Bridging the Gap Between Biological and Artificial Intelligence: A Review

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Abstract.

The combination of biotechnology and computer science gives a unique chance to develop the concept of intelligence and improve algorithms. This review aims to present the attempts made in this objective in an interdisciplinary manner, based on assembling concepts from these domains, including neural mechanisms, spiking neural networks, and brain-inspired architectures. Examining previous works, the paper presents findings that include, but are not limited to, improved neural emulation, predictive modeling, and efficient AI architectures. Comparing the methodologies and results, patterns and issues such as ability to scale, ethics, and energy consumption are identified. Furthermore, the review provides an outlook on open research questions, focusing on the possibility of enhancing an even greater fusion of biology and electronics by using neuromorphic chips or brain-computer interfaces. On that basis, this systematic review organizes the data and delivers specific findings and suggestions for enhancing innovation in both disciplines. In the end, its goal is to call for combined action and to advance people's awareness towards intelligent consensus to blend the biological and artificial worlds.

Keywords: Biological, Artificial Intelligence, Machine Learning, Disease, Performance.

1 Introduction

The synthesis of biology and artificial intelligence (AI) is one of the most engaging topics in the current world's research. In essence, this interdisciplinary course aims to understand the forgotten factors in biological intelligence in artificial systems [1]. It aims to produce machines with a capacity for cognition, judgment, and learning as what, through the exploration of the fundamental principles of life, can be produced. The call to close the gap between biology and AI is not only a task of research and discovery; it is a goal and a vision that can reimagine science and technology, cure diseases, and even define intelligence—the language of neurons and how to mimic the wonders of the human brain in software. Long before the creation of contemporary AI, the imagination of imitating human intelligence emerged [2]. Reasoning was defined by philosophers such as Aristotle to give birth to the concept of formal thinking in human society. But in the middle of the twentieth century, the relationship between biological processes and artificial systems came out [3]. The concept of machine intelligence was looked at by such scientists as Alan Turing and such scientists as Walter Pitts and Warren McCulloch, and they compared artificial networks and neurons [4]. Stupendous

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phases in this journey were the initial formation of neural networks during the 1950s and then the advancement into twenty-first-century deep learning. These kinds of developments arose from a fundamental need to mimic the way the human brain attains knowledge, evolves, and processes data [5].

The integration of AI into biological sciences has brought a revolutionary change in many disciplines. In the present world, machine learning algorithms are essential tools for interpreting complex biological information, such as protein conformations, cell imaging, and gene mapping [6]. Neuroscience applies AI to study brain connections, mimic brain behavior, and even convert thoughts into voice. Just as so, AI has dramatically enhanced medical diagnosis, treatment, treatment individualization, and prediction of patient outcomes. AI is also greatly advancing in recording animal activity, learning about the web of life, and solving the mysteries of evolution, including human anatomy. The true strength of this combination is the ability of AI to manage and analyze biological data far beyond the capabilities of traditional solutions in terms of both scope and speed. With its help, researchers can find things that were impossible to find otherwise [7].

It is for such reasons as the comprehension of biological intelligence holding the solution to some of the most stringent issues of artificial intelligence that this inquiry has been undertaken. Self-organization, organizational responsiveness, and productivity in biological systems, although continually advancing, are still higher than even the current AI systems. AI systems themselves can be improved, and more can be understood about what makes a human mind function in the ways that it does, by studying and mimicking the designs found in biology [8]. I should also note that this is a truly interdisciplinary work that can help resolve crucial social questions, for instance, accelerate the development of new drugs, design smarter prosthetics, and possibly even understand consciousness. The motive is obvious: we stand an even better chance to construct wiser robots and free the opportunity latent within man by closing the gap between biological and artificial systems.

2 Literature Review

The following Table 1 summarizes the existing work done related to the present topic.

