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HUMAN BRAIN FUNCTION ABOVE ALL OTHER AND THE CREATION MODEL

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ABSTRACT

The human brain functions at a level beyond any other brain among all animals. Since human beings are made in the image of God (*Imago Dei*), there must be signatures of this fact in its design. This paper will introduce an engineering methodology for exploring this concept. In terms of scope, this paper will focus its brain exploration on a key neurological building block, neurons, and networks of them. Later works will explore other aspects. An architectural model of neurons and neural networks in the human brain, the central nervous system, and the body is developed. Additionally, a Creation Model is constructed. Utilizing these models offer the potential to unpack human *Imago Dei* reality. This premise provides a rich area to explore that leverages the Biblical creation to capture the engineering framework God used in fashioning creation and His crowning achievement, human beings. By including the design and purpose of man from a biblical point of view, the most significant engineering context for human brain processing can be captured. A computer science full compute stack model will map neuron and neural network functions to computing layers. To adequately include human capabilities, it is shown that an extra full compute stack layer is required. The resulting insight from its inclusion is discussed. The paper will analyze brain neurons and neural networks using systems engineering methods and the systems modeling language (SysML) to capture architectural drivers. The aim is to provide new insight and guide future work. Two complimentary architectural modeling points of view are included, (1) neuroscience: where biological neuron and neural network details are captured at a top level, and (2) neuromorphic computing: where the artificial implementation approaches of neuron and neural network are highlighted. The answers to three research questions are discussed. (1) How does a Creation Model provide additional insights and context for the implementation and mission of human beings? (2) What modifications to the full compute stack model are required to capture unique human brain function? (3) What observations about human brain function can be made from the neuron and neural network architectural models?

KEYWORDS

Neuroscience, neuromorphic computing, neuron modeling, spiking neural networks, design patterns, model-based systems engineering (MBSE), systems modeling language (SysML), architectural modeling, biomimicry, creation model

I. INTRODUCTION

A. Overview

Man is created in the image of God, and as a result, humanity has computational and reasoning abilities unparalleled by any animal. This puts humankind in a unique position. No other being has this distinction. How can the unique characteristics captured in the human brain be explored and show the differences between human brain function and every other animal brain function? It can take much work to navigate. Active neuroscience research is ongoing to clarify our understanding of human brain biology. Plus, biomimicry seeking to make more efficient neuromorphic computing capability is being pursued with a good potential return on investment.

In this paper, the neuroscience research findings will be assessed from an engineering point of view. If one asks, “How should one design the human brain?,” it would require going through a structured systems engineering effort. Unfortunately, there are many gaps in our understanding of how the human brain works at many levels, making reverse engineering difficult and currently incomplete. Still, a structured engineering process can uncover the architectural and design trades required to develop a functional design.

Below are several term definitions used in the paper, which may be unfamiliar to some.

- **Full Compute Stack** is a computer science-based model term used to describe a layered approach to capturing the levels of computing.
- **Neural Circuits** are biological neural networks. At times the term neural network is also used.
- **Neuromorphic Computing** is a term used to describe artificial neural networks that aim to do involved computational tasks characteristically done by biological brains. There may not be an exact one-for-one mapping between biological and artificial implementations.
- **Neural Networks** are connections of neurons that cooperatively work together in artificial implementations of computational capabilities.

- **Spiking Neural Networks** is a term usually referring to artificial neural network implementations that seek to capture biological neural networks' capability that "spikes" or pulses when neurons are activated as required to participate in a group-distributed task. Otherwise, the neurons stay in a very low-energy mode. Since this is based on biological function, it is sometimes used to describe biological neural circuits.

B. Research questions

Three research questions that build upon each other are answered in this paper. These questions bound the efforts for this research effort. The portions of the Results section that refers to each question are highlighted. The discussion section will provide the most complete answer to each one that can be inferred from the architectural model and assessment.

First, how does a Creation Model provide additional insight and context for the implementation and mission of human beings? Since God created the heavens and the Earth, God the engineer had a master plan for His implementation. With human beings being made last as the crowning part of creation, there are many ways and many levels in which they engage with these resources.

Second, what modifications to the full compute stack model are required to capture unique human brain function? The full compute stack model cannot capture our *Imago Dei* faculties without modifications. Human brain function, above all others, shows a clear differentiation from animals with the human spirit and the manifold engagements that occur with the Holy Spirit.

Third, what observations about human brain function can be made from the neuron and neural network architectural models? Much work has been done in both neuroscience and neuromorphic computing. With so many basic features in neuroscience that still are unknown, capturing architecture models can provide a framework for how to view this complex information.

With these three questions answered, it will be clearer why human brain function is above all else and how this occurs, with the focus in this paper being from the perspective of neuronal and neural circuits.

C. Scope

This paper focuses on neurons and neural networks' contributions to brain function. Since both neuroscience and neuromorphic computing research is being done at this level, it is beneficial to draw these two domains together in the context of the three research questions shared above.

This paper does not explore the higher-level implications of neural networks, like generative artificial intelligence. Thoughts from Jovanovic and Campbell, who discuss generative artificial intelligence capability, help draw out a few scope-related points. "Generative modeling is an artificial intelligence (AI) technique that generates synthetic artifacts by analyzing training examples; learning their patterns and distributions, and then creating realistic facsimiles. Generative AI (GAI) uses genitive modeling and advances in deep learning (DL) to produce diverse content at scale by utilizing existing media such as text, graphics, audio, and video (Jovanovic 2022)." Regarding GAI and this paper's research questions, there are similarities and differences between GAI and human brain function. Human brains learn, but not like GAI. Human brains can think abstractly and interface with the Holy Spirit, which GAI cannot. This difference is pointed out by the limitations found in the full compute stack model without modification. The details of these differences will be explored in future papers that build upon the neuron and neural network observations in this paper.

D. Use of systems engineering tools

Systems engineering is an engineering discipline that focuses on successfully designing and integrating functional modules to work together as a system. Often, a systems engineer will know only some of the details of how each module works, and they have a great deal of insight into how it integrates all the parts. When considering the human brain, this approach can uncover interrelationships and dependencies that must be accounted for.

E. Compute architecture

Computing architectural levels can be considered as layers feeding into one another, starting at the lowest level and working up to the more involved levels. The full compute stack provides a framework to place functional elements in a structured context. This is used in computer science and applied to neuromorphic computing, the discipline of computing that mimics brain function.

Deoxyribonucleic acid (DNA) sequencing has found an innovative way to access the bits of information in the double helix and get that densely packed information. Unfortunately, it is a destructive process that breaks the DNA strands into many pieces. Then, through a painstaking process, the pieces are assembled in an orderly fashion into the original sequence. A layout of what it should look like is commonly used to help fit the pieces together. Like the picture on the jigsaw pieces, it guides how to make them fit. As discussed by Waterson, the term used for mapping and assembly of DNA sequences is *scaffolding*. A set of overlapping DNA sequences can be put together in a consensus region called a contig. Massing together contigs can form scaffolds. These steps help to construct the full genetic sequence of an organism. (Waterson, 2002). The methodological concept of scaffolding is applied in this architecture modeling exploration. For the application in this paper, the full compute stack is an architecture that can be used as a scaffolding or a guide to determine how functional elements should relate to one another (Schuman 2022).

F. Neurons

The neuron is the primary building block in the brain, the central nervous system, and the interfaces with senses, muscles, and control functions. This powerful nerve cell has computing, memory, and input and output capabilities. It is a small computer. A unique feature of neurons is that they link together. The brain is full of these linked nerve cells. The number of connections between the neurons is orders of magnitudes greater than the number of neurons.

In contrast to a classical computer with separate units for (1) the central processing unit, (2) the memory, and (3) the input and output within a Von Neumann architecture, each neuron has a version of all three of these features in the same unit. As will be discussed in the results section, the computing capability of one neuron is not analogous to a laptop central processing unit, but it is at a lower level of computing functionality within the central processing unit.

Thus, a neuron divides computing elements at a lower level than in electronic computing. Plus, a network of neurons forms a grid of computers, making a computer cluster commonly called a *neural network*. Although the Von Neuman architecture does not completely characterize the features of biological neurons and neural networks (Zhang 2020), it is still a useful and familiar benchmark to frame some aspects of the nature of the neuronal computing landscape. Perhaps a biological neural network can be viewed as exemplifying an implementation of a Von Neumann architecture like an artificial neural network (Christensen 2022). While the aggregate neural network forms a more comprehensive central processing unit, each neuron contains a more focused processing capability which has yet to be comprehensively characterized.

Although there is a standard classification of neurons, there are variations in the type of neurons throughout the human body. Neurons in the brain are focused on commutating. The central nervous system neurons are often more focused on connections and signaling. Neurons connected to sensory organs focus on receiving signals and translating information into spiking pulses that can be passed on to the brain for processing and resulting decisions from the inputs.

G. Neural network computing

Once neurons connect, they form neural networks. When these connections are established, they work together to determine a solution. How the neurons work together involves a variety of factors. Several neurons can pass a signal to the next-level neuron, which weighs the inputs from the various inputs and produces a result. This forms the basis for creating a neural network.

Neural networks are a widely used and essential architectural feature in artificial intelligence and machine learning. In the brain, localized areas focus on different types of functions. A degree of human brain mapping has been done by direct brain stimulation during some cranial operations where it required having the brain exposed (Kim 2018; Huang 2017; Böhm 2016; Wanner 2018; Ryu 2018; Huckleberry 2018; Faraut 2018). Thus, there are categories of neural networks localized to specific parts of every human brain.

II. METHODOLOGY

A. Engineering perspective toward biological systems

In terms of method orientation, this paper utilizes an engineering perspective when analyzing neuron-related biological data and how to consider architecture and function. This contrasts with the excellent and extensive body of neuroscience and neurology research work. This paper aims to provide a new context that can uncover additional insight. Systems engineering is a mature discipline with a well-defined architectural and design methodology. One can conceive of a needed capability, define the requirements, and progress to a functional layout. A design is selected and developed after making design trades and analyzing alternatives. Manufacturing and testing then take place.

Another methodological consideration throughout this paper is a parallel discussion of biological and artificial neuronal systems. Exploring biological systems can aid in artificial designs that aid neuromorphic computing, neural networks, and machine learning applications. The exploration of artificial systems provides insights into detailed system developments that can be compared with a biological counterpart to see what is the same and what differs. Thus, each neuronal system evaluation can benefit from the other.

This project assumes that an architecture is already in place when looking at biological systems. Therefore, reverse engineering can be done to uncover the approach and the design choices taken. Engineering tools can help in this process, and they are discussed next.

B. Use of systems engineering tools

System design and development have matured over several centuries, if not for millennia. As this process has matured, the development and application of engineering tools have become more standardized, and their utility has been demonstrated to provide a significant return on investment in product development. Applying these tools to biological systems is just starting to show its utility. This paper will not focus on a historical survey of this progress but instead jump in and use these tools.

Systems engineering methods can help product development over all the phases of a system being evaluated, designed, tested, and deployed. This is readily applied in neuromorphic computing and the creation of artificial neural networks (Christensen 2022; Zheng 2019; Schuman 2022; Shrestha 2022).

An orderly way of exploring neurons and neuromorphic computing is to group the topics into architectural levels. The layers of the compute stack are used to frame the neuronal capability. This process is developed in Section 4. Each of these levels is defined, along with research questions identified with each of them.

C. Utilization of a Creation Model

This paper will include a creation week model. Using engineering tools, it will point out the created works mentioned each day and the order by which things were created. It will show how creating human beings last is significant.

III. RESULTS

This section will discuss the Creation Model, the architecture framework that utilizes the full stack compute model, neuron models, and neural circuit and neural network models. In terms of the paper's research questions, each of these topics will help answer them. The neuron and neural network architectural models provide a larger context for their operations. The Creation Model converts the creation account into engineering and architectural terms to compare it with the neural models and the full compute stack framework. Since the full compute stack model cannot adequately address the mental facilities of human beings, a use case that includes lower-level brain function captured in the full compute stack, higher-level abstracting thinking that goes beyond generative artificial intelligence, and the engagements with the Holy Spirit.

Note that the architectural model diagrams may seem straightforward or simplistic. There is an engineering rationale behind this. Systems engineering thinking tries to see the big picture. To do this requires thinking about "black boxes" and their relationships, where the details within individual architecture components, or black boxes, may not be considered at this moment of high-level exploration to see the big picture. This is part of the methodology being addressed in this paper.

Getting a perspective of what has been used in thinking through these concepts is useful. There are many related areas in neuron research and neuromorphic computing. The areas examined in this paper are neuron models, classifications, and architecture; neural circuits and response experiments; spiking neural networks; neuromorphic computing; and neuromorphic computing simulation, as shown in Fig. 1.

Fig. 2 highlights five thematic areas that are addressed in this research paper: (1) neuron models, classifications, and architecture, (2) neural circuits and response experiments, (3) spiking neural networks, and (4) neuromorphic computing. Note that there are two major areas where the literature can be grouped, neuroscience and neuromorphic computing. The details of this literature review are included in the appendix.

A Neurons Models, Class., and Architecture
1 Molecular Biology of the Neuron
2 Models of Neurons
3 Mapping Proteins to Parts of the Brain
4 Retinal Neuron Classification
5 Structural and Functional Units of the Neuron
6 Relationship between Brain Neurons and Models
7 Neuron Gene Expression
8 Method for Recording Single Neuron Activity
9 Vis. of Neuronal Structures from Human Brain Testing
10 Neuronal Activity Mapper
11 Proposed Architecture of Human Memory
12 Methylation of Neurons
13 Limitations of Artificial Neural Networks

B Neuron Circuit and Response Experiments
1 Organic Electronic Sensor Nerve Driving a Motor
2 Brain Circuit Findings from Testing Drosophila Flies
3 Experimental Results of Spinal Cord Circuit Testing
4 Neuron Activity Mapping from Zebrafish Experiments
5 Vision System and Simulation Response Comparison
6 Neuron Types in the Neocortex
7 Neuron Memory Experimental Results
8 Neuron Activity and Memory Human Trial Results

C Spiking Neuron Networks
1 Visual System Neuron Spiking Model
2 Neuron Sensor Firing to the Brain
3 Neuron Algorithms and Trades
4 Spiking Neuron Algorithms
5 Brain Neural Networks
6 Phosphorylation Signaling in Proteins
7 Human Learning

D Neuromorphic Computing
1 Energy-Efficient Neuromorphic Computing
2 Neuromorphic Computing Chip
3 Neuromorphic Computing Roadmap
4 Neuromorphic Computing Algorithms & Apps
5 Human Brain in Silicon
6 Big Data Applications of Neuromorphic Computing

Figure 1. Literature review highlights.

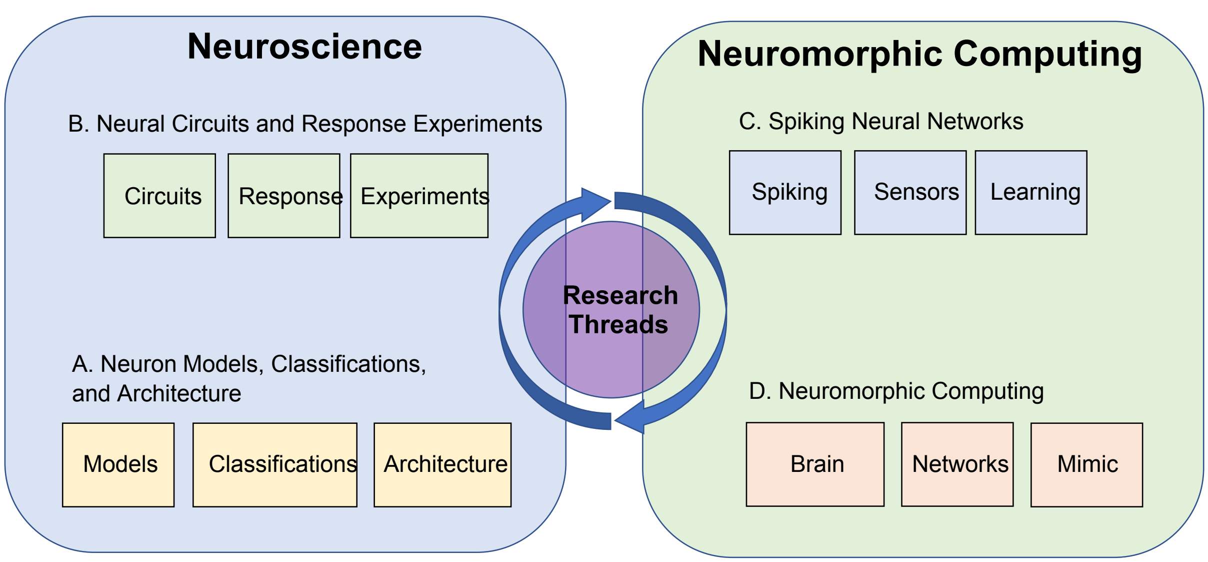

Figure 2. Research focus areas.

