IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

NEUROMORPHIC COMPUTING

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Abstract : This study has been undertaken to investigate the determinants of stock returns in Karachi Stock Exchange (KSE) Compared to von Neumann's computer architecture, neuromorphic systems offer unique and novel solutions to artificial intelligence. Inspired by biology, this novel system has applied the modeling theory of the human brain by connecting neurons made with synapses to reveal new concepts of neuroscience. Many researchers have invested heavily in neuro-inspired models, algorithms, learning methods, neuromorphic system testing systems and using many compatible applications. Recently, some researchers demonstrated the power of Hopfield algorithms in some major hardware projects and saw significant progress. This paper introduces a comprehensive review and focuses on the Hopfield algorithm model and potential developments in new research programs. Finally, we conclude with a broad discussion and a working framework for the latest system prospects to make it easier for engineers to better understand the above-mentioned model in terms of building their performance-oriented projects.

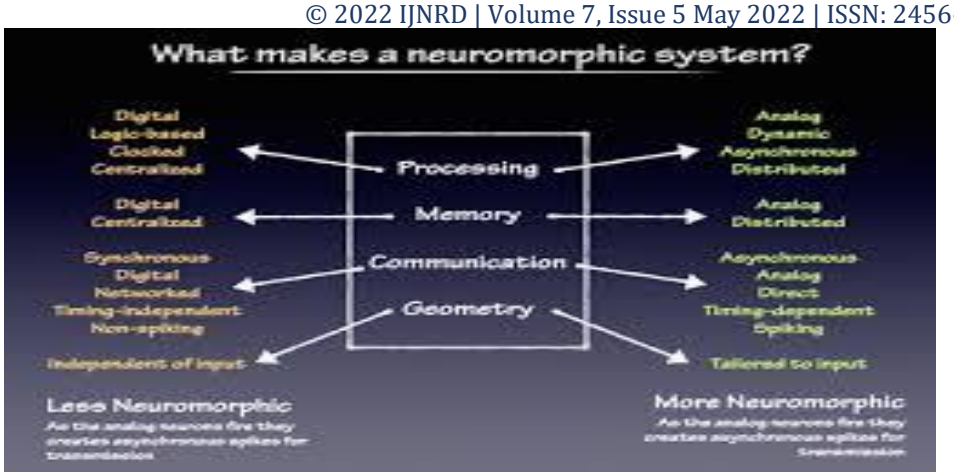
IndexTerms - : artificial intelligence, synapse, Artificial neural network. ,spiking neural network

I .INTRODUCTION

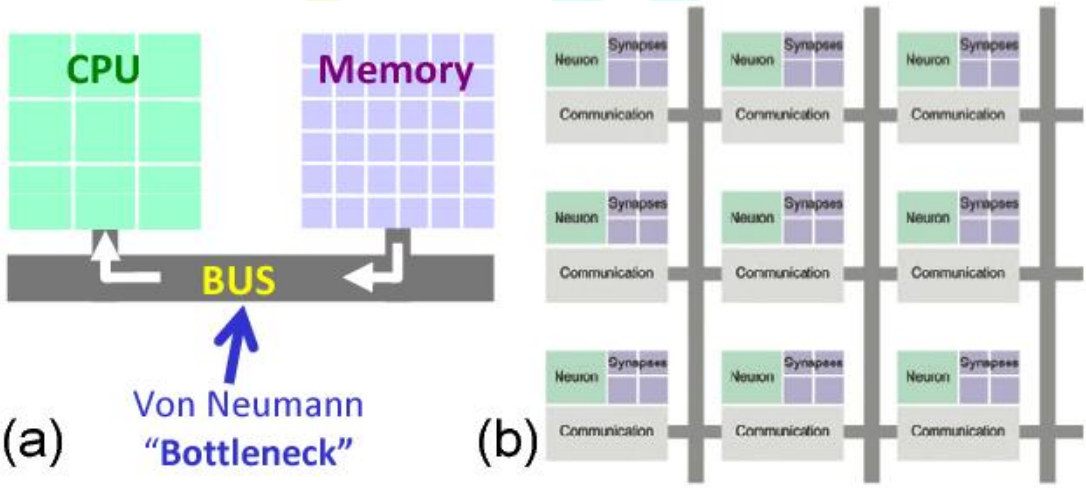
Neuromorphic engineering, also called Neuromorphic computing, is a type of neuromorphic engineering. It refers back to the development of computer-based computer programs found in the human mind and anxious gadget. The concept of Neuromorphic computing was developed using Caver Mead in the 1980s. It says about the use of big-scale-integration (VLSI) systems that include electrical anolog circuits to mimic the neurobiological structures present in a shocking machine. As the name suggests, neuromorphic computing uses a model that is stimulated by brain function. Neuromorphic computing can completely change everything about it. Neuromorphic computing technology will be important for the future of computing, but much of the work in neuromorphic computing is focused on hardware development. Here, we review the latest results on computer computer neuromorphic algorithms and applications. We highlight the features of computer neuromorphic technology that make them attractive for the future of computing and discuss the potential for future development of algorithms and applications in these systems.

