks partially or fully overlapping. FIG. **7** illustrates an example of such an embodiment. It shows a 3D IC **700** with a neural network that is formed by two sub-networks **705** and **707**. As shown, the first sub-network **705** is on a first IC die **702** while the second sub-network **707** is on a second IC die **704**. The footprints of these two sub-networks **705** and **707** on the two different IC dies **702** and **704** partially or fully overlap.

[0066] As further shown in FIG. **7**, the components on the IC's dies **702** and **704** are interconnected by several vertical connections **710**, which in some embodiments are DBI connections. In other embodiments, these connections are other types of direct bonding connections or TSV connections. As shown, numerous such connections **710** are used to electrically connect nodes on the two sub-networks **705** and **707** on the dies **702** and **704**.

[0067] In some embodiments, the sub-network **705** are the neurons that are used to implement the odd layer neurons in the multi-layer neuron arrangement (e.g., the multi-layer arrangement shown in FIG. **6**), while the sub-network **707** are the neurons that are used to implement the even layer neurons in this arrangement. In other embodiments, each sub-network has multiple layers (stages) of neurons (e.g., two layers of neurons) for implementing multiple adjacent layers of neurons (e.g., sub-network **705** implements even adjacent pairs of neuron layers, while sub-network **707** implements odd adjacent pairs of neuron layers, where even and odd layer pairs sequentially alternate and the first layer pair are the first two neuron layers).

[0068] In some embodiments, the vertical connections **710** connect the output of neurons of subnetwork **705** on the first IC die to an output memory on the second die that connects to the subnetwork **707**, so that these values can be stored in the output memory. From this memory, the stored output values are supplied to neurons of the sub-network **707** on the second die so that these neurons can perform computations based on the outputs of the neurons of the sub-network **705** that implement an earlier stage of the neural network's operation.

[0069] In some of these embodiments, the outputs of the neurons of the sub-network **707** are then passed through the vertical connections **710** to an output memory on the first die **702** that connects to the sub-network **705**. From the output memory on the first die **702**, the outputs of the neurons of the sub-network **707** of the second die are supplied to the neurons of the sub-network **705** of the first die once these neurons have been configured to perform the operation of later stage neurons of the neural network. Based on these outputs, the neurons of the sub-network **705** can then perform computations associated with the later stage neurons of the neural network. In this manner, the output values of the neurons of the sub-networks **705** and **707** can continue to pass back and forth between the two IC dies **702** and **704** as the neurons of each sub-network **705** and **707** are reconfigured to perform successive or successive sets (e.g., pairs) of stages of operation of the neural network.

[0070] Alternatively, or conjunctively, the neural network or sub-network on one bonded layer partially or fully overlaps a memory (e.g., formed by one or more memory arrays) on another bonded layer in some embodiments. This memory in some embodiments is a parameter memory that stores machine-trained parameters for configuring the neurons of the neural network or subnetwork to perform a particular operation. In other embodiments, this memory is an output memory that stores the outputs of the neurons (e.g., outputs of earlier stage neurons for later stage neurons).

[0071] While being vertically aligned with one memory, the neural network's neurons in some embodiments are on the same bonded layer with another memory. FIG. **8** illustrates one such example. It illustrates a 3D IC **800** with two IC dies **802** and **804** that have several components of the neural network. These components are several neurons **805** and an output memory **812** on the IC die **804**, and a parameter memory **815** on the IC die **802**. The output memory **812** stores values produced by the neurons **805**, while the parameter memory **815** stores machine-trained parameters for configuring the neurons. As shown, the footprints of arrangement of neurons **805** and the parameter memory **815** fully overlap in some embodiments. These footprints partially overlap in other embodiments, or do not overlap in yet other embodiments.

[0072] As further shown in FIG. **8**, the components on the IC's dies **802** and **804** are interconnected by several vertical connections **810**, which in some embodiments are DBI connections. In other embodiments, these connections are other types of direct bonding connections or TSV connections. As shown, numerous such connections **810** are used to electrically connect nodes of the neurons **805** on the IC die **804** to nodes of the parameter memory **815** on the IC die **802**. Through these connections, the neurons receive the machine-trained parameters that configure the neural network to perform a set of operations (e.g., a set of one or more tasks, such as face recognition) for which the neural network has been trained.