A. Creation Model

The Creation Model will allow for comparison, in the same engineering terms, creation features and what human brain function can be understood from the neuron and neural network models used in this paper. Thus, brain function and the environment it was created to function within are drawn together. It allows the first research question to be answered, how does a Creation Model provide additional insight and context for the implementation and mission of human beings?

Genesis 1 provides a roadmap for how creation took place. One can consider what was created each day and the order. There is an interrelationship between the parts of creation week. As the details of the creation week unfolds, the later items utilize what was already conceived. Thus, there is an intentional plan that is laid out. This section will discuss the creation week element and present the details within a Systems Modeling Language (SysML) engineering tool.

First, consider the overall flow of creation. A title for each day of creation is generated, attempting to capture in engineering terms what takes place. Each day forms part of creation, so they all feed into the block on the left. Day 1 starts creation with space, time, light, and matter. These basic building blocks must be in place before anything else can continue. Day 2 forms the Earth's expanse, creating an atmosphere and space where life can exist above the terrestrial water and below the atmospheric moisture. Day 3 makes the lands, oceans, and vegetation. Thus, several ecosystems are put in place. Day 4 establishes the space expanse. The sun, moon, and stars are correctly oriented with the Earth. Day 5 set the beginning of eukaryotic life with the animals of the sea and the birds in the air. Finally, Day 6 continues the creation week by forming animal life on land. Ultimately, the crowning portion of the creation week concludes with the creation of humanity. Humans are made in the image of God and given his divine charter to reign over creation. Note that the number of items listed in the daily creation events varies. The days with fewer items indicate they deserve a day all to themselves.

After this overall look at the creation week, it is helpful to go down to the next level of detail since it is included in the creation week account. Fig. 3 summarizes the six days of creation in one graphic.

1. Day 1 — Space, time, light, and matter

Day 1 starts with the formation of space and time. This fact is not stated but is implied in the Genesis 1:1 phrase referring to the creation of the heavens and the Earth. There can be no heavens and the Earth without space and time. So, there are two items laid out first. Continuing to the next item created there is electromagnetic radiation or light. Light requires space and time and the heavens and the Earth to have an effect. Light interacts with matter, so in the process of making the heavens and the Earth, the material matter of the heavens and the Earth is formed. Next, there is the distinction between when there is electromagnetic energy present, light, and when there is no electromagnetic energy present, darkness. More characteristics of electromagnetic energy are implied, like the occulting of light when a mass is in front of the electromagnetic energy. Hence, the necessary features for an eclipse are present. This leads into the final part of Day 1 creation, where there is the potential to have day and night. Since time is operational now, the clock has started, and a 24-hour day is now in place for an observer on Earth, although an atmosphere, land, and life have yet to be introduced.

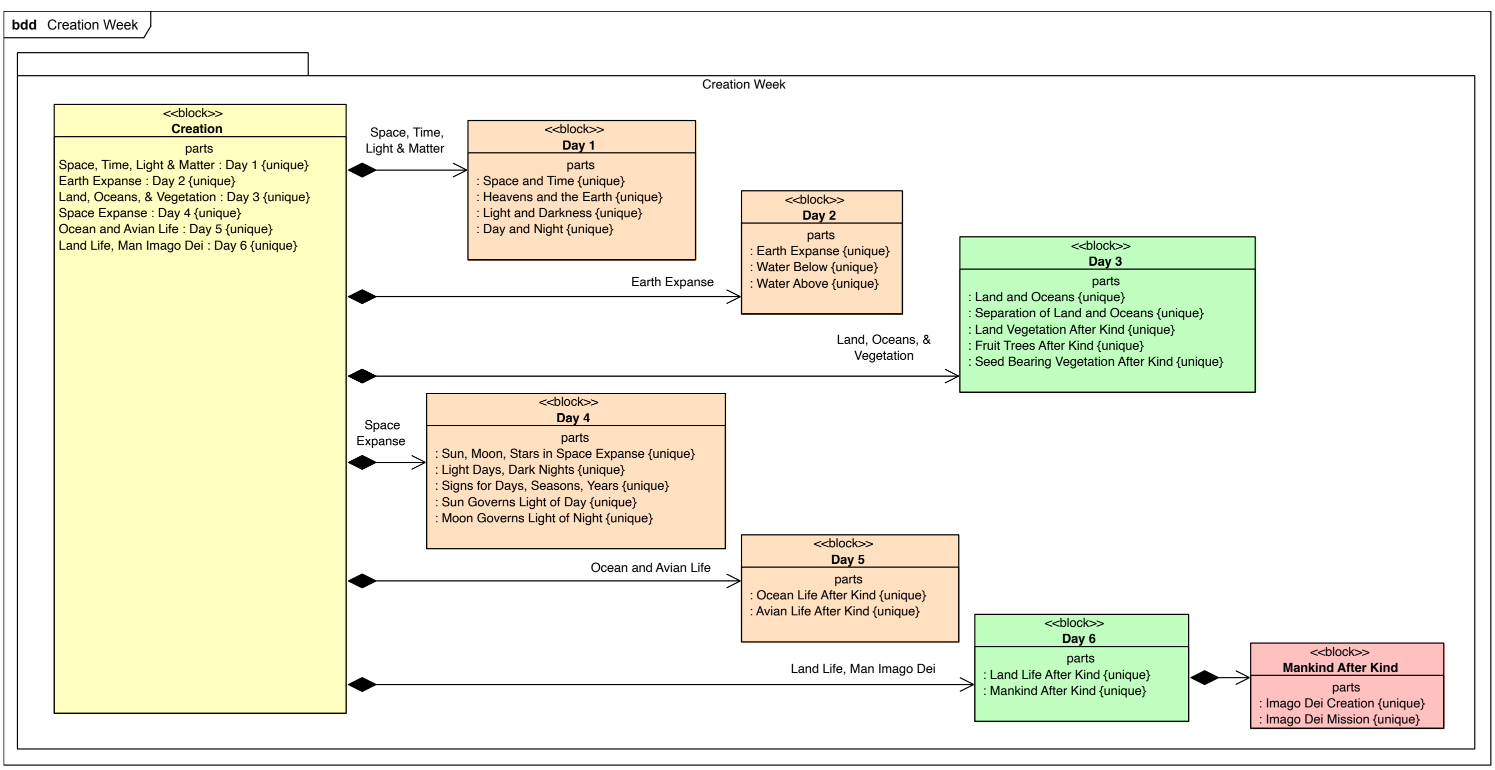

Figure 3. Top Level Creation Model.

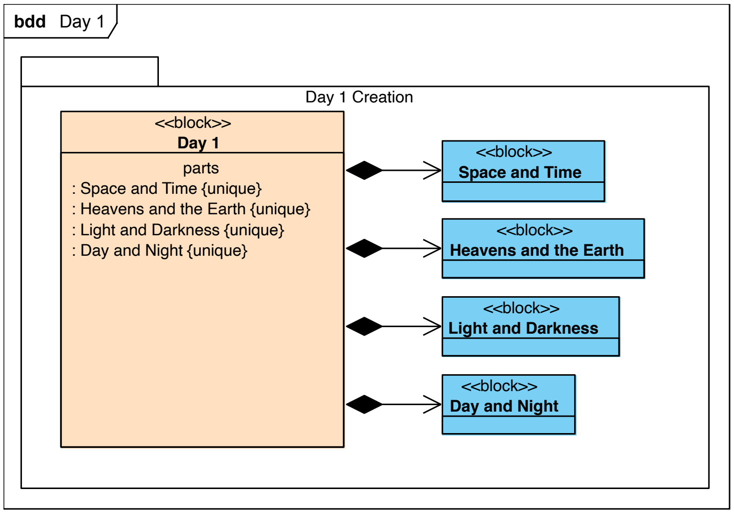

Figure 4. Day One Creation Model

2. Day 2 — Earth expanse

Day 2 creation focuses on the habitability of Earth and the basis for the Earth's expanse that exists with the numerous properties required to support abundant biological life. First, it is implied that water was created on Day 1 so it can manipulate where it is located. An atmosphere is created. Second, water is moved to subterranean locations that can be called upon to support plant and animal life. Third, some water is transformed into water vapor and resides in the upper atmosphere, acting as a shield for the Earth's expanse. Water is transparent in the human visual spectrum, so seeing the space expanse is still available. Fig. 5 highlights the creation accomplishments on Day 2.

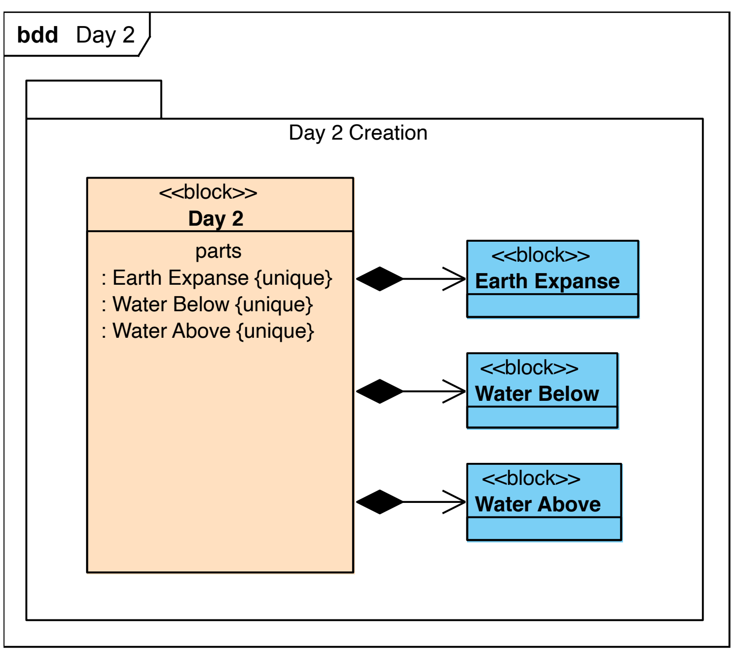

Figure 5. Day Two Creation Model

3. Day 3 — Land, oceans, and vegetation

Day 3 sees several features introduced that are crucial elements to sustain life. First, there are distinctive characteristics of land and ocean conceived. The ground will have direct access to the atmosphere. The sea can draw nutrients from the atmosphere in different ways while in the water. Second, there is the separation of the land and oceans. At this point, there is a predictable place for land and sea so each domain's animal and plant life can be adapted to its specific intended environment. Third, there is the general creation of vegetation over the Earth. Fourth, there is the first mention of vegetation, which includes providing food for others. Fifth, there are various kinds of seed-bearing vegetation, including grains. So, there is another type of food source and a reproductive method for vegetation to reproduce with seeds. Fig. 6 highlights the creation accomplishments on Day 3.

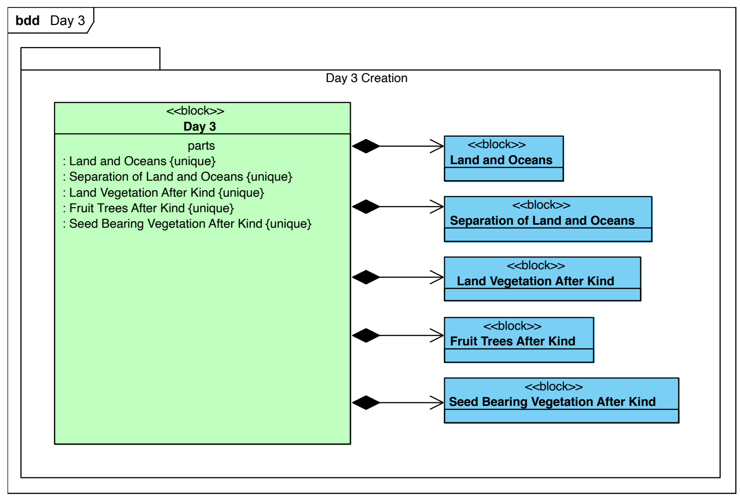

Figure 6. Day Three Creation Model

4. Day 4 — Space expanse

Day 4 focuses on the space expanse. First, the sun, moon, and stars are placed within the space expanse. Second, the properties of electromagnetic radiation and matter or leveraged to enable the day to be light, with the electromagnetic energy coming from the sun and the darkness of night with no direct access to the light of the sun. Third, specific orbital relationships are set up between the Earth, the Moon, the solar system, and the Milky Way galaxy. This allows for the signs of the days, the months, the seasons, and the years when there is a completion of the regular cycles that the Earth travels through over time. Fourth, the sun governs the light and brightness of the day. The light and warmth of the sun promote life. Fifth, the reflected light from the Sun on the Moon governs the brightness of the night, for the times the Moon is visible at a particular location on the Earth. Fig. 7 highlights the creation accomplishments on Day 4.

5. Day 5 — Ocean and avian life

Day 5 begins the process of creating animal life. The description is short but focuses on two significant biospheres of Earth. First, the oceans are populated with animal life after their kind. Second, the

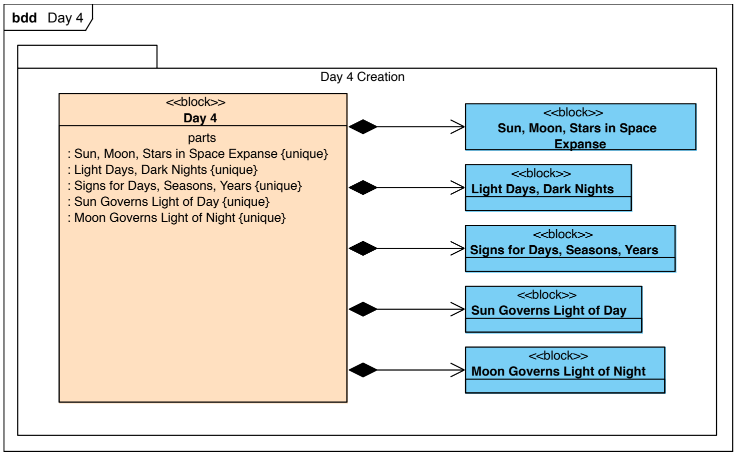

Figure 7. Day Four Creation Model

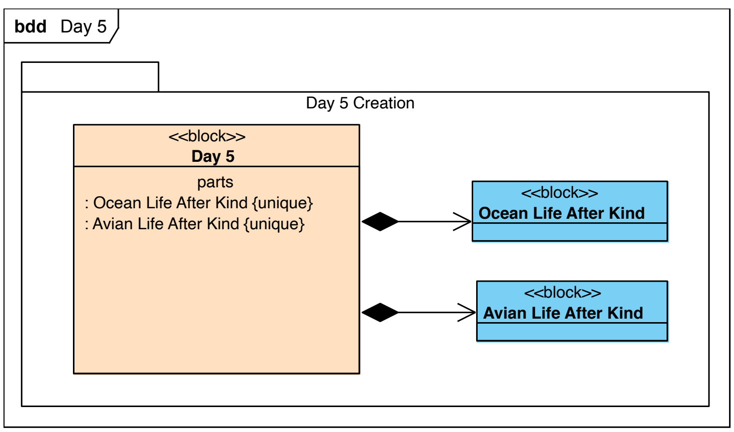

Figure 8. Day Five Creation Model

air is filled with birds after their kind. Before the land was filled with life, the oceans and skies above were called forth to teem with living creatures. Fig. 8 highlights the creation accomplishments on Day 5.

6. Day 6 — Land life and *Imago Dei* man

Day 6 covers two significant areas in populating the land. First, God created the land animals after their kind. Second, God spends more detail focusing on the crowning portion of creation, describing the details of creation man in the image of God. Two things are explained, unlike any other part of creation, man is uniquely created in God's image, enabling him to be creative and think at an abstract level that no other part of creation can. Then man is given a mission, to rule over creation, and to be God's representative. Fig. 9 highlights the creation accomplishments on Day 6.