II.VON NEUMANN ARCHITECTURE .

Historically there were 2 types of computer systems
• Fixed program computer
• Computer software stored
System computers are very accurate and cannot be configured. Eg: counters
Stored application computers are able to perform unusual tasks as most packages are stored on them.
Modern computer programs are based on the concept of a stored system. submitted by John von Neumann. here programs and records are stored in a separate archive called reminiscences. It is in this way that a computer made of this technology is much easier to redesign.
Also known as IAS PC and has 3 simple units:
1. The main processing unit
2. the main memory unit
3. Input / output tool

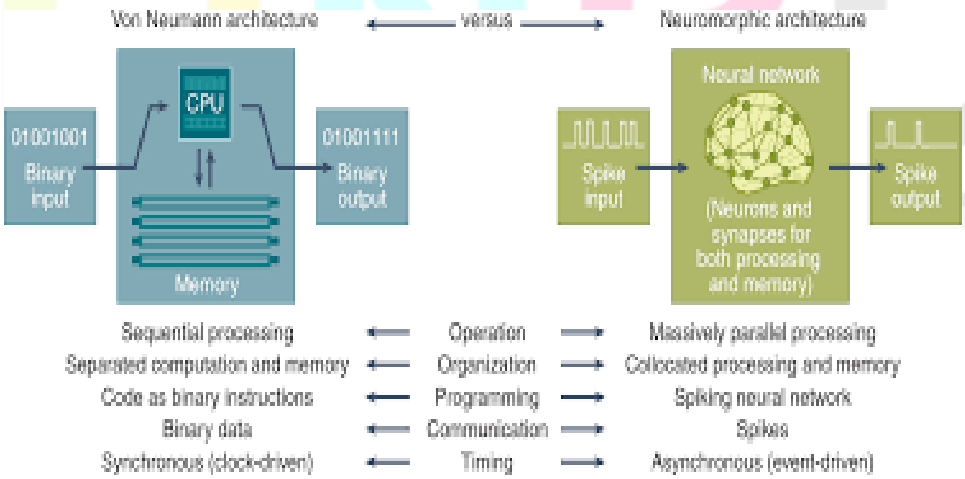


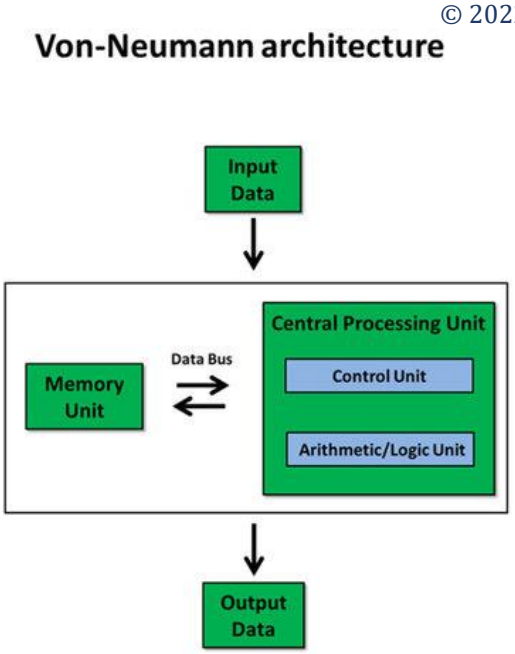
III.VON NEUMANN BOTTLE NECK

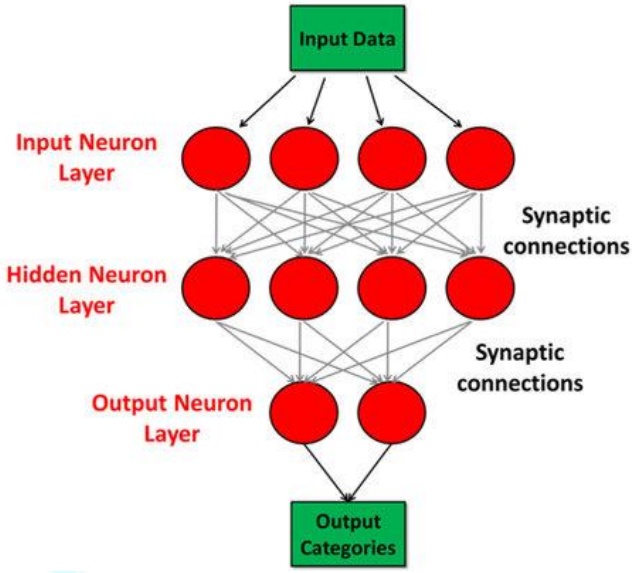


Something we are doing to improve performance, we cannot break free from the fact that instructions can be better done sequentially and can be used one at a time and can be improved sequentially. Both of those features keep the CPU capacity low. this is often referred to as the 'Von Neumann bottleneck'.

To overcome this they need a better idea. Later neuromorphic computer interactions occurred.





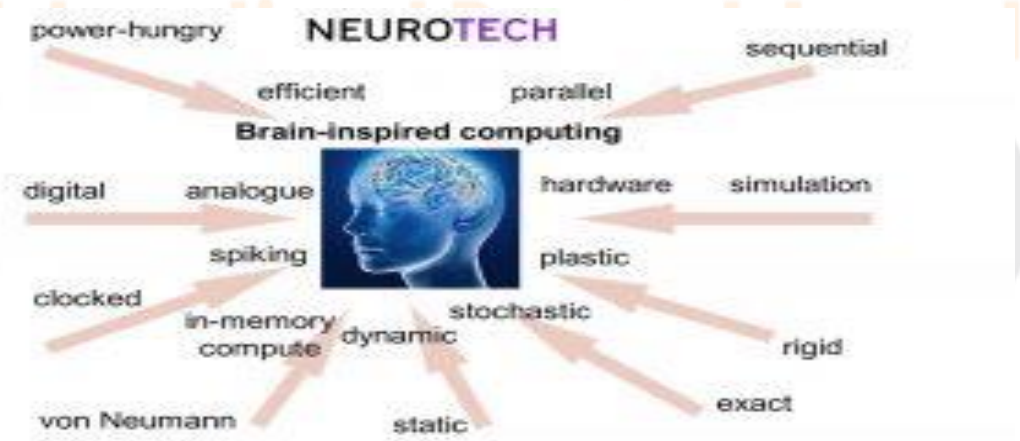


IV.WHAT IS NEUROMORPHIC COMPUTING

Neuromorphic computing is a method of computer engineering in which computer components are modeled according to systems in the human brain and nervous system. The term refers to the design of both hardware and software computing elements.

Neuromorphic engineers are taking a number of fields of study - including computer science, biology, mathematics, electronics, and physics - to build sensory systems that are being developed by biological structures.

There are two main purposes of computer neuromorphic (sometimes called neuromorphic engineering). The first is to make a machine that can read, store information and hold real money the way the human brain can do - a machine of understanding. The second goal is to discover new information - and perhaps prove the most accurate theory - about how the human brain works.



V.EFFICIENCY COMPARED TO HUNGER FOR ENERGY

Training neural networking networks to learn how to perform pattern recognition tasks in Graphics Processing Units often requires hundreds of Watts. Copying even the smallest parts of an animal's brain into a larger computer requires tens of Mega Watts. In comparison, the human brain uses only 20 watts to perform complex cognitive and cognitive tasks. Neuromorphic technology seeks to mimic the neural processing circuits that close this huge energy consumption gap.

5.1 Similarity vs sequence

Although each neuron tends to spin a few times per second in biological neural processing systems, the high similarity of neurons and their many synapses allows them to perform more sophisticated tasks per second than those of sensory network mimicking computers. Approaching high levels of compliance (thousands of systems and more) in integrated and efficient hardware platforms will require major changes in the design of computers and electronics.