[0073] The neurons **805** connect to the output memory **812** through one or more interconnect layers (also called metal layers or wiring layers) of the IC die **804**. As known in the art, each IC die is manufactured with multiple interconnect layers that interconnect the circuit components (e.g., transistors) defined on the IC die's substrate. Through its connection with the output memory, the outputs of the neurons are stored so that these outputs can later be retrieved as inputs for later stage neurons or for the output of the neural network.

[0074] FIG. **9** illustrates another example of a 3D IC with different components of a neural network on different IC dies. This figure illustrates a 3D IC **900** with two IC dies **902** and **904** that have several components of the neural network. These components are several neurons **905** and a parameter memory **915** on the IC die **904**, and an output memory **912** on the IC die **902**. As shown, the footprints of arrangement of neurons **905** and the output memory **912** partially overlap in some embodiments. In other embodiments, these footprints fully overlap, while in yet other embodiments, they do not overlap.

[0075] As further shown in FIG. **9**, the components on the IC's dies **902** and **904** are interconnected by several vertical connections **910**, which in some embodiments are DBI connections. In other embodiments, these connections are other types of direct bonding connections or TSV connections. As shown, numerous such connections **910** are used to electrically connect nodes of the neurons **905** on the IC die **904** to nodes of the output memory **912** on the IC die **902**. Through these connections, the outputs of the neurons are stored so that these outputs can later be retrieved as inputs for later stage neurons or for the output of the neural network. As described above, the 3D IC of some embodiments has output memories and neurons on each of two face-to-face mounted dies (like dies **902** and **904**) with the output memory on each die receiving outputs from neurons on another die and providing its content to neurons on its own die.

[0076] The neurons **905** connect to the parameter memory **915** through one or more interconnect layers of the IC die **904**. Through its connection with the parameter memory, the neurons receive the machine-trained parameters (e.g., weight values for the linear operators of the neurons) that configure the neural network to perform a set of one or more tasks (e.g., face recognition) for which the neural network has been trained. When neurons are placed on both face-to-face mounted dies, some embodiments also place parameter memories on both dies in order to provide machine-trained parameters to neurons on the same IC die or to neurons on the other IC die.

[0077] FIG. **10** illustrates another example of a 3D IC with different components of a neural network on different IC dies. This figure illustrates a 3D IC **1000** with two IC dies **1002** and **1004** that have several components of the neural network. These components are several neurons **1005** on the IC die **1004**, and an output memory **1012** and a parameter memory **1015** on the IC die **1002**. As shown, the footprint of arrangement of neurons **1005** partially overlaps the output memory **1012** and the parameter memory **1015**.

[0078] As further shown in FIG. **10**, the components on the IC's dies **1002** and **1004** are interconnected by several vertical connections **1010**, which in some embodiments are DBI connections. In other embodiments, these connections are other types of direct bonding connections or TSV connections. As shown, numerous such connections **1010** are used to electrically connect nodes of the neurons **1005** on the IC die **1004** to either nodes of the output memory **1012** on the IC die **1002**, or to nodes of the parameter memory **1015** on the IC die **1002**. Through the connections **1010** with the output memory **1012**, the outputs of the neurons are stored so that these outputs can later be retrieved as inputs for later stage neurons or for the output of the neural network. Also, through the connections **1010** with the parameter memory **1015**, the neurons receive the machine-trained parameters (e.g., weight values for the linear operators of the neurons) that configure the neural network to perform a set of one or more tasks (e.g., face recognition) for which the neural network has been trained.

[0079] In some embodiments, the neurons on one bonded layer partially or fully overlap two memories on two different layers, with one memory storing machine-trained parameters and the other memory storing neuron output values. FIG. **11** illustrates one such example. This figure illustrates a 3D IC **1100** with multiple IC dies **1102**, **1104**, and **1106**, each of which has a component of the neural network. These components are several neurons **1105** on the IC die **1104**, an output memory **1112** on the IC die **1102**, and a parameter memory **1115** on the IC die **1106**. As shown, the footprints of the arrangement of neurons **1105** on the IC die **1104** and the output memory **1112** on the IC die **1102** partially or fully overlap. The footprint of the arrangement of neurons **1105** on the IC die **1104** also partially or fully overlaps with the footprint of the parameter memory **1115** on the IC die **1106**.