7. Human brain function above all other

As the crowning act of creation, humans engage with the other parts of God's creation differently and more involvedly. Human beings can observe, think, and evaluate what is seen in a manner not equaled by any other creation. In the created order, it is clear how what was made earlier is shown as a precursor and necessary dependence on what is created later. A fish must have an ocean. A bird must have an atmosphere to fly in. Ultimately this is played out to the greatest

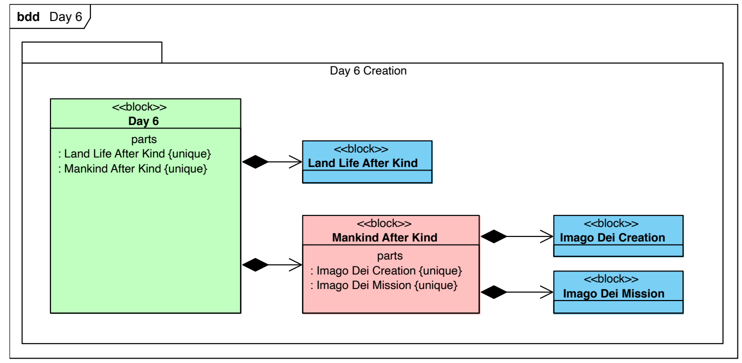

Figure 9. Day Six Creation Model

extent with humanity. Everything up to this point is leveraged for the highest form of creation. There are interdependencies between everything created up to the creation of man.

B. Architecture framework

The full compute stack model provides a manner to explore brain function. It lays out a scaffolding for the layers that go from simple to complex. Utilizing the full compute stack model with brain function creates a basis to determine whether the model is adequate to cover human brain function or just animal brain function. Thus, it can address the second research question, what modifications to the full compute stack model are required to capture unique brain function?

This section introduces an approach to compare biological and artificial neurons and neural networks by leveraging a framework that has been used in engineering development and benchmarking computational capability. This only can capture so much in terms of the human brain and how humans leverage our biology but are not only physical beings. Still, it is helpful to examine these compute layers to point in the right direction where additional capability lies for humanity, being made in the image of God.

1. Use of the full compute stack for architectural levels

An architectural framework bounds a project and provides a structure to organize major thrusts in a system. This will be utilized in this paper. An existing architectural framework will be utilized to structure areas of exploration in neuron and neuronal system evaluation.

The layers of the full compute stack are used as a framework to capture the multilayered functional operation of neural systems. The full compute stack is a layered abstraction of what a computing capability can offer and fits well with the purpose of this project. These layers are (1) materials, (2) components and devices, (3) circuits, (4) microarchitecture, (5) system architecture, (6) algorithms, and (7) applications. The layers are highlighted in Schuman's neuromorphic computing algorithm and applications survey (Schuman 2022), and Christensen's neuromorphic computing roadmap (Christensen 2022). These references are also discussed in the literature review. A summary of these layers is shown in Figure 10.

These layers are discussed next, with observations on both the biological and artificial sides.

2. Materials

Materials are at the lowest level of architecture considered in this

Table 1. Days of Creation and Man's Response

EVENT	GOD'S PLAN AND MAN'S RESPONSE
Day 1 — Space, Time, Light, Matter	
Space and Time	Can experience space, distance, the passage of time
Heavens and Earth	Can experience the difference between what is far away in the heavens versus close on the Earth
Light and Darkness	Created light so man can see creation, feed plants, provide warmth, interact with seasonal signs
Day and Night	Can experience the differences between day and night
Day 2 — Earth Expanse	
Earth Expanse	God created an environment where life can thrive
Water Below	Water to support plant life
Water Above	Water to protect the Earth expanse
Day 3 — Land, Ocean, Vegetation	
Land and Oceans	God created the difference between two domains
Separation of Land and Oceans	God established the land and ocean layout
Land Vegetation After Kind	God created a lush garden environment for man to live
Fruit Trees After Kind	Man can eat the fruit
Seed Bearing Vegetation After Kind	Man can eat and plant vegetation
Day 4 — Space Expanse	
Sun, Moon, and Stars	God created space expanse objects
Light Days and Dark Nights	God defined light level for day and night
Signs for Days, Seasons, and Years	God established signs to track time and change
Sun Governs Light of Day	God established day characteristics
Moon Governs Light of Night	God established night characteristics
Day 5 — Ocean and Avian Life	
Ocean Life After Kind	God populated the oceans
Avian Life After Kind	God populated the skies
Day 6 — Land Life and Mankind	
Land Life After Kind	God populated the land
Man Made in God's Image	God created and placed man in the garden
Man Given God's Mission	God gave man his divine mission

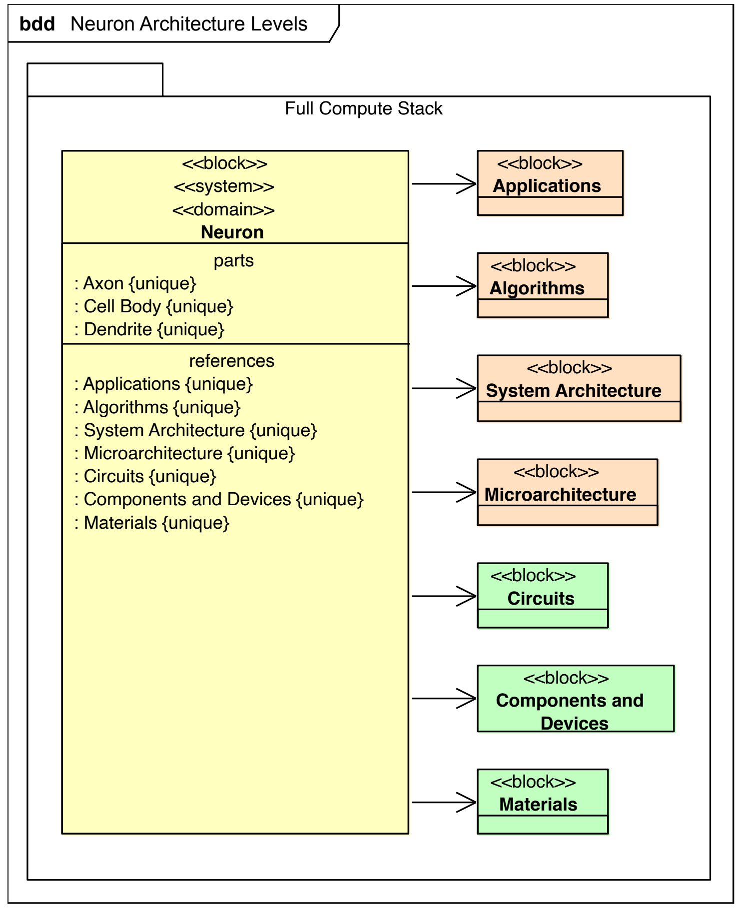

Figure 10. Full compute stack layers.

project. Looking at the periodic chart, elements have distinct characteristics. Some fall into categories, like noble gases, semiconductors, or metallic materials. Molecules for the next level combine elements to make available additional physical phenomena. Water, or H_2O, which combines two hydrogen atoms with one oxygen atom, is a simple molecular example that shows a unique compound that is an essential element of biological life.

a. artificial neuron considerations

In electronics, semiconductors are a vital material where an external signal can turn the electrical flow on, off, or modulated. Not only is it used as is, but doping a semiconductor with other materials can generate more targeted physical properties that can be used in other full-stacking computing architectural levels. Silicon is a commonly used semiconductor, but gallium arsenic is another semiconductor that is also used that has specialized properties. Gallium nitride is another semiconductor material promising in high-power applications and other areas.

b. biological neuron considerations

In biology, looking at molecular biology gives insights into what materials are used and what physical properties they contain. When considering proteins, the biochemical composition centers around nucleotides. Nucleotides are organic molecules consisting of (1) a nucleoside, which in turn is composed of a nucleobase and a five-carbon sugar, and (2) a phosphate group. This biochemical shows a jump from simple compounds to complex molecular building blocks in biological systems.

This section will briefly discuss the neuron-to-neuron communication process from the neurotransmitters to the synapses in the first neuron, to the interneuron signaling, and finally to the receiving neuron receptors. Neuroscience is an active field, and the details are not fully understood, so it is harder to characterize than the artificial systems counterparts; some perspectives on this are given below. In biological neural networks, there are far more synaptic connections than neurons. Ielmini notes that the synapse-to-neuron ratio is 10,000 (10^4). This is a considerable number of synapses compared to neurons, which can make crossbar systems quite large to achieve this enormous number (Ielmini 2018).

When considering the materials used in biological neurons and neural networks, addressing a few questions can help guide how best to compare the materials layer in biology versus electronics. First, what elements, molecules, biomolecules, and biochemical materials are used for each part of the neuron? There is active research in neuron molecular biology, but there are limited opportunities to access human neurons ethically. Some proteins have been identified to be part of neuronal processing (Davies 2006). Second, what are the critical biomolecular properties that motivate their utilization at the compound level, nucleotide level, protein level, cell circuit level, and nerve cell level? Exploring this question will be one of the themes explored as each architectural level is discussed.

The neuron-to-neuron communication process starts from the neurotransmitters to the synapses in the first neuron, to the interneuron signaling, and finally to the receiving neuron receptors. Davies, and his chapter scholars, explore the molecular biology of neurons from various active research points of view. In greater detail, it proceeds with these steps: First, the transmission of the information starts with a discussion of neurotransmitters. The neurotransmitter released from one nerve cell binds to the receptor of another nerve cell, which results in depolarization or other effects in the target nerve cell. A neuron can transfer a signal to a postsynaptic neuron by releasing certain chemicals (neurochemicals) into the synapse and activating postsynaptic receptors. There are many neurochemicals, on the order of 100. Measurement testing has shown that neurotransmission membrane potential changes at certain defined discrete levels, or quanta, must occur in multiples of quanta (Davies 2006). Second, synapse transmission is primarily controlled by neurotransmitter activity. The synapse physically connects with the receiving neuron, and several proteins are involved in this connection and exchange of information. The postsynaptic density is where the synapse connects with a receiving neuron's dendrite. There are four types of proteins present in this area: (1) plasma membrane, (2) signaling, (3) cytoskeletal, and (4) linker. They are signaling results by forming protein complexes that respond to signals from the membrane surface. Some signaling machines have been identified, which reach the next full compute stack architectural level (Davies 2006). Third, interneuron signaling utilizes signaling machines to transmit the encoded information from one neuron to another. One form of signaling is done through phosphorylation. The fact that there are several types of signaling pathways illustrates the complexity and connectivity that exists in neural networks. There is also a link between the nucleus and signaling. Calcium ions can act as messengers to link the synapses to the nucleus to pass signaling information (Davies 2006). Fourth, signal reception is accomplished by using signal receptors. Two types are ligand-gated ion channel receptors and G-protein-coupled receptors (GPCR). Fast synaptic transmission is critical for real-time brain functions. Ligand-gated ion channels can handle such rapid processing. These ligand bonding sites can bind to a particular neurotransmitter molecule, open a transmission channel, and activate signaling. There are many G-protein-coupled receptors, so much so that it comprises one percent of the human genome. These GPCRs form the receptors for neurotransmitters, odorants, lipids, neuropeptides, and large glycoprotein hormones (Davies 2006).

Fig. 11 shows the materials and devices that compose the biological nucleotide.

3. Components and devices

Components and devices are at the next layer in the full compute stack. At this level, material physics phenomena are captured in a helpful way that can form a building block for a higher-level computing function. On the artificial or electronic side, components consist of various types of transistors, phase-change or memristor memories, optical devices, and switching devices. On the biological side, components include protein complexes that respond to signals, ligand receptors, phosphorylation, and methylation in cytosine-phosphate-guanine (CpG) groups. CpG sites are regions of DNA where a cytosine nucleotide is followed by a guanine nucleotide and can be impacted (silencing genes, switching on or off, or muting them to some degree) by inserting a phosphate group between them. To a degree, one can show a mapping of similar functions between the artificial and biological, but the material and components and devices' full compute stack layers are implemented with very different materials and physical phenomena to produce the desired effects. At the device level, the basic building block is the neuron. Both artificial and biological neural networks have other support devices included, but the primary focus here is exploring the nature and design of the neuron.

A few questions can be asked here to explore a path forward. First, what physical phenomenological properties can be used for the full compute stack components and devices layer functions? The Von Neumann architecture describes the three necessary building blocks for a computing system as (1) a central processing unit (CPU), (2) memory, and (3) input and output devices. Components must exist to enable these functions as they are put together to form a functional and flexible neuron. Second, how are these functions translated into functional parts within a particular design motif, like silicon for artificial neurons and nucleotides in biological neurons? One must consider what materials will the components and devices be built upon. With an extensive legacy of parts and infrastructure, the artificial neuron finds plenty of value in continuing development in silicon. Using this design motif allows a smaller near-term investment. However, in the long term, there will continue to be a big difference between the artificial and biological realization of neurons.

a. artificial neuron considerations

In the roadmap he developed, Christensen offered many options for the components, devices, and circuits necessary to create an artificial neuron capability, along with functional and efficient neural networks. Synapse transmitters and dendrite receptors interconnections

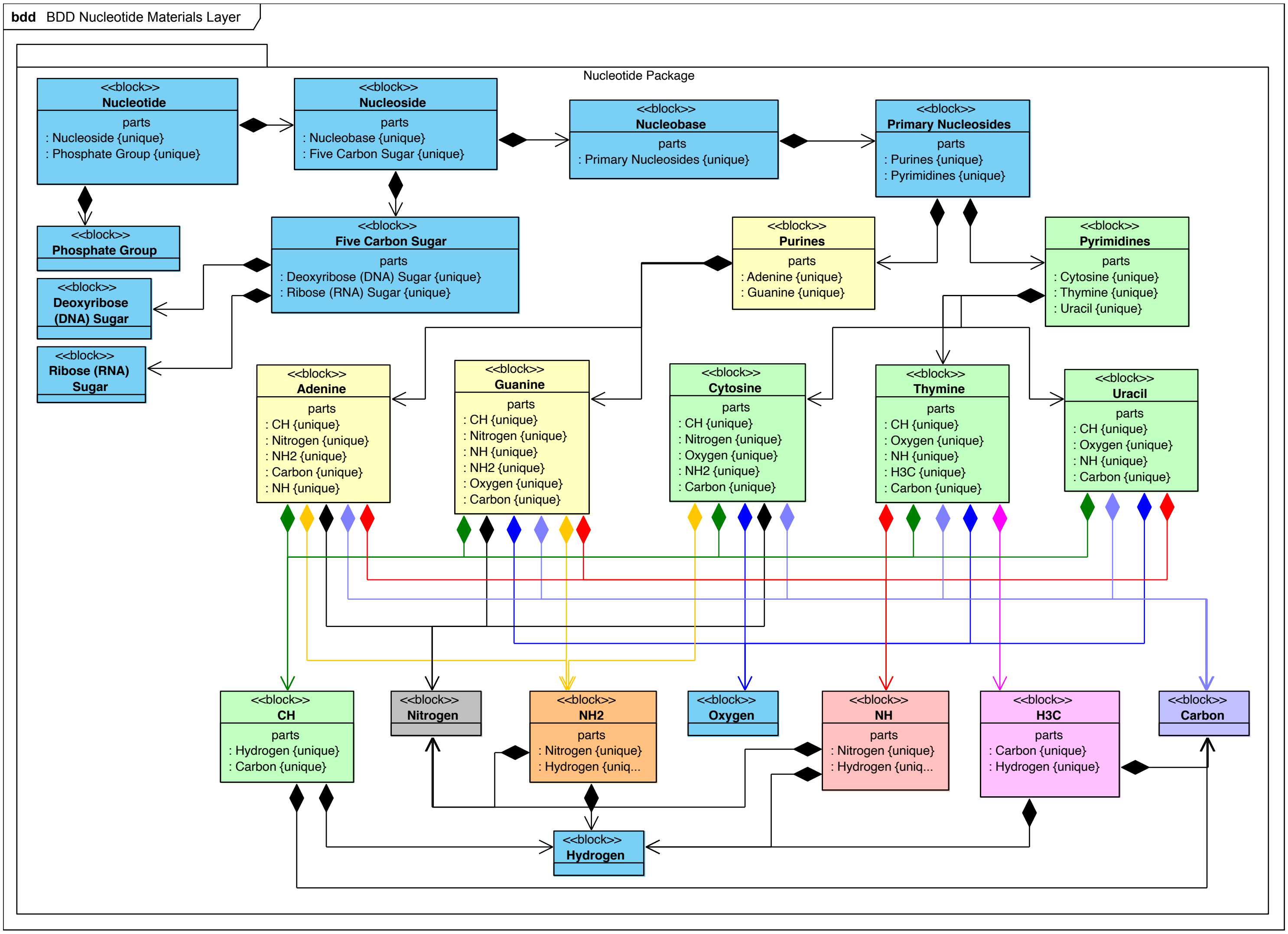

Figure 11. Nucleotide material composition mapping.

can be created using a programable switching device. Axon connections can be accomplished using nanowires. Sensor and motor function interfaces are more specialized connections with more stressing transmission, reception, and signaling requirements. Memory can be accomplished using emerging technologies like memristors, phase-change memory, valance-change memory, or resistive random access memory (RRAM). Neuron nucleus processing can be accomplished with a CPU core or a more focused microcontroller (Christensen 2022).

b. biological neuron considerations

The biological components of the neuron continue to be clarified with neuroscience research. Due to easier access, most experimental neuroscience research focuses on sensor processing (Ryu 2018) and central nervous system transmission and processing (Böhm 2016). Synapse transmitters and dendrite receptors interconnections have the typical characteristics of general neural circuits for these functions, but they are optimized for the specialized functions in their locations. Sensor interconnects circuits are optimized for quick reception. Central nervous system interconnects circuits are optimized for high signal-to-noise ratio signal transmission, with periodic transmission signal cleanup to maintain signal integrity. Axon connections can extend in the 3-D space of the body over long distances (especially for the central nervous system) to make the necessary interconnects (Böhm 2016). Sensor and motor function interfaces require high-fidelity signaling to accurately convey the information to the brain for the bulk of processing (Kim 2018; Böhm 2016; Ryu 2018). Memory is embedded in a dual-use fashion of signal-connecting circuits of the neuron. Neuron processing is done in the nucleus and embedded in a multiuse fashion in the signal-connecting circuits of the axons, synapses, and dendrites.