5.2 In-memory computing vs. von Neumann architecture

In typical computer systems, much of the power consumption and delay is due to the transfer of information between different physical memory and computer components. For neural network algorithms, this problem ('von Neumann bottleneck') is important because large numbers of parameters need to be maintained and dealt with regularly. Neuromorphic technology aims to bring memory and computer together, as in the brain where the computer (neurons) and memory (synapses and network topology) are fully connected.

5.3 Plastic vs. Strong

Learning, both in the brain and in neural networks algorithms, is accompanied by repeated synapses to a set of connections that allow the network to perform tasks accurately. For normal computers, this is done by a clear modification of the memory storage banks. Neuromorphic technology aims to create systems where weights change on their own with local laws and synaptic plastic machines, as is done in the brain.

5.4 Analogue vs Digital

Ordinary computers rely on digital writing (zero and one). In the brain, electrical energy in the lining of neurons can absorb continuous amounts, as well as synaptic weights. Reproducing such behavior with digital encoding takes major circuits. Switching them off using analogue components - either CMOS transistors or emerging nanodevices - that directly mimic neural behavior can improve efficiency. However, a greater fulfillment is yet to come.

5.5 Dynamic vs. Static

Ordinary computers use the stability of their circuits to compile information. In contrast, indirect oscillator neurons emit voltage. They are individually integrated and able to behave collaboratively such as synchronization, temporary power and the edge of chaos. Neuromorphic technology aims to mimic such a complex dynamic system to transcend the possibilities of static emotional networks, especially in relation to learning.

5.6 Spiking vs. Clock

Ordinary computers are powered by a clock that sets the speed of all circuits. There is no such clock in the brain. In a sensory computer, for example, the brain accomplishes a large part of its function by performing an event-based process, where signals are taken as a sample only and transmitted when new information arrives or is counted. Neuromorphic computing aims to design spiking structures that support the system.

5.7 Stochastic vs. Directly

Ordinary computers aim to have the highest accuracy, in contrast to the brain, neurons and synapses showing variability and stochasticity. Such indirect resistance seems to be a key asset of neural networks. Releasing obstacles to the accuracy of computer components and steps to reduce power consumption while maintaining accurate results is the goal of neuromorphic technology.

Each of these guides represents the success of the current computer paradigm. Thus, neuromorphic computing represents a qualitative effort that involves multiple disciplines. Each router will require significant improvements in computer theory, architecture, and device physics.

VI.HISTORY OF NEUROMORPHIC COMPUTING

The forerunner of synthetic neurons used in sensory networks today can be traced back to 1958 with the introduction of perceptron. The perceptron was a rare attempt to mimic the elements of an organic sensory network using limited knowledge of the internal brain activity that was available at the time. The perceptron was intended to be a custom-made hardware used for image recognition tasks by the U.S. Navy. Technology has achieved a great deal before it becomes clear that technology cannot accomplish the required task.

Neuromorphic computing was first proposed by Caltech professor Carver Mead in the 1980's. Mead described the first analog silicon retina, representing a new type of physical calculation developed by the neural paradigm.

Mead was also quoted in a book on neural computation in analog VLSI as saying he believes there is nothing a human nervous system can do with computers if there is a complete understanding of how the nervous system works.

However, the recent investment and hype surrounding neuromorphic research may be partially attributed to the widespread and increasing use of AI, machine learning and neural networks in consumer and business technologies. Much can also be said about considering the end of Moore's law among many IT professionals. Moore's law states that the number of microelements that can be added to a chip will double twice a year, the cost remains the same.

Because neuromorphic computing promises to avoid traditional structures and achieve amazing new levels of efficiency, it has received a lot of attention from major chip manufacturers such as IBM and Intel - Intel launched Loihi in 2017 - as a Law of Moore.

Mead who broke Gordon Moore's knowledge and did More's Law was also quoted in 2013 as saying, "Going to multicore chips helped, but now we have reached eight cores and it doesn't look like we can keep going. hit the wall before they pay attention. . "This theory confirms the fact that the popular talk and hype surrounding AI is passing.

VII.ARTIFICIAL NEURAL NETWORK

The Artificial Neural Network (ANN) is a compilation and collection of nodes promoted by the human biological brain. ANN aims to perform psychological tasks such as problem solving and machine learning. The ANN mathematical models were introduced in the 1940s however, they were silent for a long time . These days, ANNs are best known for the success of ImageNet2 in 2009. The reason for this is the development of ANN models and hardware programs that can manage and use these models.

