Muskaan Shahzad

ITAI 4374 - Neuroscience as Model for AI

Professor Patricia McManus

Spring 2025

**Lab 03 - Exploring Neural Information Processing**

Information processing in biological and artificial neurons differs significantly in structure and function. Biological neurons are highly complex, consisting of dendrites that receive signals, a cell body that processes them, and an axon that transmits outputs. These neurons communicate through electrochemical signals, adapting dynamically through synaptic plasticity. This enables learning and memory formation in an organic manner. Artificial neurons, on the other hand, are mathematical models that process inputs as weighted sums, apply an activation function, and produce an output. They are simplified approximations that lack the intricate biochemical processes of biological neurons. Despite their limitations, artificial neurons are scalable and can process vast amounts of data efficiently, making them useful for machine learning applications.

Biological principles have inspired the development of more advanced AI systems. One key concept is synaptic plasticity, which influences how biological neurons strengthen or weaken connections over time, based on experience. Implementing similar mechanisms in artificial neural networks, such as dynamic weight adjustments or neuromorphic computing, could improve learning efficiency and adaptability. Additionally, energy efficiency in biological brains is significantly higher than in traditional AI hardware. Mimicking this efficiency through spiking neural networks or specialized hardware like neuromorphic chips may enhance AI performance while reducing energy consumption. Moreover, hierarchical and modular structures seen in the brain could lead to more structured and interpretable AI models, improving their ability to generalize knowledge across different domains. Another aspect of biological intelligence is its ability to function under uncertain and noisy conditions. The human brain can make decisions with incomplete or ambiguous data, whereas artificial models often struggle with robustness. Developing AI that can better handle uncertainty, possibly by incorporating probabilistic reasoning and reinforcement learning, could make these systems more reliable in real-world applications.

Despite their success, artificial neuron models face several limitations. One major drawback is their reliance on large amounts of labeled data for training, whereas biological neurons learn from fewer examples through experience and context. This gap suggests that AI systems need more efficient learning mechanisms. Another limitation is the lack of explainability in deep learning models; biological brains can justify decisions, whereas artificial neural networks often act as black boxes. Efforts to improve transparency, such as attention mechanisms and interpretable AI techniques, are crucial. Additionally, artificial neurons process information in discrete steps and rely on predefined architectures, whereas biological systems operate continuously and flexibly adapt their connections. Future advancements may include more biologically plausible architecture, such as spiking neural networks or self-organizing models, that better capture the dynamic nature of biological cognition. Furthermore, artificial models still struggle with creativity, emotional intelligence, and common-sense reasoning; abilities that biological intelligence demonstrates naturally. Addressing these gaps may require integrating symbolic reasoning with neural networks or developing hybrid AI systems that combine various approaches for better adaptability.

In conclusion, while artificial neurons have achieved remarkable progress, they remain simplified versions of their biological counterparts. Integrating biological principles into AI development can lead to more efficient, adaptive, and interpretable systems. Addressing current limitations, such as data efficiency, explainability, and energy consumption, will be key to advancing the next generation of AI technologies. Additionally, as AI continues to evolve, interdisciplinary research between neuroscience, cognitive science, and computer science will play a crucial role in developing more intelligent and human-like systems. By further understanding how the human brain functions and incorporating its mechanisms into AI, researchers can build more robust, efficient, and generalized models that push the boundaries of artificial intelligence.

From my findings in the implementation, I observed that biological and artificial neurons process information in fundamentally different ways. In my simulations, the biological neuron model demonstrated how membrane potential changes dynamically in response to input currents, highlighting key features such as threshold activation and action potential generation. This behavior reflects the complex, adaptive nature of biological neurons, which respond to stimuli in a nonlinear and energy-efficient manner. In contrast, the artificial neuron model functioned based on weighted sums and activation functions, producing structured and predictable outputs. While this approach is computationally efficient, it lacks the adaptability and self-organizing nature of biological neurons.

Additionally, my findings reinforced the idea that artificial neurons, while powerful, have significant limitations compared to their biological counterparts. The artificial model required precise tuning of weights and thresholds, whereas biological neurons naturally adjust their connections over time through learning and experience. This suggests that incorporating features such as synaptic plasticity, spiking behavior, and self-adaptive learning could improve artificial neural networks' efficiency and flexibility. These insights highlight the importance of developing AI systems that more closely mirror the functioning of the human brain to achieve greater intelligence, efficiency, and interpretability.