3. Circuits

Neurons, in their various forms, are the major building blocks in neural operational architectures; as a result, the primary circuit that is explored in this paper is the neuron. Circuits are composed of several parts that are organized in such a way as to produce the desired function. Neuroscience research has shown that the neuron is the central building block of the brain, the central nervous system, sensor processing, and motor control. Just like a Von Neuman computer can be constructed entirely from digital logic gates (or circuits), a neural circuit can be made from neurons. Thus, there is the introduction of the basis for a neural network at the circuit level.

Once again, the capabilities discussed in subsection three above will be examined here, but now at the next architectural level of the circuit in the full compute stack model, specifically (1) dendrite receptors, (2) neuron nucleus (soma) processing, (3) neuron memory, (4) sensor interfaces, (5) motor function interfaces, (6) axon connections, (7) synapse transmitters, and (8) synapse spiking signaling. Simplifications in the spike implementation are used for artificial spiking neural network implementation, and the way voltage is handed will vary since biological and electronic circuits are very different at the materials level and the component and device level. These details are not covered in this paper.

a. artificial neuron considerations

Synapse transmitters and dendrite receptors interconnections at the circuit level can be created using a two-dimensional (2-D) crossbar. This may not be the most efficient, but it can create a robust interconnection fabric. Axon connections can be accomplished using nanowires, but only within the 2-D organization made available in chip electronics. Since sensor and motor function interfaces are more specialized interfaces for transmission, reception, and signaling, there will have to be separate circuit designs for each one. Memory can be accomplished using chip electronic circuit modules made of memristors, phase-change memory, valance-change memory, or RRAM devices. Neuron nucleus processing can be accomplished with CPU cores made available to a handful of neural circuits, an arithmetic logic unit, or a microcontroller circuit. Once a neural circuit is available, it is possible to make networks of neural circuits available (Christensen 2022).

b. biological neuron considerations

Neuroscience research has a basic understanding of what a neuron is and how it functions. It explores the various facets of neurons in humans and animals from various points of view. Various animal testing ranging from flies, cockroaches, mice, and zebrafish, have been reviewed in the literature (Kim 2018, Huang 2017, Ryu 2018, Mitani 2018. For example, Mitani et al., by inserting microprobes into a mouse's brain, gained insight into the spiking nature of neuron firing from specific condition tasks (Mitani 2018). The biological neuron receives information from the dendrites, processes the inputs in the cell nucleus (soma), transmits responses through the axons, and connects with other neurons through the synapses.

4. Microarchitecture

Now that materials, components, devices, and circuits are available, they can be brought together to form a low-level architecture, which will be called a microarchitecture. Within a localized function, a microarchitecture is generated to execute a specific activity. A microarchitecture has greater complexity than a circuit but is not a complete architecture for a specific activity. It forms an essential building block as the next step in forming a complete neural capability. Microarchitectures form multilayer neural networks. Circuits are combined to form higher-level functional systems. In this process, multilayer neural networks are generated. The formation of neural sensing, cognition, motor function, and control microarchitectures are examples of functions that can be captured with this layer. For artificial neural network considerations, simple single-stage artificial neural networks are a focus of microarchitectures. Neurons function together to form a microarchitecture. For biological neural network considerations, biological microarchitectures would be the first step in cognitive development, where basic neuron connections are formed.

5. System architecture

System architectures form the next higher level of organization of function, interfaces, and interdependent operation of various microarchitectures. A system architecture can be considered a system of systems, or a system of microarchitectures that operate interdependently. In neural systems, a system architecture is used for neural systems that perform a complete system function, like sensing, motor control, or a computing module category.

The integration of neural systems like neural sensing, cognition, motor function, and control are examples of what are aggregated as a systems-of-systems architecture in this layer. For artificial neural network considerations, multilayer neural networks are a focus of system architecture, where more complicated architectures are formed that have more capability. For biological neural network considerations, rather than just single neurons connecting to other ones, with a system architecture, there are multiple layers of neurons connecting that are adapting in a manner that has a more specific focused function that can repeatably be called upon.

6. Algorithms

Algorithms can utilize system architectures to generate a close coupling of "hardware" and "software." They form approaches that are tied together and can then be made available as cyber-physical application capabilities that will be discussed in the next section. Algorithms tie one or more system architectures together with other resources, including the interdependence of multiple algorithms.

a. sensing

Algorithms are generated from architectures and circuits for each type of sense: (1) visual, (2) auditory, (3) taste, (4) olfactory, or (5) tactile detection of pressure and temperature.

b. motor response

Motor response aggregates tactile sensing, motor operation, proper response replication, and control computing. All these elements work together to provide a tuned functional motor response.

c. learning

Learning takes training data fed into neural networks and tunes the response within its neurons to produce the desired result more effectively. Learning is closely coupled with spiking neural networks. Once the neural connections have been established and properly conditioned, they can be activated in a tuned manner by future spiking events coming into the neural network.

d. computing

Computing requires processing, memory, and input and output connections to be correctly in place. Spiking neural networks process computational requests, especially in the brain.

7. Applications

Applications combine major functional categories like cognition, specific motor control operation, sensory data processing, data analysis, and information interpretation. Applications show a complete coupling realization of the "hardware" and the "software." They form cyber-physical capabilities in which the neural system will operate. A comprehensive vision system is an example where location, color, and intensity data are received into the sensors, information is transported to the brain, a neural network performs signal interpretation, a neural network performs object detection, and a neural network generates a computational response.

Applications can vary between biological system drivers and artificial neuromorphic system drivers. Biological system drivers capture the functionality in human and animal brain and nervous system activity. Neuroscience is actively exploring this front. Artificial system drivers seek bounded capability targeting areas like autonomous vehicles, robotics, embedded systems, perception engineering, and image-processing computational engines. Applications are based on integration or augmentation with human sensing methods.

Considering the biological neuron and neural network linkage of full stack layers, Fig. 12 shows the use case relationships between the layers, and Fig. 13 shows the types of activities and linkages between the layers. Many interdependent elements must function together to accomplish the desired computing and processing goals. Although many details are presented, it is still notional, trying to capture how a use case scenario for critical applications connects to all the lower levels in the full compute state.

8. Human brain operation layer above all other neural networks

An additional layer is proposed to account for the human brain's unique characteristics adequately. This attempts to account for human beings made in the image of God and the fact that man has a body and soul that intersect in the physical world but includes a transcendent element that extends beyond the realm of the spirit.

It is essential to consider how mankind transcends the mental capability of any other created organism. Being made in God's image, human brain function must consider the spiritual dimension. Neurons and neural network descriptions do not adequately cover this dimension. Schaeffer notes that just realizing a neural network does not mean that learning will occur all on its own (Schaeffer 2022). No human-level emergent properties are manifested by just building neural network hardware. Schaeffer may be giving evidence for brain activity that engages with non-physical input. Humans must be animated with a spirit to be alive in the sense that God intended for humanity.

Leveraging theological knowledge, conceiving abductive arguments that capture how human consciousness is more than neural networks is straightforward. Although not explained in current neuroscience research, knowing that man is created in the image of God, there must be interfaces such as (1) between the human brain biology and the soul (along with the soul to spirit if considered separate), and (2) between the spirit and God. This is a possible extrapolation for what Schaeffer is pointing out when he argues that there is no free lunch. Creating elaborate neural networks is not enough to capture what is required to capture the type of learning that can be done in the human brain. Only neural networks with external interfacing capabilities allowing for abstract thinking can capture the full design of human consciousness. Fig. 14 shows a use-case scenario for the *Imago Dei* layer that must be included.

C. Neuron models

By capturing in architectural models of neuron function, it creates the first of two parts that are necessary to capture brain function from a top-level point of view. A great deal of engineering forethought has gone into its elegant and efficient operation and design. Mapping this information enables answering the first part of our third research question, what observations about human brain function can be made from the neuron and neural network architecture models?

This section explores the nature of the biological neuron and characterizes its functional components using a model-based systems engineering tool that utilizes the SysML.

1. What is a neuron?

A neuron is a specialized cell that receives, processes, and transmits nerve impulses. In a learning mode, it develops connections with other neurons to collaborate in computation efforts as needed (Davies 2006).

From a computing point of view, a neuron can be considered a computational device that consists of a processing unit, memory, and input and output devices. In contrast to a centralized Von Neumann computing architecture with separate processing, memory, and input and out modules, each neuron is a self-contained computing agent that can be networked with other neurons to form networks. How a neuron implements each of the three Von Neumann architecture elements is explained next to clarify what is meant by comparing an individual neuron with a computational element. Stallings is used as an in-depth reference for electronic computer organization and architecture that explores the implementation and refinements that have taken place over many decades (Stallings 2019).

First, neurons process and condition the information it receives. This

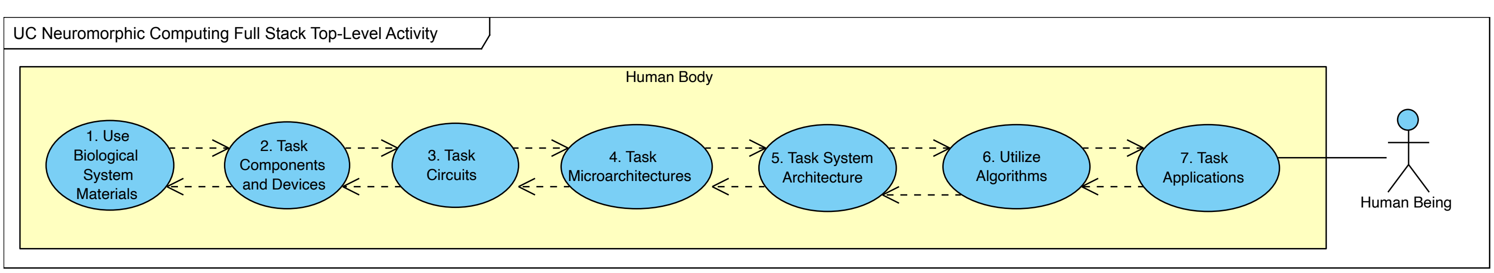

Figure 12. Neuromorphic computing use case with full compute stack.

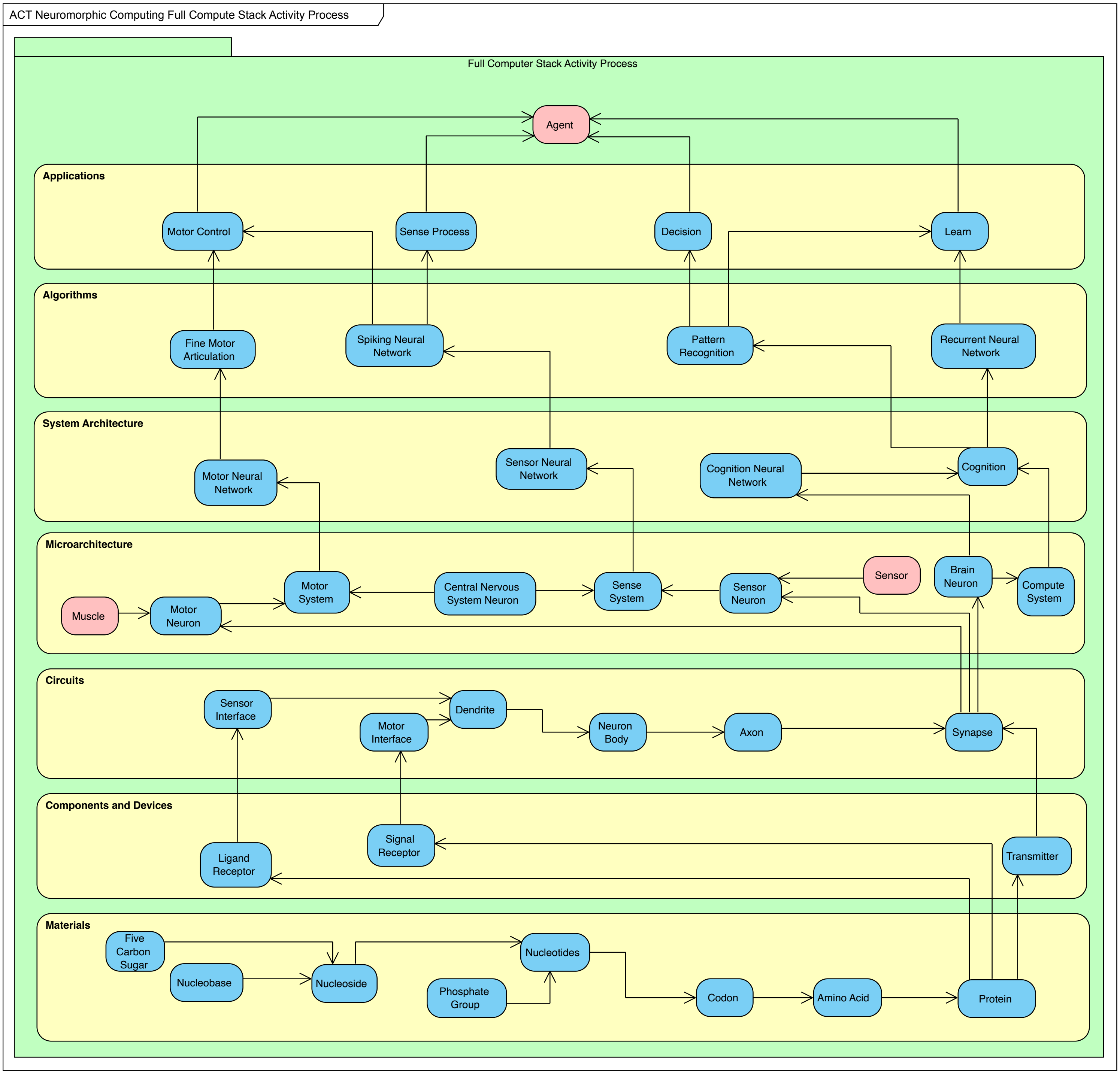

Figure 13. Neuromorphic computing activity model with full compute stack.

processing level is lower than one would associate with a laptop's central processing unit (CPU). However, looking at a CPU and its architecture, one can find a better level of processing comparison. A relatively recent innovation in processor implementation has multiple processing cores. Thus, with multiple cores, a CPU shares duties with multiple processing elements and assigns duties to each based on how it is engineered. A key workhorse element called the arithmetic unit (ALU) is within a processor core. The ALU is a device that can be commanded and reconfigured to perform various computational operations. This is done by software with a low-level programming language called assembly language. A more appropriate analogy exists with an individual neuron at this more targeted ALU level. A network of neurons could be considered similar to a multicore processor. Thus, a single neuron can be considered an ALU with a handful of programmable and reconfigurable states. In one of these states, a single neuron is configured to do some basic function like sum three inputs, pass the signal if a condition is met, amplify the input, or modify the input in a particular fashion. Various paper ref-

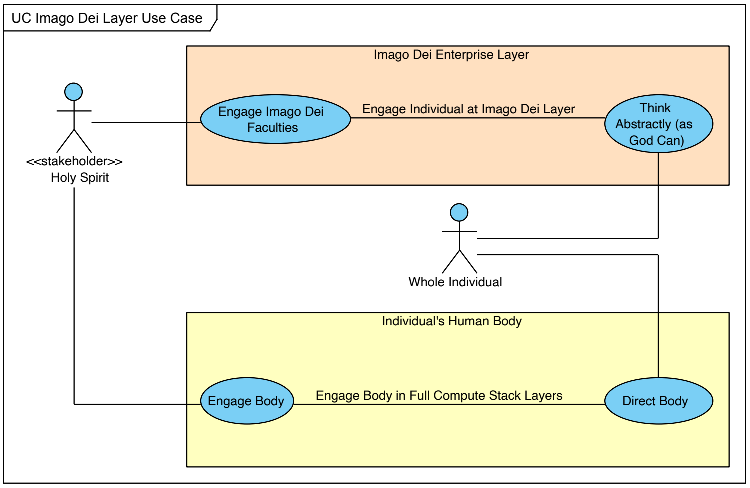

Figure 14. *Imago Dei* Enterprise Layer Above Full Compute Stack

erences refer to neuroscience and neuromorphic computing research insights that correlate with the processing portion of a neural computing architecture (Aljadeff 2016; Benjamin 2008; Bouvier 2019; Doberjeh 2016; Masqueler 2011; Rizzardi, 2019).

