Proceedings of CONF-CIAP 2026 Symposium: International Conference on Atomic Magnetometer and Applications
DOI: 10.54254/2753-8818/2026.HZ27831

The Application of Complex-Valued Neural Networks in Neuroscience

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Abstract. This study investigates the application of complex-valued neural networks (CVNNs) in cognitive modeling, examining their potential benefits and critically analyzing the associated challenges. The study first shows the theoretical foundation of CVNNs and their relevance to modeling biological cognitive processes. Through detailed analysis of medical imaging case studies, the paper illustrates CVNNs' superior capability in processing complex neural signals compared to traditional real-valued networks. However, this research also identifies major barriers, including theoretical interpretability issues, computational complexity, training instability, and an absence of a uniform evaluation standard. To address these challenges, the study proposes massive solutions that include interdisciplinary collaboration, specialized algorithm development, standardized benchmarking, and industrial application promotion. Overall, these recommendations form a strategic guide for translating CVNNs from theoretical constructs into practical, deployable technologies. The opinions derived from this work are particularly valuable for researchers and practitioners aiming to develop more biologically plausible and computationally efficient artificial intelligence systems.

Keywords: Complex-valued Neural Networks, Cognitive Modeling, Artificial Intelligence, Computational Neuroscience, Model Interpretability

1. Introduction

1.1. Research background

Studying how the brain thinks is a meaningful task. It can promote further understanding of the world's truth and deeply influence the public's lives. Traditional cognition models largely depend on linear algebra and real-valued computations within artificial neural networks. The models have already achieved striking success in many aspects, such as image recognition, natural language processing, and game competition. These new developments have largely made life more convenient for many people. However, the traditional cognition model still has some disadvantages as it cannot capture the fundamental oscillatory and dynamic characteristics of neural processes. They represent information as static magnitudes and overlook the rich temporal and phase information in brain signals. This discrepancy has become a bottleneck in developing a truly cognitive model. To

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DOI: 10.54254/2753-8818/2026.HZ27831

overcome these limitations, a mathematical structure that captures dynamic and phase-based information is needed. Complex-valued neural networks (CVNNs) present a helpful solution.

Closing this gap is crucial not only for academic research but also for practical applications. For example, in clinical neurology, building accurate models of brain disorders needs tools that can interpret brain activity; in artificial intelligence, as systems turn into more general context-aware systems, there is an increasing need to handle complicated relationships between concepts. However, it is difficult for traditional models to achieve this. CVNNs offer a more natural way to work with this kind of information. When compared to real-valued networks, complex-valued networks have several clear advantages: they naturally work with complex data, like sound waves or electromagnetic signals; they can often perform as well or better with smaller networks, because complex weights can represent more information efficiently; they handle uneven data better by using rotations to make it more symmetric; and they keep and use phase information, which is usually hard for real-valued models to process [1].

1.2. Literature review

A growing body of research is concentrating on complex-valued neural networks. Akira Hirose proposed the importance of complex-valued neural networks and illustrated the algorithm and use of complex-valued neural networks. Specifically, he mentioned that CVNNs have wonderful generalization ability in the learning of two-dimensional rotation and scaling, respectively. Its origin is the sparsity in themselves as complex numbers. The ability is useful in particular in adaptive processing of waves consisting of complex amplitude (amplitude and phase) and/or polarization. One can consider an example in communications where one deals with channel prediction to discuss the superiority of CVNNs and their basics [2]. Andrei Caragea proposed that, though having vectors of real numbers as inputs and outputs has achieved overwhelming success, recent applied works have shown that in some concrete instances (for example, magnetic resonance imaging) where the problem to be modeled is natively expressed with complex numbers, it is beneficial to use complex-valued neural networks [3]. Shao-Qun Zhang, Wei Gao, and Zhi-Hua Zhou found that the research progress of complex-valued neural networks shows that they have significant advantages in terms of approximation complexity, optimization dynamics, and representation ability [4].

Most scholars and articles mainly focus on applying complex-valued neural networks to specific, low-level signal processing tasks, such as radar and telecommunications. Many research studies are driven by the improvement of engineering performance instead of the goal of developing proper biologically cognitive models. By contrast, very few scholars systematically studied the deep meaning of complex-valued calculation in advanced cognitive modeling. There is a significant gap in exploring how the inherent characteristics of a complex domain can be used to model the core cognitive functions. Therefore, the potential of complex-valued neural networks remains largely undeveloped. Specifically, there is a lack of research exploring CVNNs for high-level cognitive functions, such as reasoning, context understanding, and concept integration, which move beyond low-level signal processing.

1.3. Research framework

To bridge this gap, this paper will first give a description of the basic circumstances and current development status of complex-valued neural networks, including the current situation of the application of complex-valued neural networks in certain occupations, to show the practical advantages. Second, the paper will illustrate and analyze the current problems with the application

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of complex-valued neural networks. Third, it will provide the future research structure and solution toward the unsolved challenges to eventually achieve the goal of bridging the gap between artificial neural networks and biological cognition.

2. Case description

The application of complex-valued neural networks (CVNNs) in medical imaging provides a compelling case study for their potential in cognitive modeling. This is because modalities like fMRI directly measure neural activity, and processing this data effectively is a prerequisite for building accurate cognitive models.