[0080] As further shown in FIG. **11**, the components on the IC's dies **1102**, **1104**, and **1106** are interconnected by several vertical connections **1110** and **1111**. In this example, IC dies **1102** and **1104** are face-to-face mounted, while the IC dies **1106** and **1104** are face-to-back mounted with the face of the IC die **1106** mounted with the back of the IC die **1104**. In some embodiments, the vertical connections **1110** between the dies **1102** and **1104** are direct bonded connections (like DBI connections), while the vertical connections **1111** between dies **1104** and **1106** are TSVs.

[0081] As shown, numerous such connections **1110** and **1111** are used to electrically connect nodes of the neurons **1105** on the IC die **1104** to either nodes of the output memory **1112** on the IC die **1102**, or to nodes of the parameter memory **1115** on the IC die **1106**. Through the connections **1110** with the output memory **1112**, the outputs of the neurons are stored so that these outputs can later be retrieved as inputs for later stage neurons or for the output of the neural network. Also, through the connections **1111** with the parameter memory **1115**, the neurons receive the machine-trained parameters that configure the neural network to perform a set of one or more tasks (e.g., face recognition) for which the neural network has been trained.

[0082] One of ordinary skill will realize that other permutations of 3D circuit structures are also possible. For instance, in some embodiments, the 3D circuit has neurons on two or more bonded layers with parameter and/or output memories on the same or different bonded layers. Also, in the above-described embodiments, the bonded layers (two or more) that contain a neural network's neurons and memories do not have any intervening bonded layer in some embodiments. In other embodiments, however, these bonded layers have one or more intervening bonded layers between or among them.

[0083] In some embodiments, the output and parameter memories of the neural network have different memory structures (i.e., are different types of memories). For instance, in some embodiments, the output memory (e.g., memory **812**,**912**, **1012**, or **1112**) has a different type of output interface than the parameter memory (e.g., the memory **815**, **915**, **1015**, or **1115**). For example, the output memory's output interface allows for random access of this memory's storage locations, while the parameter memory's output interface only supports sequential read access.

[0084] Alternatively, or conjunctively, the parameter memory (e.g., the memory **815**, **915**, **1015**, or **1115**) of the neural network is a read-only memory (ROM), while the output memory (e.g., memory **812**, **912**, **1012**, or **1112**) of the neural network is a read-write memory in some embodiments. The parameter memory in some embodiments is a sequential ROM that sequentially reads out locations in the ROM to output the parameters that configure the neural network to perform certain machine-trained task(s).

[0085] The output memory (e.g., memory **812**, **912**, **1012**, or **1112**) in some embodiments is a dynamic random access memory (DRAM). In other embodiments, the output memory is an ephemeral RAM (ERAM) that has one or more arrays of storage cells (e.g., capacitive cells) and pass transistors like traditional DRAMs. However, unlike traditional DRAMs, the ERAM output memory does not use read-independent refresh cycles to charge the storage cells. This is because the values in the ERAM output memory are written and read at such rates that these values do not need to be refreshed with separate refresh cycles. In other words, because intermediate output values of the neural network only need to be used as input into the next layer (or few layers) of the neural network, they are temporary in nature. Thus, the output memory can be implemented with a compact, DRAM-like memory architecture without the use of the read-independent refresh cycles of traditional DRAMs.

[0086] Using different dies for the output memory **1112** and parameter memory **1115** allows these dies to be manufactured by processes that are optimal for these types of memories. Similarly, using a different die for the neurons of the neural network than for the output memory and/or parameter memory also allows each of these components to be manufactured by processes that are optimal for each of these types of components.