Second, there is memory in a neuron. Each neuron must maintain awareness of what it must do at a given moment. Through learning activities, a neuron can respond to a stimulus in the same way repeatedly. Networks of neurons require memory to execute multi-stage activities. Each action requires memory, and various paper references explore aspects of neuroscience research concerning neuron and neural network memory (Huckleberry 2018; Faraut 2018).

Third, neurons have capabilities for inputs and outputs, as demonstrated by studies examining and visualizing neural network structures. Computational load can be shared by having neurons work together in the appropriate input and output connections. The central nervous system connects neurons to pass sensor information and control and monitor motor functions. Neural circuits have been experimentally traced. Several paper references explore neuron and neural network interconnections (Boorboor 2016; Böhm 2016; Huang 2017; Wang 2021).

Based on what is known about neurons to date, there are several characteristics that all neurons have. Neurons have dendrites, a cell body, and an axon, which according to this modeling approach, the synapse is included as a part that attaches to the axon. Neurons connect with other neurons through synapses, which capture the specific interneuron signaling approaches. Fig. 15 shows these functional blocks.

2. Neuron classification

There are multiple ways one can categorize the classifications of neurons. One can consider the function and the structure. Fig. 16 shows the grouping of two classification categories that are used in this assessment. Since neurons are a key focus for this paper, this section provides useful characterization for this basic building block. Showcasing information via an architectural model perspective highlights taxonomy and implementation information in biological neurons and what approaches in biomimicry have been done in artificial neurons. Neural network models are shown in Fig. 22. Spiking neural networks are implemented in biological neurons. Artificial neural network models are simplifying attempts to implement some of the features in biological spiking neural networks within the current limitations of electronic chip part fabrication methods.

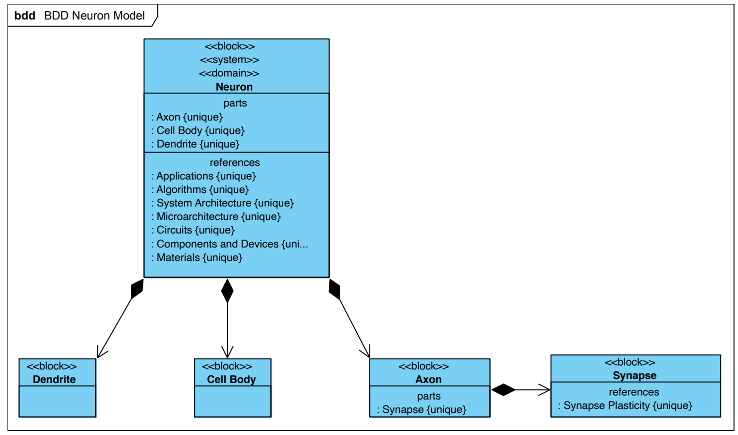

Figure 15. Neuron model showing major components.

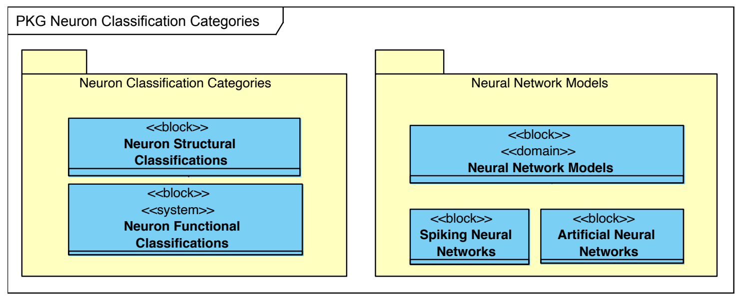

Figure 16. Neuron classification categories.

Functional and structural classifications are highlighted below. Functional classifications capture the capabilities that are in the top-level biological neuron types by location in human beings. Structural classifications summarize the major biological neuron implementation types.

a. functional classification

Functional classification captures the significant types of neurons and their locations. The location of the neurons relates to their function. These functional locations are near the senses (sensory neurons), inside the brain (interneurons), inside the central nervous system (interneurons), and near muscles (motor neurons), as shown in Fig. 17. Neuroscience research seeks to refine this understanding, but from an architectural modeling point of view, these classifications are enough to provide a top-level understanding of sensing, motor function, computing, and learning.

Neuron functional classifications highlight what neurons are intended to do and the architectural layout used to embrace its purpose. It does not fit directly one-to-one into a Von Neumann architecture of processor, memory, and input and output. Still, it does show all three of these Von Neumann features. There is not a clear distinction between hardware and software. Digital computing is not necessarily its base, but spikes are used to trigger action and pass information. A different architectural paradigm is utilized for this important connecting and computational building block. It is optimized to promote

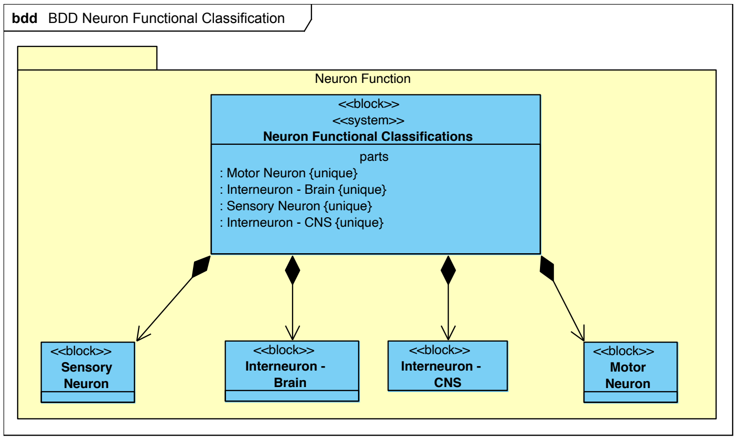

Figure 17. Neuron functional classifications.

interconnections, share computational loads, learn from past events, process sensory data, and do motor functions. All of these can be boiled down to this worker bee module. Describing the next layer of specification, neurons can be grouped into four functions, sensors neurons that interface with the senses, interneurons in the brain that focus on computation and learning, interneurons in the central nervous system that focus on connections and signal processing of the information being transported, and motor neurons that focus on motor control. To accomplish many activities requires two or more of these functional neuron categories to work together. Note that none of these functions capture the unique qualities found in human beings or the special qualities that are part of humans' *Imago Dei* charter.

b. structural classification

Structural classification (Fig. 18) captures the number of connections a type of neuron can have. The three classes are unipolar and pseudo unipolar, bipolar, and multipolar. A unipolar neuron has a single dendrite. A bipolar neuron has one dendrite and one axon. Multipolar neurons are typical in the nervous system and have long axons. This type of architectural classification approach groups neurons by their physiology. Neuroscience research is actively working to characterize neuron operation neurons when they can be exposed in their operational mode. In contrast to functional descriptions, this structural taxonomy highlights the observable features accessible by physical observation.

Biological neuron structure takes advantage of the three-dimensional space where they exist to make connections. Each structural classification does the same basic function of transferring information

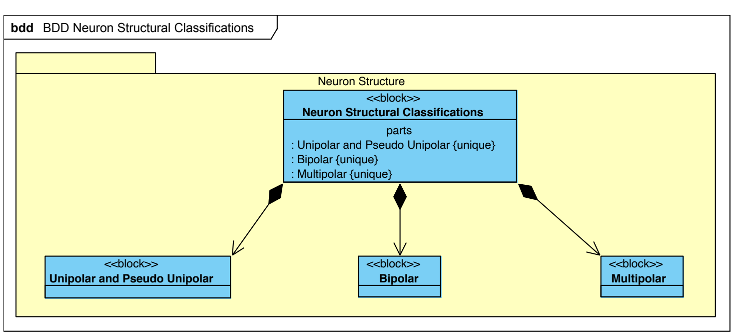

Figure 18. Neuron structural classifications.

through the organism, with each also doing signal conditioning or computational processing of the information. Unipolar neurons exist in invertebrates like insects but not in humans. They are part of gland and muscle function. Pseudo-unipolar neurons exist as sensory neurons. Their primary function is to route sensor data back to the brain for processing. Bipolar neurons represent the classical structure of a neuron in one input node via the dendrite and one output node with the axon and synapses. Multipolar neurons are the most common type of neuron and are heavily populated in the central nervous system. This diversity in structural options for the neuron shows how flexible its general capability can be utilized to serve many functions (Ludwig 2023).

3. Biological versus artificial neuron comparison

The discussion in the architecture framework section introduced the comparison of biological and artificial neurons, thinking within the application context of neural networks. Tab. 2 shows the similarities and differences between these two approaches.

- For the material layer, biological neurons leverage biomolecules that form nucleotides. Their physical properties are altered by adding elements like phosphate groups. The materials of artificial neurons center around semiconductors. Physical properties can be altered by doping the semiconductor substrate in specific locations when building the correct order of materials via material deposition, one stage at a time.
- For the components and devices layer, there are two parts:

Table 2. Biological vs. Artificial Neuron Comparison

ELEMENT	BIOLOGICAL NEURON	ARTIFICIAL NEURON
Material	Biomolecules	Semiconductors
Component	Proteins	Doping, Device Physics
Device	Receivers, Transmitters, Ligands	Transistors
Layout	Cell Layout	Chip Packaging
Receive Connect	Dendrites	Crossbar Interconnections
Transmit Connect	Axons	Crossbar Interconnections
Transmit	Synapse Signal Transmitters	Transmit Protocol
Receive	Dendrite Signal Receptors	Receive Protocol
Memory	Nerve Body	Embedded Local Memory
CPU	Nerve Body and Axons	Microcontroller, Processing Unit
Form Factor	Modular Neuron Nerve Cell	Neuromorphic Chip
Energy	External Chemical (e.g., ATP) Energy	External Electrical Energy

  - For the components, biological neurons utilize proteins, which are an array of nucleotides configured in the proper order and folded into a functional formation to perform a specific component function. Artificial neurons leverage the device physical properties for building components.
  - For the devices, biological neurons construct things like signal receptors, transmitters, and storage devices like chemical ligand receptors with biomolecules and protein configurations. Artificial neurons rely significantly on several transistor types for generating devices.
- For biological neurons, the layout is based on a typical neuron cell layout and configuration. There is no standardized approach for artificial neurons other than they will each be assembled as an integrated circuit chip with flexible capability within the package.
- For receive and transmit connections, a biological neuron utilizes dendrites for receive connections, axons, and the synaptic transmit elements for transmit connections. They take advantage of 3-D space to interconnect. Artificial neurons use crossbar interconnect devices for the receive and transmit connections.
- For transmit signal protocols, biological neurons use synaptic signaling transmitters, and for receivers, they use dendrite signal receptors. Artificial neurons use a digital signaling protocol, like TCP/IP, for a transmit and receive protocol.
- For memory, biological neurons enable memory by mechanisms in the neuron cell body. Artificial neurons require collocating embedded local memory processing with neural circuits.
- For the CPU, the biological neuron has signal conditioning and processing within the nerve body and axons. As signals pass through, the characteristics are modified. Artificial neurons require a microcontroller or a simple processing unit in each neuron module.
- For form factor, the biological neuron is contained in a single nerve cell that is modular and designed to work together with many other nerve cells. Artificial neurons place all the various neural circuitry into a neuromorphic chip that contains a discrete number of neurons.
- For energy, biological neurons use external chemical energy only when the neuron is activated to participate in a computational function. Artificial neurons utilize electrical energy, often supplied via a continuous power stream to all the neurons in a neuromorphic chip.

a. biological neuron realization

When looking at the neuron from various points of view, one can see the complementary elements that must work together. There are a variety of biological elements that must be in place to generate a functional biological neuron. With many neuron classifications, a different emphasis is seen from one neuron type to another.

b. electronics neuron realization

Leveraging what has been done in chip electronics, various electronic neuron elements must be generated to have a functional artificial neuron. Computer architectures have adapted and changed as new ways to improve performance have been discovered. There are several critical artificial neuron differences. With a unique architecture, there are places where it needs to be clarified how to make systems more biologically similar without completely changing the way architectures are devised.

4. Neuron molecular biological composition

This section will explore the composition of biological neurons and the primary biomolecules utilized. Unfortunately, much research is still required to clarify the molecular biological composition of neurons further. Active research is exploring this composition.

Exploring the molecular architecture of neurons provides insight into the physics of materials and phenomenology utilized to implement neuron capabilities. The physical layer of biological neurons differs entirely from artificial neurons implemented in chip electronics. Examining from an engineering perspective how biological neurons are constructed at the lowest level may suggest new approaches for electronic biomimicry.

DNA holds the building instructions for biological components like proteins. Nucleotides are the basic building blocks that DNA is made from. These nucleotides are organic molecules consisting of a nucleoside (a nucleobase and five-carbon sugar) and a phosphate group that forms the structural parts (nucleic acid polymers) of DNA and ribonucleic acid (RNA). The four nucleotides utilized in DNA are adenine (A), cytosine (C), thymine (T), and guanine (G). They are the fundamental building block molecules used in biological life. RNA uses uracil (U) rather than thymine (T). Segments of the DNA code for an organism are transcribed to RNA strands and transferred to building centers (ribosomes) to manufacture proteins. Nucleotides form triplets called codons, and specific codons correspond to amino acids as laid out in the standard codon table. Each of these biochemical layers is part of the physical layer that impacts the physical characteristics of the biological component. This process forms neuron componentry and other biological microsystems and systems. Neuron components are composed of specific proteins optimized for their neuron function.

Unfortunately, at the time of this paper's development, a complete protein characterization of any specific neuron type is incomplete. According to the human protein atlas, the following proteins are characterized parts of the human neuron, as listed below. It is a limited list, and the complete molecular biological layout of the human brain, or portions of the brain, is still being determined. However, there are genes from the various parts of the neuron taken from human and animal scans in representative brain areas (Sjöstedt 2020).

- Neuronal dendrite – CAMK2B, ARHGEF33
- Neuronal soma (cell body) – RBFOX3, ELAVL3
- Neuronal nucleus – ZNF3, CBFA2T2
- Neuronal axon – SLC6A4, SPTBN4
- Neuronal synapse – SYNJ2BP, SYP

Neuromorphic computing approaches have sought to mimic brain function at higher levels of abstraction.

Biological life has a great deal of interdependence between the layers of the biological system in an organism. The architectural framework section suggests that only parts of these interdependencies have been characterized.