ANNs can be divided into three generations based on their computational and performance units (Figure 1).

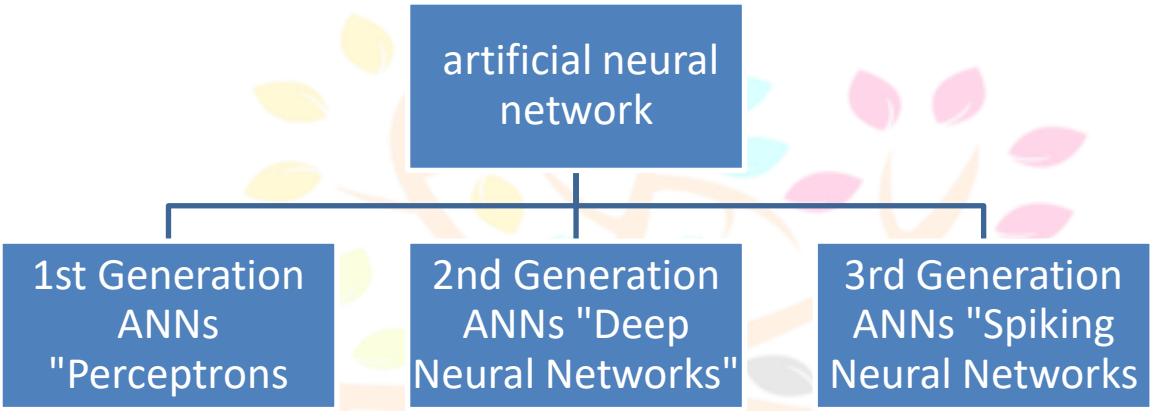


Figure 1- Generations of Artificial Neural Networks

The first generation of the ANNs began in 1943 with the work of Mc-Culloch and Pitts . Their work was based on a mathematical model of neural networks in which each neuron is called a "perceptron". Their model was later developed with additional hidden layers (Multi-Layer Perceptron) for better accuracy - called MADALINE - by Widrow and his students in the 1960s . However, first-generation ANNs were far from biological models and provided digital results. Basically, they were conditional-pruning trees if and in other conditions.

The Second Generation ANNs have donated to the previous generation by using activities in the first generation model decision trees. The functions work between the visible and hidden layers of the perceptron and create a structure called "deep neural networks". Therefore, second-generation models are closer to biology.

The activities of second-generation models are still an active area of research and existing models are in high demand in the market and science. Most of the current developments regarding artificial intelligence (AI) are based on these second-generation models and have proven its accuracy in cognitive processes.

The Third Generation of ANNs are called Spiking Neural Networks (SNNs). They are biologically inspired structures in which information is represented as binary events (spikes). Their learning style is different from previous generations and is influenced by the principles of the brain . The SNNs are independent of the fire cycle-based mechanism. They provide an outlet (spike) when neurons collect enough data beyond the internal limit. In addition, neuron structures may function similarly . In theory, because of these two traits SNNs consume less energy and work faster than second-generation ANNs

The advantages of SNNs over ANNs are:

- Effective modeling of temporary data - spatio temporal or spectro temporal.
- Effective modeling of processes involving different time scales.
- Combining high quality work with "low" genetics.
- Integration of processes, such as sound and vision, into a single system
- Predictable modeling and event prediction
- Fast and highly relevant information processing

• Combined information processing
• Expandable structures
• Low power consumption, when used on neuromorphic bases
• In-depth learning and representation of in-depth knowledge in the brain-inspired (BI) SNN
• Enable BI-AI enhancement when using brain-inspired SNN

Although there appear to be many advantages for SNNs compared to ANNs , advances in related microchips are a stepping-stone, which allows a scientist to gradually create these complex structures and discover new learning algorithms (Lee, et al., 2016) , most recent (after 2010). The technology of Spiking Neural Networks, which has only been implemented in the area for ten years, is relatively small, therefore, compared to the second generation. Therefore, it must be constantly researched and applied in depth in order to use its benefits effectively and efficiently.