[0087] FIG. **12** illustrates a device **1200** that uses a 3D IC **1205**, such as 3D IC **100**, **600**, **700**, **800**,**900**, or **1000**. In this example, the 3D IC **1205** is formed by two face-to-face mounted IC dies **1202** and **1204** that have numerous direct bonded connections **1210** between them. In other examples, the 3D IC **1205** includes three or more vertically stacked IC dies, such as the 3D IC **1100**. In some embodiments, the 3D IC **1205** implements a neural network that has gone through a machine-learning process to train its configurable components to perform a certain task (e.g., to perform face recognition).

[0088] As shown, the 3D IC **1205** includes a case **1250** (sometimes called a cap or epoxy packaging) that encapsulates the dies**1202** and **1204** of this IC in a secure housing **1215**. On the back side of the die **1204** one or more interconnect layers **1206** are defined to connect the 3D IC to a ball grid array **1220** that allows this to be mounted on a printed circuit board **1230** of the device **1200**. In some embodiments, the 3D IC includes packaging with a substrate on which the die **1204** is mounted (i.e., between the ball grid array and the IC die **1204**), while in other embodiments this packaging does not have any such substrate.

[0089] Some embodiments of the invention provide an integrated circuit (IC) with a defect-tolerant neural network. The neural network has one or more redundant neurons in some embodiments. After the IC is manufactured, a defective neuron in the neural network can be replaced by a redundant neuron (i.e., the redundant neuron can be assigned the operation of the defective neuron). The routing fabric of the neural network can be reconfigured so that it re-routes signals around the discarded, defective neuron. In some embodiments, the re-configured routing fabric does not provide any signal to or forward any signal from the discarded, defective neuron, and instead provides signals to and forwards signals from the redundant neuron that takes the defective neuron's position in the neural network.

[0090] In the embodiments that implement a neural network by re-purposing (i.e., reconfiguring) one or more individual neurons to implement neurons of multiple stages of the neural network, the IC discards a defective neuron by removing it from the pool of neurons that it configures to perform the operation(s) of neurons in one or more stages of neurons, and assigning this defective neuron's configuration (s) (i.e., its machine-trained parameter set(s)) to a redundant neuron. In some of these embodiments, the IC would re-route around the defective neuron and route to the redundant neuron, by (1) supplying machine-trained parameters and input signals (e.g., previous stage neuron outputs) to the redundant neuron instead of supplying these parameters and signals to the defective neuron, and (2) storing the output(s) of the defective neuron instead of storing the output(s) of the defective neuron.

[0091] FIGS. **13** and **14** illustrate an example of one such neural network. These figures show a machine-trained circuit **1300** that has two sets of neurons **1305** and **1310** that are re-purposed (reconfigured) to implement a multi-stage neural network **1350**. In this example, the neural network **1350** has nine layers. Each of these neuron sets has one redundant neuron **1325** or **1330** to replace any defective neuron in its set, as further described below.

[0092] The machine-trained circuit **1300** has two parameter memories **1315***a* and **1315***b* that respectively store machine-trained parameters for the neuron sets **1305** and **1310**. These machine-trained parameters iteratively configure each neuron set to implement a different stage in the multistage network. In the example illustrated in FIG. **13**, the parameters in memory **1315***a* store parameters that sequentially re-configure the neuron set **1305** to implement the odd neuron layers (i.e., the first, third, fifth, seventh and ninth layers) of the neural network, while the memory **1315***b* stores parameters that sequentially re-configure the neuron set **1310** to implement the even neuron layers (i.e., the second, fourth, sixth and eight layers). The parameters in the memories **1315***a* and **1315***b* were generated through machine-learning processes, and configure the neurons in the sets **1305** and **1310** to perform a set of one or more operations (e.g., to perform face recognition or voice recognition).

[0093] The machine-trained circuit **1300** also has an output memory **1312**. The output of each neuron is stored in the output memory **1312**. With the exception of the neurons in the first neuron stage, the inputs of the neurons in the other stages are retrieved from the output memory. Based on their inputs, the neurons compute their outputs, which again are stored in the output memory **1312** for feeding the next stage neurons (when intermediate neurons compute the outputs) or for providing the output of the neural network (when the final stage neurons compute their outputs).