Table 1. Existing work done

Citation	Technology Used	Characteristics	Limitations	Outcomes	Future Scope

[9]	Spiking Neural Networks (SNN)	Biological interpretability, focusing on spiking neurons, theoretical basis for neural circuits.	Limited generalization to broader artificial intelligence applications.	Attracts researchers, advances brain intelligence and artificial intelligence.	Development of general artificial intelligence, interdisciplinary collaborations.
[10]	Digital Twin Brain (DTB)	Bridges biological and artificial intelligence, and uses brain atlases for structure and function emulation.	Open questions in interdisciplinary collaboration and integration challenges.	Advances in understanding of intelligence and neurological disorders, facilitates precision mental healthcare.	Improved integration of biological and artificial intelligence; expanded applications in precision healthcare.
[11]	Large Language Models (LLMs) and Biological Design Tools (BDTs)	Dual-use potential for biosecurity, creation of pandemic pathogens, and autonomous lab assistants.	Risk of misuse, biosecurity concerns, and potential harm from biological agents.	Raises awareness of biosecurity risks and highlights need for pre-release evaluations and safeguards.	Development of safeguards, ethical AI frameworks, enhanced biosecurity measures.
[12]	AI-Guided Bioinformatics	Integration of genomics, AI, planetary health; manages genomic/multiomics big data effectively.	Sociotechnical and ethical challenges, critical policy barriers.	Transforms genomics, agriculture, and planetary health; advances precision medicine.	Transnational collaborations, interdisciplinary innovation, and improved data sharing.
[13]	Artificial Intelligence and Space Biology	Automated, intelligent experiments; deepens understanding of spaceflight effects on organisms.	Reliance on automated and reproducible experiments; resource-intensive setup.	Supports deep space exploration with AI-driven biological monitoring and habitat stabilization.	AI-driven bioengineering of spacecraft and habitats for multi-planetary life.

[14]	Deep Learning-Based ECG Analysis	Estimates biological heart age and predicts mortality and cardiovascular outcomes.	Accuracy dependent on data quality; potential misestimation of heart age.	Facilitates primary prevention and improves cardiovascular health outcomes.	Further validation of AI models, integration into routine cardiovascular care.
[15]	AI in Pharmaceutical Technology	Identifies disease targets, predicts drug interactions, optimizes drug development processes.	Dependence on data quality and potential errors in pharmacokinetics predictions.	Enhances drug discovery, reduces development costs, enables personalized medicine.	Expansion of AI applications in drug development and optimization of personalized treatments.

3 Methodology

Figure 1. Proposed Methodology

This methodology offers a theoretical concept about how to understand gap between the biological and artificial intelligence using the different studies that have been done in the field as shown in Figure 1.

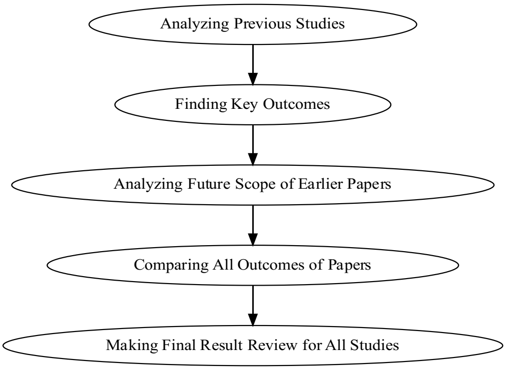

Figure 1 Proposed Methodology

3.1 Analyzing previous studies

We conducted an analysis of prior works to establish a strong foundation for this review. This process involved the purposeful collection of research articles, case studies, and review studies from diverse fields involving neuroscience, cognitive sciences, and artificial intelligence, among others. We focused on the methodologies, techniques, and technologies used in these works. The articles addressing spiking neural networks, brain-computer interfacing, and neuromorphic computing received significant attention. Also, the discussion included works on the structural and functional connectivity of the human brain, the topography of the tracts, and their computational models. We established regularities by sorting the study findings based on their aim and observed results. Limitations and gaps in previous literature also formed part of this analysis. The goal was not only learning the linear evolution process but also identifying lessons a priori to show how the integration of biology and artificial intelligence happened. This step provided a basis for further analysis and comparison in response to subsequent questions put to our models.

3.1.1 **Finding Key Outcomes**

Subsequently, the authors characterized the studies and summarized their main findings about outcomes. The process involved reviewing the results from each study, focusing on the roles of biological and artificial intelligence. We illustrated these beneficial outcomes in terms of progression in neural emulation, spiking neural networks, and the probability of new brain-like architectures. Researchers placed significant emphasis on identifying technologies that can replicate biological processes, such as neural plasticity and connectivity. We grouped them into three categories: technology development outcomes, theory-based outcomes, and real-life application outcomes. These categorizations helped to determine how various studies fit into the overall goal of integration. Furthermore, the results analyzed focused on frequent issues, like scalability, energy efficiency, and ethics. Thus, compiling these outcomes has allowed for reviewing and evaluating the state of the research in the field, as well as for defining further directions of research and possible gaps.