Large-scale SNNs can be used in both brain simulation software such as "NEST" with a highly efficient computer or with Neuromorphic chips developed by SNNs (Knight & Nowotny, 2018). The SNN simulations used in Medium Processing Units (CPUs) or Graphics Units (GPUs) are not suitable to express the efficiency and power of spike connections. (Knight & Nowotny, 2018) SNNs can fully demonstrate their competitive advantages of low power consumption and high efficiency when used in Neuromorphic chips. Today, the Neuromorphic chip industry is of great interest worldwide (Figure 23) (Figure 28) and chips are gradually being developed for scientific and industrial use. In line with the discovery of chips, AI scientists are also developing and discovering new and more effective SNN learning methods.

VIII.NEUROMORPHIC COMPUTING AND TRUE TECHNOLOGY

Artificial Intelligence technology aims to transfer human skills to computers to enable them to function as human beings. On the other hand, neuromorphic computing attempts to make computers work like the human brain. Combining millions of artificial neurons that transmit electrical signals to each other, neuromorphic computing has become a method.

There are real-world examples of neuromorphic systems that exist today, albeit primarily for research purposes. These include:

• **Tianjic chip**.

It is used to power a self-driving bike that can track a person, navigate obstacles, and respond to voice commands. It had 40,000 neurons, 10 million synapses and performed 160 times better and 120,000 times more efficient than a comparable GPU.

• **Intel's Loihi chips**.

Have 130 million synapses and 131,000 neurons per chip. Optimized for neural spiking networks.

• **Computers at Intel's Pohoiki Beach**.

It consists of 8.3 million neurons. It delivers 1,000 times better performance and 10,000 times better performance than comparable GPUs.

- **Intel loihi**

Intel released its neuromorphic chip “Loihi” in 2018 (Davies, et al., 2018). The chip is digital and the on-chip is configurable. This provides chip flexibility so that researchers can work on a variety of learning methods, from DNN to SNN conversion, native SNN, etc. At present, Loihi is a highly efficient and energy-efficient chip (among neuromorphic chips).

Like IBM, Intel also invests in the trading of neuromorphic chips and learning methods. Mike Davies ’Lab is collaborating with universities and research institutes to increase the visibility of Loihi.

Intel does not have the primary goal of researching brain neurons, but they are very interested in brain function. They expect to have a deadly app to solve real-world problems. They also believe that such an application should be related to the field of robots, which is where neuromorphic chips can significantly express their competitive advantages, namely "real-time definition with low power consumption".

According to Mike Davies in his presentation at NICE 2019, one of Intel's priorities is to grow the neuromorphic research community by sponsoring various workshops. The group has its own special event called "Telluride Workshop" to promote their great desire to have

• **TrueNorth IBM chip**.

It has more than 1 million neurons and more than 268 million synapses. It operates 10,000 times more energy efficient than conventional microprocessors and uses energy only when needed.IBM in partnership with the DARPA SYNAPSE6 program has developed a chip "TrueNorth". TrueNorth is a digital chip produced to speed up research on SNNs and to trade with it (Merolla, et al., 2014). It is not a flexible on-chip so it can be used for speculation. (Liu, et al., 2019). This is detrimental to on-chip training research and at the same time limits the use of the chip in critical programs (such as self-driving driving that requires continuous training) Effective training - as mentioned earlier - is unfortunate for neuromorphic hardware. does not happen in TrueNorth.

One goal of IBM'S is to use the chip in perceptual applications such as robots, partitions, action partitions, audio processing, stereo view, etc. The chip actually proven to be useful in terms of low power consumption compared to GPUs (DeBole, et al.., 2019). However, TrueNorth has not yet been sold to end users, it is only possible to request it for research reasons.

• A highly compact, compact computer designed at the University of Manchester. Currently used for the Human Brain Project.

• BrainScaleS of Heidelberg University. It uses neuromorphic hybrid systems that combine biological testing and integrated analysis to study brain information processing.

Examples from IBM and Intel are closer to neuromorphic computing from a computational point of view, focusing on improved performance and processing. University models take a neuroscience-first approach, using neuromorphic computers as a way to study the human brain. Both methods are important in the field of neuromorphic computing, as both types of information are needed to develop AI.

IX.NEUROMORPHIC COMPUTING AND ARTIFICIAL GENERAL INTELLIGENCE (AGI)

The term Artificial General Intelligence (AGI) means AI that reflects the same intelligence as human beings. One could say that the holy grail of all AI. Machines have not yet arrived and may not have reached that level of intelligence. However, neuromorphic computing offers new ways to improve on it.