5. How many types of neurons exist?

Research is still actively exploring this challenging question to quantify the result. Studies indicate there are many neuron classes, each optimized slightly differently for different purposes (Matani 2018; Yuste 2015). Within the brain, there could be thousands of neuron types. Exploring neuron categories is a logical next step to bound the number of neuron types that need to be explored and learn how to consider neuron function better. This paper generally characterizes neurons, and it shows how they feed into an interneuron network from a top-level perspective.

In the brain are sensory neurons, interneurons (processing neurons), interneurons interfacing with the central nervous system (connecting neurons with some processing capability), and motor neurons that control movement.

6. Methylation adaptation and signaling responses

DNA methylation is a form of adaption that also results in signaling response changes. Sensitivity or on-off switching of gene function is accomplished. Epigenetic memory keeps this setting until some other influence changes it. Methylation occurs by attaching a phosphate group between a cytosine and guanine pair, forming a CpG site. Demethylation occurs through the removal of the phosphate group from this site. Other types of methylation help cellular processes adapt to change. Research has shown that epigenetic modifications result in stable patterns in the brain that can be transcribed into new cells. Methylation can occur in specific brain parts in response to various environmental and other inputs (Rutishauser 2021).

Methylation modification is not the type of memory that makes sense to consider as part of a neural network Von Neumann computing architecture. Instead, methylation modifications would equate to a more global type of change rather than a frequently changing memory cell in a neuron. To give an analogy, methylation would be like updating a computer's Basic Input-Output System (BIOS) or reprogramming a more straightforward Internet of Things (IoT) device program by reimaging the Programmable Read-Only Memory (PROM) memory. Thus, methylation changes (like BIOS or PROM changes) will persist and impact the control logic of the biological system operations.

7. Neuron synapse signaling

Several steps occur when information is sent from one neuron to another. The axon prepares information for proper transmission to the synapses. Then the neurotransmitter takes this processed information and makes it ready to leave the synapse and transition the physical bond from the transmitting neuron to the receiving neuron. Next, the receiving neuron takes in the information, and the transmission is complete. Fig. 19 shows this neuron synapse signaling process.

Since sensory input is a comprehensive function done with a collection of neurons, it is important to characterize the relationships between components that are part of this activity. Fig. 20 shows this sensory neuron activity process flow.

8. At what levels can neuron hardware implementation be done?

Various abstraction levels can be utilized to create a biomimicry implementation of brain neural networks. Typically, these do not consider the physical layer since biological circuitry fundamentally differs from semiconductor hardware.

With chip electronic circuit size approaching the molecular level, this could be revisited. Molecular biology with its various signaling paths and paradigms should be considered for biomimicry inspiration.

A spiking neural network (SNN) is the biological neural network signaling approach. The network activates a subset of connected neurons, optimized to process a scenario based on previous learning when necessary to complete a computational task. Neurons are linked through learning mechanisms. Once learning activities are completed, the spiking neural network remembers the proper computational function and response, so it can recall it again when the same scenario occurs. Various learned connections in the brain's spiking neural network computing fabric can be recalled when needed.

9. Human brain neuron models

Research has been done to comprehend how the human brain operates. The brain contains nearly 100 billion neurons, each with the same flexible configuration. Not only is there a vast number of neurons, but there are 100 trillion synaptic interconnections. Neurons have input connections from sensors, a cell body that receives

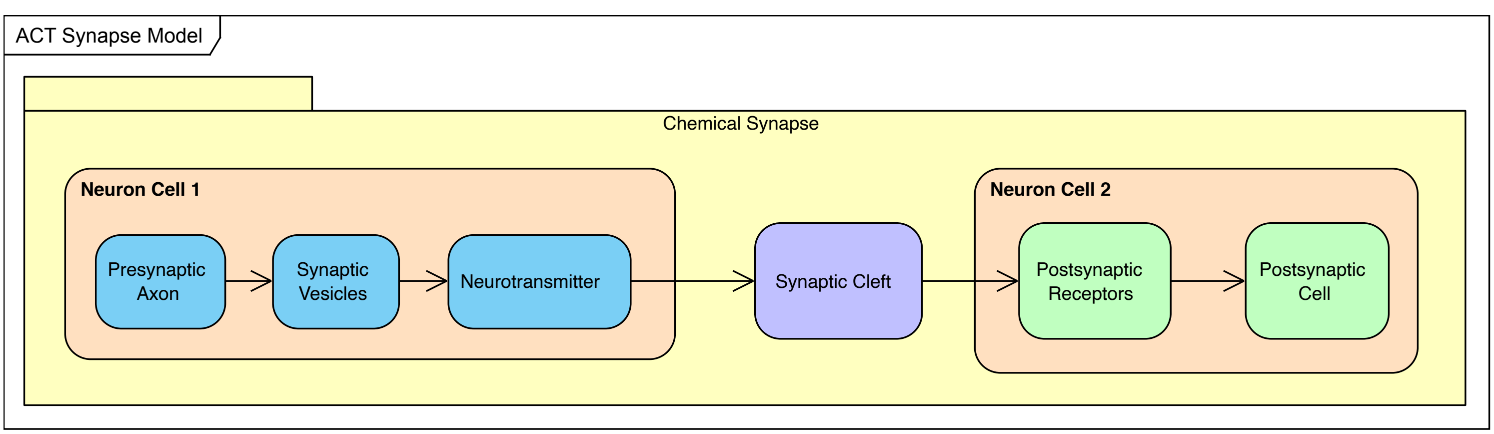

Figure 19. Synaptic communication activity model.

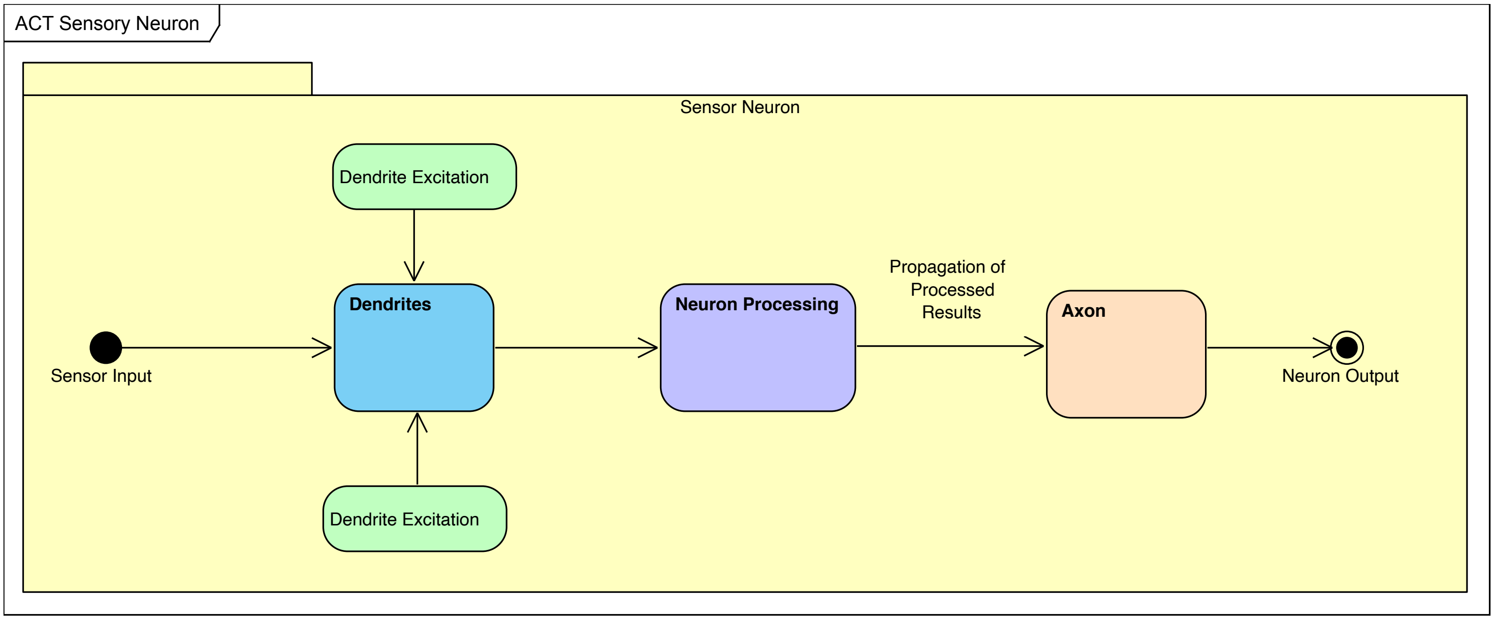

Figure 20. Sensory neuron activity model.

and processes those signals, and an output interconnection fabric that allows it to establish connections with other neurons. The input connections from sensors are called dendrites. The cell body is where these signals are brought together and processed. The axon is where the output is sent. Neurons connect so one neuron can pass on processed information to one or more other neurons. Through biomimicry, aspects of this architecture have been translated into neural networks. The most basic model is a perceptron, which combines multiple inputs and process results. Combining artificial neurons creates multilayer perceptions or an artificial neural network. A more accurate model of the human brain is to include the spiking signal nature of impulses that propagate through neural networks. Spike time-dependent plasticity is a key to understanding brain computation. As discussed in Section 5.11, many details are required to emulate the processing and advantages of human brain function. Framing it as in the Von Neumann architecture, to create neuromorphic computing capability, three elements must be present in each neuron: (1) a processing capability, (3) memory, and (3) an interconnection neuron fabric that includes inputs, interconnections, and outputs.

D. Biological neural circuits and artificial neural networks models

Capturing the architectural models of neuron circuits and neural networks creates the second of two parts that are necessary to capture brain function from a top-level point of view. A great deal of engineering forethought has gone into the ability of neurons to network together and share the computational load. This feature allows for learning. Mapping this information enables answering the second part of our third research question, what observations about human brain function can be made from the neuron and neural network architecture models?

This section will summarize and contrast characteristics and models for biological neural circuits (or biological neural networks) and artificial neural networks. It leverages the information from the architecture framework development, where biological and artificial implementations for each layer of the full compute stack model were discussed.

A biological neural circuit is a collection of neurons interconnected by synapses that carry out a function when activated. When these networks are elaborated, they form large-scale brain networks. The literature review looked at a variety of research result findings. Sensor nerves drive motor function (Kim 2018), brain circuits (Huang 2017), spinal circuits (Böhm 2016), neuron activity mapping (Wanner 2018), vision systems (Ryu 2018), neocortex neuron types (Matani 2018), memory neurons (Huckleberry 2018), and human neuron and memory (Faraut 2018). These are fascinating topics and have made noteworthy advances in neural circuit understanding. However, they still point out the difficulty characterizing these neural circuit systems in their operational state. Evasive tests often lead to animal or human mortality and do not allow for monitoring in a normal operating state. Pulling these factors together into an architectural model is difficult since the research topics are specific and limited by the creative ways researchers have figured out how to access the biological systems of certain organisms when the brain, central nervous system, senses, or motor subsystems can partially be observed. Some aspects of artificial neural network developments can provide some useful insight.

An artificial neural network is an approach to computation that seeks to embrace at least some of the features of its biological counterpart. Pavone and Plebe argue that it is unnecessary to stick with brain analogies to succeed in neuromorphic computing. As a result, many approaches are indeed possible, but they will not perform in the same manner as a brain (Pavone 2021). The more an artificial neural network diverges from its biological equivalent, the more engineering modification will result in different performance outcomes. This will impact how well artificial alternative designs will help clarify brain function.

There is a relationship between neural networks and neuromorphic computing. The term neuromorphic has developed over time. Initially, it dealt with emulating the biophysics of neurons and synapses. More recently, it has grown to include descriptions of spike-based processing systems and neural architectures that implement neuron and synapse circuits. Neuromorphic computing definitions vary from a high-fidelity mimicking of neuroscience principles to a higher-level, loosely brain-inspired set of design principles. There is also a fruitful interchange between the more accurate neuron model approach of SNNs and the lower fidelity of the replication approach of artificial neural networks (ANN) (Christensen 2022). This paper will not explore neuromorphic computing. A future article will discuss neuromorphic computing and consider how a brain computing architecture can help improve computational capability, but it is briefly commented on here. Although significant differences exist in neuromorphic computing systems' implementation, they all utilize a Von Neumann computing construct. Trying to quantize a fixed number of neurons into a chip is not how a biological brain operates. Brain interconnects take place in a three-dimensional space. Electronics cannot do this. Crossbar interconnects are inefficient and do match the dynamic, programmable, and low-power manner synapses connect. Neuron computational engines are embedded in a fundamentally different way as compared to electronics. Simple, streamlined, and optimized neuron computational engines are very different from the CPUs found in electronic computing platforms. (Shrestha 2022).

1. Neuron network models

Since most neurons are deep within the brain, it is tough to access and experimentally uncover the functions of neurons. Fig. 21 shows the two types of neural network models considered. An artificial neural network is much easier to implement. Depending on the model used, it can range from modest to average realization of what occurs in a spiking neural network.

Fig. 22 shows a high-level process flow of the Loihi neural network microarchitecture. This represents its level of adoption of biological neural network concepts. The Loihi and Loihi 2 chips have sought to implement a spiking neural network in chip electronics that can be used with conventional electronics. Biomimicry is done at a functional level because it is not conceived in biological materials (Davies 2018).

2. Artificial neural networks

Artificial neural networks aim to reflect the behavior of the human brain and provide a basis for creating brain-inspired computing models. A neural network structure aims to create computer architectures that recognize patterns and solve problems. If it is done well, the resulting capability should approach a focused cognitive function seen in the human brain. Thus, applied neuroscience can be viewed as intersecting with the overlapping fields of artificial intelligence, machine learning, and deep learning.

Schaeffer et al. argue that there is no free lunch for deep learning in neuroscience. Deep learning is part of the machine learning methods family that deals with representation learning. Researchers have been using neural networks to model and mimic the function of brain grid cells. Grid cells are a type of neuron that is crucial to the brain's navigation system. They help individuals know where they are in a 3-D position and move within the confines of that domain. Feeding training information into a deep learning neural network is not enough to produce the brain function that results in successful navigation with grid cells. Only when applying specific constraints that are not part of the neural network can successful navigation take place. As a result, it takes more than just neural network hardware to generate an operational neural network. The authors' main observation is that deep learning models cannot reproduce grid cells capability simply from task training (Schaeffer 2022).

When looking to design a system, how should a neural network be architected? A classical Von Neumann architecture must have a processing unit, memory, and input and output capabilities. A neural network is only composed of neurons, so each designed neuron must have processing, memory, and input and output functions. These are straightforward concepts, but at what biomimicry level should a de-

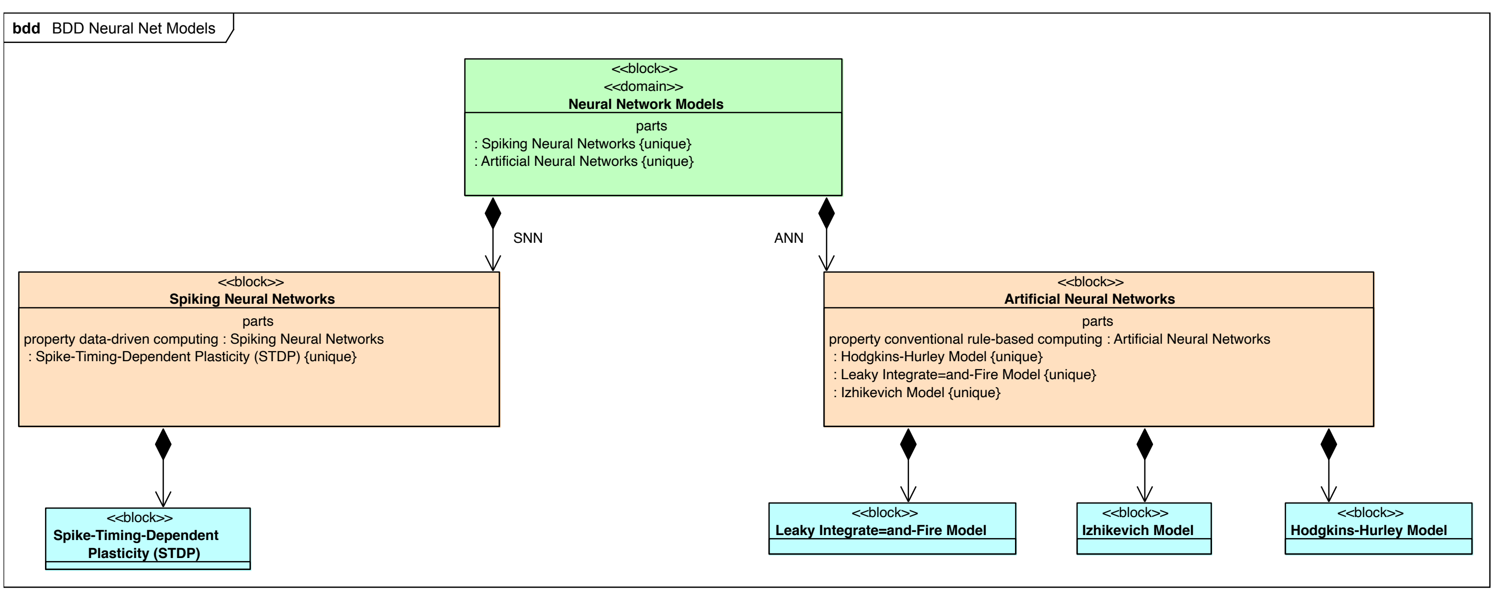

Figure 21. Neural network models.