3.1.2 **Analyzing the Future Scope of Earlier Papers**

The next approach was to establish and, therefore, compile an outline of the identified results of the reviewed works. In this process, it was necessary to reconsider the outcomes proposed in the described studies about the discussed approaches to overcoming the gap between biology and AI. The main results were the progress in neural emulation, in other words, the creation of spiking neural networks, and in brain-inspired architectures. The selection of technologies that mimic the plasticity and connectivity of biological systems was a major focus. To assess development, we classified the results into three categories: technology, theory, and application. This categorization helped me gain a better perspective on how specific research has made some input to the overall goal of integration. Furthermore, the issues raised in this paper included scalability, energy maintainability, and ethical issues as some of the emerging and reoccurring problems. Aggregating these outcomes of the studied papers, this step offered an evaluation of the present state of the field that is essential for future research direction and gap identification.

3.1.3 **Comparing All Outcomes of Papers Review for All Studies**

As part of this step, pairwise comparisons of all the outcomes reported in the examined studies were made to offer a holistic picture of the results. The authors compared the methodologies, findings, and implications drawn from the two studies to make a comparison. The authors also adopted measures such as accuracy, scalability, and applicability of the various approaches. We emphasized works that focused on quantitative outcomes, as they provide a more focused and less subjective comparison. It also investigated how those studies managed issues like computational complexity, data availability, and issues to do with ethics. Specifically, this approach enabled highlighting of the patterns, shortages, and commonalities in the field, as well as revealing the compared outcomes. This provided a way to compare current approaches to identify their advantages and disadvantages. Additionally, it served to integrate the results and draw conclusions about the ongoing advancement of merging biological and artificial intelligence.

3.1.4 **Making the Final Results**

The last step before writing the conclusions was combining all presented results coming from previous steps to create a coherent review of the studies. The goal of this synthesis was to provide a comprehensive overview of the current state of biological and artificial intelligence convergence. The final list synthesized earlier key outcomes and trends, prioritizing the most valuable additions to the field. The review also brought attention to the existing limitations and unresolved issues, suggesting future research directions. The integration of these domains was also pursued responsibly, and ethical considerations and societal implications were stressed for these purposes. We summarized the findings descriptively in the final section, enhancing their readability with tables and figures. This review not only imposed organization on the existing knowledge base but also highlighted practical implications and future research implications. To this end, this review sought to bring together researchers from the fields of biology and artificial intelligence to build a bridge and meet in the middle so that advancements could happen within both areas.