[0094] In some embodiments, all the components **1305**, **1310**, **1312**, and **1315** of the circuit **1300** are on one bonded layer (e.g., one IC die or wafer). In other embodiments, different components are on different layers. For instance, the neurons **1305** and **1310** can be on a different IC die than the IC die that includes one of the memories **1312** or **1315**, or both memories **1312** and **1315**. Alternatively, in some embodiments, the neurons **1305** are on one IC die while the neurons **1310** are on another IC die. In some of these embodiments, the IC die of neurons **1305** or neurons **1310** also include one or both of the parameter and output memories.

[0095] In the example illustrated in FIG. **13**, none of the neurons are defective. Hence, the redundant neurons **1325** and **1330** are not used to implement any of the neuron stages of the neural network **1350**. FIG. **14**, however, illustrates an example where one neuron **1405** in the first neuron set **1305** is defective and a neural network **1450** is implemented by using the redundant neuron **1325** of the first neuron set **1305**. This figure illustrates a machine-trained circuit **1400** that is identical to the machine-trained circuit **1300**, except that the neuron **1405** in the first neuron set **1305** is defective.

[0096] To address this defect, a defect-curing process that configures the circuit **1400** removes the defective neuron **1405** from the first neuron set and replaces this defective neuron with the redundant neuron **1325** of this set. The defect-curing process assigns to the redundant neuron the machine-trained parameters that would have been assigned to the defective neuron, in order to allow this neuron to implement one of the neurons in the odd stages of the neural network **1450**. This process also changes the storage and retrieval logic of the machine-trained circuit **1400** to ensure that the redundant neuron **1325** receives the desired input from and stores its output in the output memory **1312**. FIG. **14** shows the neural network **1450** implemented with the set of neurons **1305**R implementing the odd stages of this network. Here, the designation R is indicative that the neuron set **1305** is using its redundant neuron **1325**.

[0097] FIG. **15** illustrates a defect-curing process **1500** of some embodiments. In some embodiments, this process is performed each time the IC with the neural network is initializing (i.e., is powering up). The process **1500** initially determines (at **1505**) whether a setting stored on the IC indicates that one or more neurons are defective. In some embodiments, this setting is stored in a ROM of the IC during a testing phase of the IC after it has been manufactured. This testing phase identifies defective neurons and stores the identity of the defective neuron on the ROM in some embodiments. If only one redundant neuron exists for each neuron set (e.g., **1305** or **1310**) of the IC, the testing process in some embodiments discards any IC with more than one defective neuron in each neuron set.

[0098] When the setting does not identify any defective neuron, the process **1500** loads (at **1515**) the settings that allow the neurons to be configured with a user-design that has been provided in order to configure the neural network to implement a set of operations. After **1515**, the process ends. On the other hand, when the setting identifies a defective neuron, the process **1500** removes (at **1520**) the defective neuron from the pool of neurons, and replaces (at **1520**) this defective neuron with the redundant neuron. The defect-curing process then assigns (at **1525**) to the redundant neuron the machine-trained parameters that would have been assigned to the defective neuron to allow this neuron to implement operations of the defective neuron that are needed to implement the neural network. At **1530**, the process changes the storage and retrieval logic of the machine-trained circuit to ensure that the redundant neuron receives the desired input from and stores its output in the output memory. Finally, at **1535**, the process **1500** directs the neural network to start operating based on the new settings that were specified at **1525** and **1530**. After **1335**, the process ends.

[0099] While the invention has been described with reference to numerous specific details, one of ordinary skill in the art will recognize that the invention can be embodied in other specific forms without departing from the spirit of the invention. For instance, one of ordinary skill will understand that while several embodiments of the invention have been described above by reference to machine-trained neural networks with neurons, other embodiments of the invention are implemented on other machine-trained networks with other kinds of machine-trained processing nodes.

[0100] The 3D circuits and ICs of some embodiments have been described by reference to several 3D structures with vertically aligned IC dies. However, other embodiments are implemented with a myriad of other 3D structures. For example, in some embodiments, the 3D circuits are formed with multiple smaller dies placed on a larger die or wafer. Also, some embodiments are implemented in a 3D structure that is formed by vertically stacking two sets of vertically stacked multi-die structures. Therefore, one of ordinary skill in the art would understand that the invention is not to be limited by the foregoing illustrative details, but rather is to be defined by the appended claims.