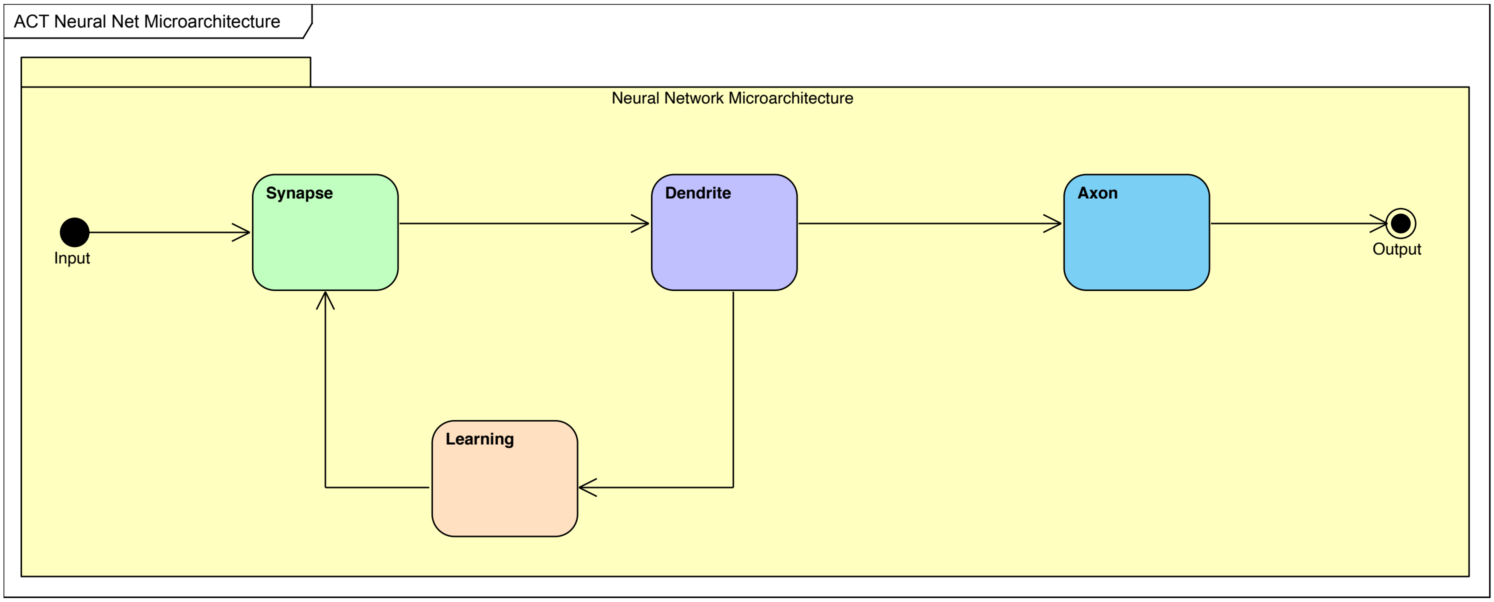

Figure 22. Neural network microarchitecture.

sign be implemented?

Electronics have specific functions, but technologically sophisticated device physics are harnessed. There is interdependence to a degree where external power, temperature control, and proper placement of parts within a larger design must be done.

3. Comparison between biological and artificial neural networks

Table 3 below highlights the differences between biological and artificial neural network systems. (1) Power for biological neural networks is only required when a computation activates a neuron. This results in significant power savings. Electronics in chips typically apply power constantly to electronic devices. Neuromorphic computing architectures are trying to move away from that paradigm. (2) Biological neural networks use chemical energy when computing is required. Electronics require electrical energy, which cannot easily be stored in an artificial neuron and activated when necessary. (3) Biological neural networks use a complete three-dimensional (3D) architecture such that neurons can connect with other neurons anywhere in a three-dimensional space. This eases access to a more significant number of neurons. Electronics in chips typically only can connect in a two-dimensional (2D) planar manner. With the stacking of chips within a part package, there is the possibility for 2.5 D stacking access. Still, this is limited in comparison to biological systems. (4) Input and output connections are grown in biological neurons, with the axons having synaptic connections reaching out as far as necessary to access more neurons. Artificial neurons use switching fabrics, like a 2D crossbar, that connect any input to any output in a matrix fashion. This gives lots of flexibility but requires lots of hardware. (5) Memory and computing (central processing unit or CPU) resources are embedded in the biological neurons. The number of resources per neuron is tailored for its operation being distributed across elements. To mimic this behavior, artificial neural networks must embed memory modules and microcontrollers in each neuron or neuron cluster. The device physics differs between biological and artificial neurons. (6) Biological neural networks utilize molecular signaling mechanisms, including phosphorylation. Artificial neural networks utilize semiconductor properties where control inputs can modify signals. (7) Regarding parts architectures, biological neural networks are primarily composed of neurons, with various classification types used. Artificial neural networks use a variety of integrated circuit parts that are aggregated together. (8) In terms of learning, biological neural networks recruit other neurons for groups that can be recalled for duty to accomplish a learned task across the distributed network. Artificial neural networks must allocate hardware and software resources to accomplish the desired function. (9) Connecting sensors to computational resources is done slightly differently. For biological neural networks, the whole architecture consists of neurons, starting with neurons adapted to connect to the sensors, connected to transport neurons in the central nervous system. These are then connected to computational neurons in a neural network generated to interpret sensor data. For artificial neural networks, read-out electronics take sensor data and route it via an interconnect matrix to a computational neural network preprogrammed to process the specific sensor data. (10) For biological neural networks, brain computational network actuator commands are relayed via central nervous system neurons to the actuator neurons connected to the muscle. Response data is sent back to the neural network forming a closed-loop system. For artificial neural networks, the neural network feeds interconnect resources that connect to actuators controlling motors. Sensors send feedback signals back to the neural network.

IV. DISCUSSION

A. Summary

This paper explored the human brain function and architecture. It introduced a way of comparing biological and artificial systems. This study examined the neuron and neural network architectures seeking to observe their construction, operation, optimization, and adaptability. Regarding methodology, the study sought to look at the neuron and neural network systems from an engineering perspective and leverage systems engineering tools as part of the assessment. From the literature review, it is clear extensive relevant work is being done in neuroscience, machine learning, and neuromorphic computing. Various publications describe how complex biological neurons and neural networks are and how challenging it is to emulate them fully.

Table 3. Biological vs. Artificial Neural Network Capability Comparison

CAPABILITY	BIOLOGICAL	ARTIFICIAL
Power	Power on Demand	Power Continuously
Energy	Chemical	Electrical
Architecture	3D in Brain	2D (or 2.5D Stacking) in Chips
Input & Output	Grow Axonal Connections	2D Crossbar Interconnection
Memory	Embedded in Neurons	Von Neumann Modules
CPU	Embedded in Neurons	Von Neumann Modules
Device Physics	Signaling, Phosphorylation	Semiconductor Properties
Part Arch.	Homogenous Neurons	Heterogeneous IC Parts
Learning	Recruit Neurons	Utilize More Modules
Sensing	Sensor to Sensor Neurons to Brain	Sensor to Circuits to Neural Net
Motor Control	Brain to Motor Neurons to Muscle	Neural Net to Circuits to Actuator

To give a context for how human brain function should be considered, a creation model is developed, showing the significant thrusts captured on each day and how everything fashioned by the hand of God led to His crowning creative work by forming man in the image of God.

The architecture framework section examined and contrasted biological and artificial neurons and neural networks using a seven-layer full compute stack model that can characterize computing systems. The neuron functional modeling section made observations about the nature of the neuron and how neuron functions can be characterized from various points of view. In terms of neuromorphic computing, artificial neural networks and neuromorphic computing systems are being organized and experimented with, with promising results in computing capability but challenging issues regarding the resources required to make them function as compared to their biological counterparts. Systems engineering evaluation of the neuron and neuromorphic computing are included. This paper focused on characterizing both and did not create a complete Systems Modeling Language (SysML) model. Instead, block definition diagrams, package diagrams, use case diagrams, and activity diagrams were utilized to help frame the systems engineering discussion.

As noted by Schaeffer, there is no free lunch when creating neural networks. Having a neural network configured does not equate to a functional computing capability. There are external resources required to make it work. When considering the status of humankind created in the image of God, this suggests evidence that humans require more than biological neural networks to think (Schaeffer 2022). Creating a human brain in silicon is not possible. (Plebe 2015). There are plans for further exploration of the topics in this area.

B. Answers to research questions

In this subsection, the various elements discussed in this paper are drawn together to answer the three research questions proposed in the introduction.

1. Creation model and human mission insights

How does a Creation Model provide additional insight and context for the implementation and mission of human beings?

Since God created the heavens and the Earth, God the engineer had a master plan for His implementation. With human beings being made last as the crowning part of creation, there are many ways and many levels in which they engage with these resources. The creation model translates the creation narrative into an engineering format that is much easier to use for design evaluation. With this model and what is developed by the full compute stack model discussed next, there can be a comparison of some aspects of human beings in terms of the environment in which they were created to prosper within. Human beings indeed engage with the physical and biological world like other animals. Still, the capabilities they possess go far beyond basic living functions. With the resources available, individuals can create, design, and engineer many things that can improve their ability to fulfill their *Imago Dei* charter. Human beings transcend beyond just existing. They can leverage the physical and biological order laid out in creation to think in some ways as God does. They can create from the resources God has provided.

2. Full compute stack model modifications for human brain function

What modifications to the full compute stack model are required to capture unique human brain function?

Without modifications, our *Imago Dei* faculties cannot be captured with a full compute stack model. Human brain function above all other shows a clear differentiation from animals with the human spirit and the manifold engagements that occur with the Holy Spirit. The full compute stack model targets general computational purposes and has been demonstrated to capture capability layers in neuromorphic computing. It does not allow for distinguishing the difference between an animal and human beings with the additional insight given in Scripture about human nature. It might be possible to pursue a generative artificial intelligence-inspired approach that assumes every part of human faculties can be mapped exclusively into a physicalist implementation understanding of functions. This contradicts the level of agencies that is captured in the *Imago Dei* charter humanity has been given. Thus, there must be modifications to the model to allow for higher-level faculty that includes abstract thinking and the human spirit that animates the human body.

3. Neuron and neural network architectural modeling

What observations about human brain function can be made from neuron and neural network architectural models?

Much work has been done in both neuroscience and neuromorphic computing. With so many basic features in neuroscience that still are unknown, capturing architecture models can provide a framework for how to view this complex information. Since the biological neuron implementation details are complex and not wholly characterized, architectural modeling offers a different approach to identifying design methods and interdependencies. Neurons are a fundamental building block in every part of human neural systems. In general, they accomplish the same function using a common basic architecture. There is specialized tuned functionality when moving towards more individualized neuron types as one compares capabilities like sensing, motor control, computing, and learning. Below are the insights that can be drawn from functional and structural classifications.

a. Functional classification

One way of showing functional neuron classifications is to bin neuron types into sensor, interneuron, and motor neurons. Interneurons have two sub-classifications, one in the central nervous system and the other in the brain. Even at this high-level view, there is a tree structure where all neurons have a variety of common characteristics. Still, then there are additional specialized features that are utilized for their specific mission. Sensor neurons cooperatively work with the sensors. Motor neurons are tailored to work with muscles and ensure proper control. Interneurons focus on relaying information and doing a portion of the computational load. The central nervous system is primarily a transport mechanism, while brain neurons take relayed information and perform computations and learning functions.

b. Structural classification

Structural neuron classifications focus on physical implementation differences and how they vary from one neuron class to another. Major structural differences group neurons into unipolar, bipolar, and multipolar. A unipolar neuron has a single dendrite. A bipolar neuron has one dendrite and one axon, which is useful for direct and indirect cell pathways like in the eyes. Multipolar neurons are typical in the nervous system and have long axons. This type of architectural classification approach groups neurons by their physiology.

c. Thoughts on the divergence of biological versus artificial neural system goals

Neurons are very resource efficient in accomplishing their purposes. Neuromorphic computing implementation of artificial neuron finds it very difficult to accomplish. Some features do not translate well when electronic neuron-like materials instead of biological neuron materials are used. In contrast to what Pavone and Plebe suggest by proposing that neuromorphic computing systems should minimize trying to achieve their goals by mimicking biological brain architectures (Pavone and Plebe 2019), it is impossible to separate the reason why God created the human brain from its implementation. Understanding its creation context makes a huge difference. As the Creation Model shows, all creation in its original context works together harmoniously with key performance goals in mind. God wanted to engage with humanity. God did not want a man to be alone (Gen 2:18). God wanted man to fulfill his *Imago Dei* calling (Gen 1:28). God did not intend as a central focus for man to become augmented with technology just to increase personal capability. Instead, it is all about relationships and drawing all aspects of creation back to greater intimacy with God.

4. Drawing the observations of the three research questions together

Human beings were designed with mental capabilities that exceeded all other animals. They were created to live in harmony within the creation fashioned for them on Earth. Utilizing the full compute stack model, the capabilities of humans go beyond what its layers can capture. With the focus on neurons and neural networks in this paper, it is possible to consider how the *Imago Dei* translates to this level with an architectural model. Much about neurons and neural networks still needs to be uncovered. Creating an architectural context along with what is already determined with neuroscience research and the challenges that have occurred with neuromorphic computing trying to implement comparable systems gives insight into how much capability is packed into the human brain. It is asserted that generative artificial intelligence will never match what humans can do. There are missing architectural layers that cannot be included in artificial systems. Human responses can be codified, and aspects of learning can be captured in machine learning approaches. Still, this does not mean that artificial intelligence systems will have the breath of life from God given to them (Gen 2:7).

V. CONCLUSIONS

Above all other parts of creation, the human brain alone can think and process abstract ideas. Humankind should be the last part of creation since there are interdependencies between man and every other aspect of God's handiwork. More importantly, humankind is called to rule and reign over creation and held accountable to be a good steward. Individuals report directly to God and carry the bidding of our sovereign God to the ends of the Earth.

Neurons are a fundamental building block for the various parts of computational tasks. Biological neurons are a complex and adaptable building block used in many human and animal physiology places. Several categories and types within each category exist. This is a very active area within neuroscience. Artificial neurons and neural networks are not able to meet the capability and the modest resources necessary that are found in their biological counterparts.

Neural networks are collections of neurons that form cooperative structures that allow them to operate together through learning and optimization from repetitive tasks. Exploring neural networks, and computation in general, in terms of full compute stack layers is a helpful way to capture the levels of functional capability that must cooperate to bring together a working computational capability. Specific engineering choices are seen in the implementations of these layers. Research continues to provide new insight into how these functions work.

Although this paper integrates various ideas for framing an understanding of neurons and neural networks, the work requires more development because there is a limited understanding of neuron and neural network biology, and artificial implementations are rapidly changing. Continuing to track the developments in neuroscience, machine learning, and neuromorphic computing will be required. Follow-up survey papers and focused research question-centered papers will continue to be developed.

From the biblical creation model, there is evident interdependence between each creation layer. As the temporal plan of creation unfolds, the later, more developed layers depend on the infrastructure from the earlier temporal steps. Once all creation is functional, each aspect has a tightly coupled and finely tuned partnership. Humankind is part of this system, but he also is unique in his ability to understand and explore its operational makeup. Similarly, the human brain is the most advanced brain that can be considered with the architectural model layers to see a similar interdependence among all the layers. This layered engineering design pattern with interdependence and fine-tuning is seen in many aspects of biological life. An additional layer is proposed to account for the human brain's unique characteristics adequately. From an architectural point of view, this accounts for human beings made in the image of God and the fact that man has a body and soul that intersect in the physical world but includes a transcendent element that extends beyond the realm of the spirit.