For example, the Human Brain Project - which includes the neuromorphic supercomputer SpiNNaker - aims to produce effective mimicry of the human brain and is one of many active research projects that are interested in AGI.

The criteria for determining whether a machine has achieved AGI are controversial, but a few that are often included in the discussion are:

• The machine can consult and make decisions under uncertainty.
• The machine can edit.
• The machine can read.
• The machine can communicate using natural language.
• The machine can represent information, including general information.
• The machine can combine these skills in pursuit of the same goal.

Sometimes the power of thought, experience of self and self-awareness is included. Other proposed ways to validate the popular AGI Turing Test, as well as the Robot College Student Test, where the machine enrolls in classes and earns human-like qualifications.

Once the machine has reached the brink of human ingenuity, there are also debates on how it should be handled morally and legally. Some argue that it should be considered a non-human animal. These conflicts have occurred in part for decades because consciousness is often not fully understood.

X.NEUROMORPHIC COMPUTING: THE PROMISES AND CHALLENGES

Neuromorphic computing is defined as the next generation of AI that combines the production and use of neural networks as analogue or digital copies in electronic circuits. Represents a new non-Turing calculation method that aims to reproduce the features of continuous flexibility and computer functionality found in the biological brain. The concept, invented by American Scientist Carver Mead in the late 1980s, usually refers to a variety of computer-inspired computers, devices, and models.

It is not surprising that future computer programs will apply more insight into the human brain through the use of neuromorphic structures and calculation principles. Neuromorphic computing promises to provide a neuroscience tool to understand the dynamic processes of learning and development in the brain and mean brain stimulation to a normal understanding computer. Unlike conventional skills, this biologically inspired approach saves energy, efficiency, resilience against environmental failure and learning ability**.**

Since AI has a large number of translations, small sets, and a theory that defines its capabilities, the main goal of this technology is to replicate human performance. Both AI and neuromorphic computing in many ways seek to mimic even beyond human intelligence. However, both technologies are limited by the power of the hardware in which these systems operate.

Neuromorphic computers are able to perform complex calculations faster, more power-efficient, and in a much smaller way than the traditional von Neumann architecture. These features present strong reasons for developing hardware that uses neuromorphic architectures. Interest in the neuromorphic computer is also driven by the power of machine learning. This teaching approach demonstrates promise in improving the overall learning functionality of specific tasks. This shift from hardware benefits to understanding the potential software benefits of a computer neuromorphic, developing real-time learning algorithms such as brain biology. Neuromorphic structures appear to be the most suitable platform for extracting machine learning algorithms in the future.

Many neuromorphic systems develop AER (event representation), which includes France's Prophesee and the Swiss company aiCTX (AI cortex) focusing on sensory processing. AER is a communication protocol for transferring spikes between bio-inspired chips. That method is equally efficient and effective, bringing the benefits of strong cable connections between neurons without all cables. This means that the information from the incoming signal can simply flow to the processor in real time, while discarding non-essential information and the rest will be processed in the sensory pipe.

CONCLUSION

In our emerging AI-based society, research and development in AI focuses on the development and implementation of deep neural networks and AI accelerators. However, there are limitations to the construction of von Neumann traditional systems, and a significant increase in data size and processing requires new and powerful solutions. Spiking Neural Networks and Neuromorphic computing, which are well-developed and well-known areas among neuroscientist and neuro-computing researchers, are part of the latest technology and novelty that is already contributing to the exploration and imitation of human learning frameworks. the brain. The report described emerging neuronal networks, the emergence of SNNs and their impact on the detection of neuromorphic chips. The limitations of traditional chips have been discussed and the final impact of neuromorphic chips in the search for AI applications. Major players have been identified locally, and have been linked to current and future applications. The study also explained the market benefits of neuromorphic chips compared to other AI semiconductors. Neuromorphic chips are associated with event-based sensory applications and emerging technologies such as photonic, graphene or fixed memory. They have great potential for AI development and could become an outstanding technology in the next decade. Hopefully, this report has worked to give a brief overview of the complexity of this challenging computer environment. While we remain committed to our goal of providing a realistic understanding of the latest developments, we have also tried to educate enough to increase the interest and visibility of the topic to a specific audience. For some students this study may represent a promising and challenging step towards a deeper understanding of the area that may eventually support road map construction, testing new industrial applications, or analyzing interactions between these novel chips and other emerging related trends. .

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