1. (canceled)

2. An integrated circuit (IC) device comprising:

a neural network IC die comprising a plurality of computational units serving as neurons of a neural network comprising a plurality of neuron layers; and

a stack of memory IC dies each comprising memory arrays communicatively coupled to the computational units and to each other through conductive vertical connections,

wherein outputs of the neuron layers and machine trained parameters of the neural network are distributed across different ones of the memory IC dies.

3. The IC device of claim **2**, wherein the memory IC dies are communicatively coupled to each other through the conductive vertical connections comprising through silicon vias (TSVs).

4. The IC device of claim **2**, wherein the stack of memory IC dies and the neural network IC die are communicatively coupled to each other through the conductive vertical connections comprising a direct bond interface (DBI) formed by hybrid direct bonding.

5. The IC device of claim **2**, wherein the outputs of the neuron layers are separately stored in different ones of the memory IC dies from the memory IC dies storing the machine trained parameters.

6. The IC device of claim **2**, wherein the memory IC dies comprise dynamic random access memory (DRAM) dies.

7. The IC device of claim **2**, wherein the IC device comprises a plurality of neural network IC dies each comprising a plurality of computational units, wherein the neurons of the neural network are distributed across different ones of the neural network IC dies.

8. The IC device of claim **7**, wherein different ones of the neural network IC dies comprise different ones of the neuron layers.

9. An integrated circuit (IC) device comprising:

a neural network IC die comprising a plurality of computational units serving as neurons of a neural network comprising a plurality of neuron layers; and

a stack of memory IC dies each comprising memory arrays communicatively coupled to each other through through silicon vias (TSVs),

wherein the neural network IC die is communicatively coupled to the stack of memory IC dies though conductive vertical connections formed at a bottom surface of the neural network IC die configured to face a substrate common to the neural network IC die and the stack of memory IC dies.

10. The IC device of claim **9**, wherein the conductive vertical connections formed at the bottom surface of the neural network IC die comprises a direct bond interface (DBI) formed by hybrid direct bonding.

11. The IC device of claim **9**, wherein outputs of the neuron layers and machine trained parameters of the neural network are distributed across different ones of the memory IC dies.

12. The IC device of claim **11**, wherein the outputs of the neuron layers and the machine trained parameters are separately stored in different ones of the memory IC dies.

13. The IC device of claim **9**, wherein the memory IC dies comprise dynamic random access memory (DRAM) dies.

14. The IC device of claim **9**, wherein the IC device comprises a plurality of neural network IC dies each comprising a plurality of computational units, wherein the neurons of the neural network are distributed across different ones of the neural network IC dies.

15. An integrated circuit (IC) device comprising:

a plurality of neural network IC dies each comprising a plurality of computational units serving as neurons of a neural network comprising a plurality of neuron layers; and

a stack of memory IC dies each comprising memory arrays communicatively coupled to the neural network IC dies and to each other through conductive vertical connections,

wherein the neurons of the neural network are distributed across different ones of the neural network IC dies.

16. The IC device of claim **15**, wherein the memory IC dies are communicatively coupled to each other through conductive vertical connections comprising through silicon vias (TSVs).

17. The IC device of claim **15**, wherein the stack of memory IC dies and the neural network IC dies are communicatively coupled to each other through conductive vertical connections comprising a direct bond interface (DBI) formed by hybrid direct bonding.

18. The IC device of claim **15**, wherein different ones of the neural network IC dies are communicatively coupled to each other through conductive vertical connections comprising a direct bond interface (DBI) formed by hybrid direct bonding.

19. The IC device of claim **15**, wherein outputs of the neuron layers and machine trained parameters of the neural network are distributed across different ones of the memory IC dies.

20. The IC device of claim **15**, wherein the memory IC dies comprise dynamic random access memory (DRAM) dies.

21. The IC device of claim **15**, wherein different ones of the neural network IC dies comprise different ones of the neuron layers.

* * * * *