Using the Creation Model, the assessment of the full compute stack, and the architectural models of neurons and neural networks show a shortfall between human brain function and what artificial neuromorphic computing systems can achieve. Using the context seen with the Creation Model, the purposes of creation become clearer from an engineering sense. Creation is about relationships and drawing all aspects of creation into greater intimacy with God. This is far different from simply increasing neuromorphic computational capability.

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APPENDIX

This literature review appendix summarizes most of the wide array of peer-reviewed information covered in this article.

A. Neuron models, classifications, and architecture

1. Molecular biology of the neuron

Davies and Morris, in their textbook *Molecular Biology of the Neuron*, examine the molecular biology of the neuron. It is a collection of the findings of subject matter experts who are knowledgeable about different parts of the neuron. They correlate function with molecular biology by analyzing neurons in action. Neurons are arguably the most complex cell in the body. Therefore, exploring their molecular composition is also challenging (Davies 2006).

2. Models of neurons

Bielecki's textbook, *Models of Neurons and Perceptrons*, examines various models of neurons and the artificial replication of neurons, sometimes called perceptrons. The central focus of the textbook is exploring artificial neural networks and how to mimic the parts of a neuron in electronics (Bielecki 2019).

3. Mapping proteins to parts of the brain

Sjöstedt et al. published their highlights of the human protein atlas project in Sweden. Their goal is to map function to portions of the brain in ways that have not been utilized previously. They combine data from transcriptomics, single-cell genomics, in situ hybridization, and antibody-based protein profiling. As a result, they have generated detailed multilevel genome-wide views of protein-coding genes in the brains of mammals (Sjöstedt 2020).

4. Retinal neuron classification

Shekhar et al. published their findings that gene expression patterns could be used to characterize and classify neuronal types. The authors proposed a systematic methodology for achieving a comprehensive molecular classification of neurons. It can identify novel neuronal types and it uncovers transcriptional differences that distinguish types within a class. They proposed a taxonomy based on molecular features (Shekhar 2016).

5. Structural and functional units of the neuron

Yuste published his findings that show how the neuron is a structural and functional unit of the nervous system. Yuste traces over 100 years the historical development of the neuron doctrine and neural network models. Groups of neurons operate as functional units in neural circuits. Neural network models may reveal the nature of neuronal code and neuroscience, like the physiological basis of learning, perception, motor planning, ideation, and mental states (Yuste 2015).

6. Relationship between neuron models and brain neurons

Pavone and Plebe published their results showing the relationship between neuron models and actual brain neurons. There are weaknesses in the analogy between the brain and a computer. Performance metrics are not enough to characterize similarities or differences. There are differences between deep learning and the human brain. Deep learning networks have developed and demonstrated utility on their own. They argue that it is unnecessary to stick with brain analogies to succeed in neuromorphic computing. Many approaches are indeed possible, but they will not perform in the same manner as a brain. This is what they argue. "The weakening of the analogy between the brain and the computer, which could be considered a value in itself in the design of the algorithmic aspects of neural networks, changes things. With the abandonment of the analogy with the brain at all costs in the design of the algorithms underlying a cognitive architecture, we have returned to an opportunistic attitude, whereby the effectiveness of a cognitive model is measured again only based on its performance: if it fulfills the task for which it was designed, then it is a good application model, otherwise not." (Pavone 2012).

7. Neuron gene expression

Pfeffer and Beltramo published their results on neuron gene expression patterns that produce categorization schemes. Current neuron classification is based on anatomical, molecular, and functional properties. Anatomical and functional properties depend on the circuits in the nervous system they are part of (Pfeffer 2017).

8. Method for recording single neuron activity

Kodandaramaiah et al. published the details on their new method to record single neuron activity, offering the ability to track spiking activity. Experiments were done with live rats with probes attached to their brains via an innovative robotic connection technique. The successful demonstration of an automation method on mice may lead to approval to do similar tests on humans in the future (Kodandaramaiah 2018).

9. Visualization of neuronal structures from human brain testing

Boorboor et al. published a workflow method they developed that visualizes neuronal structure in wide-field microscopy images of brain samples. Individual neurons were seen in wide-field microscopy images. The authors created a process to extract features with their workflow process and then visualize the results with a Unity three-dimensional (3-D) data visualization. Three visualization modes are possible: (1) bounded (select in-focus features) from out of focus and background noise view, (2) structural view, and (3) classification view (Boorboor 2016).

10. Neuronal activity mapper

Kim, Perova, and Mirrione published an automated neuronal activity mapper they developed to help search for signatures of stress responses in the entire mouse brain. Their findings indicated distinct brain activity markings that correlate with adaptive and maladaptive behavioral responses to stress, providing a framework for further studies (Kim 2016).

11. Proposed architecture of human memory

Rutishauser et al. published their proposed architecture of human memory. They focused on the medial temporal lobe recordings, including the hippocampus, where it shows two classes of cells: (1) those encoding highly selective and invariant representations of abstract concepts, and (2) memory-selective cells whose activity is related to familiarity and episodic retrieval. Visually selective cells can remain persistently active for several seconds, which revealed a cellular substrate for analyzing human memory (Rutishauser 2021).

12. Methylation of neurons

Rizzardi et al. published several ways that neuron methylation takes place. Their findings showed how methylated epigenetic modifications correlate to specific expressions of heritable traits. They explored DNA methylation that results in stable transcriptional patterns in four brain regions, the anterior cingulate gyrus, the hippocampus, the prefrontal cortex, and the nucleus bens. (Rizzardi 2019).

13. Limitations of artificial neural networks

Schaeffer et al. argued that there is no free lunch for deep learning in neuroscience. Deep learning is part of the machine learning methods family that deals with representation learning. Researchers have been using neural networks to model and mimic the function of brain grid cells. Grid cells are a type of neuron that is a crucial component in the brain's navigation system. They help individuals know where they are in a three-dimensional position and move within the confines of that domain. Feeding training information into a deep learning neural network is not enough to produce the brain function that results in successful navigation with grid cells. Only when applying specific constraints not part of the neural network can successful navigation take place. As a result, it takes more than just neural network hardware to generate an operational neural network. The authors' main observation is that deep learning models cannot reproduce grid cells capability simply from task training (Schaeffer 2022).

B. Neural circuits and response experiments

1. Organic electronic sensor nerve driving a motor function

Kim et al. published their experimental results of creating flexible organic electronics to mimic the functions of a sensory nerve that drives a motor function. The nerve collects pressure information from clusters of pressure sensors, converts the information into action potentials, and integrates these inputs together. Actuation and pressure measurements were done with a cockroach leg. They utilized organic-inspired materials and circuits in their design (Kim 2018).

2. Brain circuit findings from testing drosophila flies

Huang, Niesman, and Arasu published their findings on brain circuits and how neural circuits interconnect. The authors developed a method that reveals synaptic connections of neurons of interest. The experiments were done with Drosophila flies. Experiments confirmed that by taking advantage of the molecular mechanism of a ligand (a molecular-level chemical bonding site of a cell), along with induced intramembrane proteolysis (a protein breakdown process), neuronal circuits could be traced (Huang 2017).

3. Experimental results of spinal cord circuit testing

Bohm, Prendergast, and Djenoune published their experimental results exploring spinal cord circuits, focusing on cerebrospinal fluid-containing neurons that modulate locomotion directly onto locomotor central pattern generators. The cerebrospinal fluid-containing neurons form a mechanosensory organ that operates during locomotion to modulate the central pattern generators. Zebrafish larvae were used for the experiments (Böhm 2016).

4. Neuron activity mapping from zebrafish experiments

Wanner and Vishwanathan published their results on neuronal activity mapping as neurons connect to synaptic connections. Their premise is that for a mechanistic understanding of brain neuronal circuits, a detailed description of information flow must be characterized. Neuron function must be linked to circuit structure. Since larval zebrafish are transparent, the necessary testing and experimentation could be done (Wanner 2018).

5. Vision system and simulation response comparison

Ryu and Fried published their findings that compare the signals of a functional vision system in a mouse to those that are generated from electrical stimulation of the retina. The experiments investigated how different stimulation sites, and different stimulation conditions in the retina, shape the response of the mouse visual cortical neurons (Ryu 2018).

6. Neuron types in the neocortex

Matani et al. published their results on the neuron subtypes in the neocortex, based on experimental research done with mice that had probes added to their brains to detect and process their responses. Their performance improved from conditioning tasks. Individual inhibitory neurons can be modulated in a subtype fashion, which highlights the versatility of neural circuits (Matani 2018).

7. Neuron memory experimental results

Huckleberry et al. published their findings on adult-born neurons in the dentate gyrus, which is part of the temporal lobe portion of the brain in the hippocampal formation; it continues to produce new neurons throughout adulthood. The researchers explored how they continue to contribute to memory context, and they saw a relationship between these neuron cells and fear conditioning. Neurons born in the adult dentate gyrus integrate into functional circuits and are believed to contribute to cognitive and emotional hippocampus functions (Huckleberry 2018).

8. Neuron activity and memory human trial results

Faraut, Carlson, and Sullivan published their experimental findings from a 1,576-neuron dataset that was used to assess 42 human patients. The dataset with the patient responses helped map and characterize neuron behavior during behavioral and memory activities. It gave new insights into memory tasks, including forming new memories, retrieving, and describing those memories (Faraut 2018).

C. Spiking neural networks

1. Visual system neuron spiking model

Masquelier published the results of his research and phenomenological spiking modeling of a cat's early visual system, composed of the retina, neurons (lateral geniculate nucleus), and primary visual cortex (V1), evaluating relative spike time coding and spiking timing-dependent plasticity (STDP) orientation factors. As a result of their experimental observations of the cat's response to visual stimuli, they created a computational model. They used a virtual retina simulator and developed lateral geniculate nucleus and V1 models in MATLAB and C code (Masqueler 2011).

2. Neuron sensor firing to the brain

Aljadeff et al. published their results on neuronal firing from the sensor to the brain, seeking to better understand the neural activity. With the experimental data from rat experiments, the authors tried to interpret spiking information by using four different models (spike-triggered average [STA], spike-triggered covariance [STC]+STA, maximum noise entropy [MNE], and generalized linear model [GLM]) (Aljadeff 2016).

3. Neuron algorithms and trades

Bouvier et al. published a survey and overview of the strategies utilized by algorithms in hardware, along with the advantages and challenges (Bouvier 2019).

4. Spiking neuron algorithms

Doboerjeh et al. published their findings on an algorithmic method to explore spiking neural networks for learning, classification, and comparative brain data analysis (Doberjeh 2016).

5. Brain neural networks

Wang and Sun published their results on an example of a brain recurrent neural network (RNN) that connects the neocortex and the somatic motor cortex. Work done on artificial recurrent neural networks is useful to help understand the results that are found. "Here, we show a long-range neuronal network, which can be described as an innate RNN. It is formed with a self-feedback connectivity in the medial prefrontal cortex (mPFC; the hidden unit), which integrates inputs from basal lateral amygdala (BLA) and insular cortex (IC) neurons (the input units) and further innervates the somatic motor cortex (sMO) infragranular-layer-projecting neurons (the output units) (Wang 2021)."

6. Phosphorylation signaling in proteins

Marks, in his textbook *Protein Phosphorylation,* explores the detail of how protein phosphorylation works. He also draws out the many ways phosphorylation and neural networks have similarities (Marks 1996).

7. Human learning

Benjamin et al., in their book *Human Learning: Biology, Brain, and Neuroscience*, explore a variety of topics in human learning and cognition. They discuss the advances in cognitive neuroscience, brain chemistry, and brain imaging. The book contains four sections: (1) human learning and cognition, (2) cognitive neuroscience, (3) human motor learning, and (4) animal model systems. First, the human learning section explores the varied approaches to human learning and memory. Second, the cognitive neuroscience section discusses how thought is implemented in the brain. Third, the human motor learning section explores learning skills and the identification of neural mechanisms for motor learning and control. Fourth, the animal model systems section discusses the animal model systems that have enabled significant progress in the understanding of the neural mechanisms of learning and memory (Benjamin 2008).

D. Neuromorphic computing

1. Energy-efficient neuromorphic computing

Zheng, in his textbook *Learning in Energy-Efficient Neuromorphic Computing*, explores approaches to energy-efficient neuromorphic computing. Starting with a history of neural networks, it discusses the similarities and differences between spiking neural networks used in the brain and artificial neural networks that mimic brain neural networks to a certain level of accuracy, aiming at implementable approaches with current microelectronic means. It then explores approaches in artificial neural networks that have been utilized in machine learning for decades, how artificial neural networks have been implemented in hardware, and efforts to move toward creating more realistic spiking neural networks (Zheng 2019).

2. Neuromorphic computing chip

Davies provides an in-depth explanation of Intel's Loihi neuromorphic processor, which represents a microelectronics package that contains a biomimicry realization of neurons in an artificial neural network and implements a spiking neural network with a leaky-integrate-and-fire variant model (Davies 2018).

Intel published this article as a technology brief describing their Loihi 2 neuromorphic computing systems chip, which continues to mature the capabilities it demonstrated with its earlier Loihi chip. Using the same architectural model, Intel has created a network on a chip that is closer in some regards to what is done in a biological neural network (Intel 2021).

3. Neuromorphic computing roadmap

Christensen led the team that published an in-depth article assessing the current capability of neuromorphic computing, along with projections for future capability. Subject matter experts from academic and research laboratories discuss their research in subarticles in this paper. The article highlights the types of research that are required to attain the future desired performance. It discusses (1) materials and devices, (2) neuromorphic circuits, (3) neuromorphic algorithms, (4) applications, and (5) ethics (Christensen 2022).

4. Neuromorphic computing algorithms and applications

Schuman et al. published a survey article summarizing their assessment of the research and accomplishments in neuromorphic computing algorithms and applications. It compares the Von Neumann architecture to the neuromorphic architecture at the operation, organization, programming, communication, and timing levels. The authors consider neuromorphic computing thoughts around the full compute stack levels of materials, devices, circuits, microarchitecture, system architecture, algorithms, and applications, and propose much tighter interdependence of these levels for future designs. The full compute stack (or design stack) levels in the article are a valuable way to organize neuromorphic computing layers and provide scaffolding to analyze the design and architectural concepts (Schuman 2022).

5. Human brain in silicon

Plebe and Grasso published their assessment of efforts to design a computer hardware-inspired brain or a brain in silicon. The authors are not convinced that computing based on these principles will replace conventional Von Neumann approaches. They mention efforts to reverse engineer the brain. In the conclusion section, they state, "Until a theoretical framework emerges to capture essential aspects of neural plasticity and an appropriate technology able to mimic it is devised, the quest for the 'brain in silicon' could be severely impaired." (Plebe 2015)

6. Big data applications of neuromorphic computing

Shrestha et al. published their findings on the increase in big data applications and how the capabilities of neuromorphic computing can help meet these needs. They explored neuromorphic computing models and provided an accessible summary of important approaches and comparative details about various developed systems. They compared the TrueNorth, SpiNNaker, Loihi, BrainScaleS, Braindrop, Dynap-SEL, and Tianjic large-scale neuromorphic implemented systems. The neuromorphic computing design choices they benchmarked among these systems were (1) neuron model (Classic leaky integrate-and-fire (LIF), CUBA LIF, Exponential integrate-and-fire (IF)), (2) synapse model (number of weights), (3) implementation choice (digital, analog and mixed-signal, and digital with multiprocessor system on a chip, SoC), (4) architecture (interconnect crossbar size, number of processor cores, memory), and (5) software supported (MATLAB, object-oriented code, Python, PyNN, etc.). Although large differences exist in the systems' implementation, they all utilize a Von Neumann computing construct. Trying to quantize a fixed number of neurons into a chip is not how a biological brain operates. Brain interconnects take place in a three-dimensional space. Electronics cannot do this. Crossbar interconnects are inefficient and do match the dynamic, programmable, and low-power manner synapses connect. Neuron computational engines are embedded in a fundamentally different as compared to electronics. Simple, streamlined, and optimized neuron computational engines are very different from the CPUs found in electronic computing platforms. (Shrestha 2022).

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