4 Results

4.1 Key Challenges in Bridging Biological and Artificial Intelligence

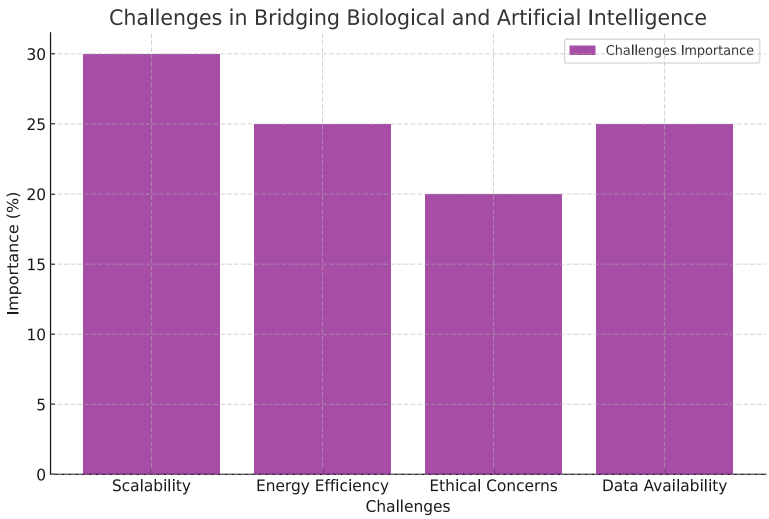

Figure 2. Challenges between Biological and Artificial Intelligence

Figure 2 shows the challenges to facilitate the integration of biological and artificial intelligence. We should undertake these challenges to facilitate the integration of biological and artificial intelligence. Scalability reveals itself as a dominant conception, pointing to the problem of how to create models and systems, which would be able to mimic the structure of the brain, being substantially more extensive. Energy efficiency is another essential issue because the emulation of the biological processes usually presupposes the use of power-consuming computing facilities, which do not meet real-world requirements. Safety issues, including privacy concerns, the dangers of using technologies for both civilian and military use, and human enhancement speak of the need to adopt and implement the right research on technologies. The development of functional artificial intelligence systems necessitates long and accurate datasets, which poses a challenge to data accessibility. All these challenges combine to affirm the fact that this is a multidisciplinary area of study. To address these issues, sustained cooperation between neuroscience, computer science, and policy-making fields is needed along with substantial research funding and the development of infrastructures that will ensure that the resultant solutions will be effective, economic, and, most importantly, moral.

4.2 Comparison of Neural Network Architectures

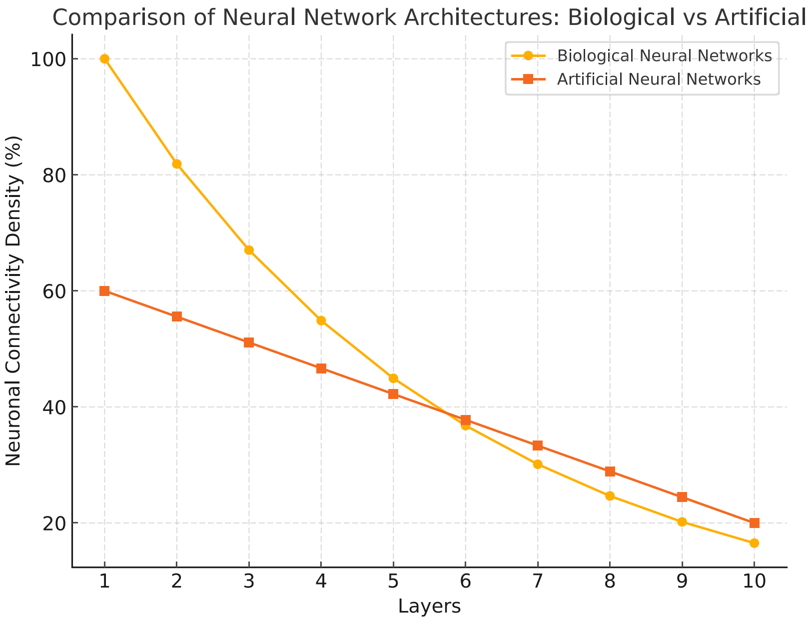

Figure 3. Neural Network Architectures: Biological Vs AI

Figure 3 shows the analysis of connectivity density in biological neural networks and artificial networks at multiple layers. Connectivity density is presented on the Y-axis as a percentage, whilst the number of layers is shown on the X-axis. Biological networks, indicated by the blue line, demonstrate that connectivity decreases exponentially as layers increase. This shows that in biological systems, there is high connectivity in layers during processing and adaptability and low density in the deeper layers for energy considerations. However, artificial networks indicated by the red line linearly decrease their connectivity. Although they are more standardized and lighter for both computation and memory across layers, they cannot readily handle a variety of situations as well as model patterns. It exposes Stamford and Boltzmann's architecture differences and how goal-oriented learning insights from biological neural networks should inform the creation of new and superior artificial counterparts.

5 Conclusion and Future Scope

However, bringing bio-inspired and artificial intelligence closer is still a work in progress but still closer to reality. AI is a more flexible, context-aware, and decision-making system based on nerve-complex design and refined through evolution. On the other hand, there is artificial intelligence, which is computationally superior in terms of speed and accuracy in solving certain problems and outperforms biological systems in certain tasks but still possesses a kind of flexibility and heuristic ability. Realizing the fundamentals of the functioning of bio-neural networks can guide intelligent engineers and scientists to design new and efficient artificial specifications for the system to develop more competent, optimistically intelligent, proficient, and efficient AI models. Moreover, matters of ethics and interdisciplinary cooperation will appear crucial to preserving responsibility when developing these technologies. Closing this knowledge gap has the prospect of recreating AI first and then using it to improve healthcare, robotics, and other fields..

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