The medical imaging industry is facing a shift driven by advanced AI. This shift mainly focuses on using the inherent complex-valued nature of imaging data. Magnetic Resonance Imaging and functional Magnetic Resonance Imaging cannot provide clear pictures in medical reports. Instead, their raw data is acquired in a complex frequency domain where each data point is a complex number with both magnitude and phase components. Historically, to make calculations easy and quick, the standard reconstruction procedure discarded the phase information, using only the magnitude to determine diagnostic images. This process intentionally ignores the most captured information because phase data contains key details about tissue properties, magnetic field inhomogeneities, and subtle physiological processes. Current development in many industries largely depends on complex-valued neural networks. Industry leaders, such as Siemens Healthineers, GE Healthcare, and artificial intelligence startups like Subtle Medical, are in the research and productization phase of exploring this field. The use of complex-valued neural networks is mainly reflected in two aspects: ultra-high-speed and high-quality image reconstruction. For example, complex-valued neural networks can predict complete datasets, which helps reconstruct medical images with reduced noise and fewer artifacts. This improves the clinical experience. Second is exploring the diagnostic potential of phase information. More and more researchers focus on uncovering the biomarkers that are hidden in the same phase information. Phase data is extremely sensitive to small changes in the magnetic field. It can show tissue metabolic activity, blood flow changes, and neural activation. These are all important parts of the active interactions behind cognitive processes. Complex-valued neural networks can show the nonlinear relationships between magnitude and phase, and are also expected to quantify these previously invisible characteristics by routine scanning, finding new approaches to accurate diagnosis in fields such as Alzheimer's disease and oncology [5,6].

In summary, complex-valued neural networks hold crucial value for the medical imaging field. They not only improve how images are processed but also play an essential role in moving toward quantitative and personalized medical imaging. By extracting meaningful biomarkers from complex biological signals, CVNNs help bridge the gap between simple pattern recognition and a deeper understanding of cognitive processes.

3. Analysis of the problem

Admittedly, the complex-valued neural networks have massive advantages. They still face some challenges.

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3.1. Positive influence identified

3.1.1. Providing a more essential mathematical representation of biological neural signals

Brain neural signals have obvious oscillations and phase properties. By using complex domain calculation, complex-valued neural networks can give a more biologically plausible mathematical representation. The representation of complex numbers through magnitude and phase aligns naturally with the intensity and timing patterns of neural oscillations. Because of this correspondence, complex-valued neural networks can capture the spatiotemporal dynamics of neural signals more effectively than real-valued neural networks [7]. For instance, studies show that complex number representations help simulate the behavior of simple cells in the visual cortex's V1 area. These cells express response properties similar to Gabor-like profiles, a finding well-supported by experimental results in neuroscience [8]. This advantage in mathematical representation is the foundation for constructing more plausible biologically computational models.

3.1.2. Demonstrating performance advantages in signal processing tasks

Complex-valued neural networks have obvious advantages in many industries. For example, they are good at processing medical imaging data and audio signals. In this processing, complex-valued neural networks improve reconstruction quality and acceleration, which significantly reduce scan times. In audio signal processing, complex convolutional neural networks reduce error rates compared to real-valued networks in tasks such as music signal classification and speech enhancement [9]. This improvement in performance is mainly caused by the fact that complex-valued neural networks can maintain signal consistency perfectly. Therefore, it is possible to avoid the phase distortion problems.

3.1.3. Providing a new theoretical framework for interdisciplinary research

Complex-valued neural networks provide a new theoretical structure for deep integration between neuroscience and computational science [10]. Unlike complex-valued neural networks, which can naturally integrate mathematical tools such as harmonic analysis and complex function theory, traditional neural networks mainly build on the foundation of statistical learning. This difference in mathematical foundation allows complex-valued neural networks to describe wave phenomena and interference effects in neural information processing. For example, using complex numbers can naturally describe synchronous activity between different brain regions, providing a new perspective for studying large-scale functional integration in the brain. Meanwhile, the similarities between complex-valued neural networks and quantum calculation offer a potential path for studying quantum cognitive models.

3.2. Problem identified analysis

Despite the promising advantages outlined above, the path towards integrating CVNNs into cognitive modeling is fraught with significant challenges. The following sections detail the key obstacles that currently hinder the realization of their full potential.

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3.2.1. Dual dilemma of theoretical interpretability and neural mechanism mapping

One of the most serious challenges for complex-valued neural networks is the lack of a theoretical explanation. Although complex-valued neural networks (CVNNs) are closer to the characteristics of neural signals, the mapping relationship between their internal representations and specific neural mechanisms remains unclear. What neurobiological entities do the real and imaginary parts of complex weights correspond to? What role does phase information play in cognitive processes? These questions lack clear answers. Moreover, there is a lack of analysis tools specifically designed for CVNNs, making traditional feature visualization methods based on real-valued networks difficult to apply directly in the complex domain. This interpretability dilemma means that CVNNs remain largely a “black box”; researchers can observe their performance improvements but find it hard to understand their internal workings, largely limiting their use in cognitive modeling [11,12].

3.2.2. Practical bottlenecks of computational complexity and training stability

CVNNs face significant calculation challenges in practical applications. Complex calculation needs to maintain both real and imaginary components at the same time, leading to a substantial increase in memory usage and computational load. Experiments show that CVNNs of the same scale consume more computational resources than real-valued networks. More importantly, complex optimization faces serious training stability issues [13]. Because the loss surface in the complex domain is more complex, traditional real-valued optimization algorithms often struggle to achieve convergence. Although researchers have proposed various complex activation functions and normalization methods, a unified best practice has not emerged. Furthermore, support for complex operations in mainstream deep learning structures remains limited, requiring developers to manually implement many basic operations, which further increases the barrier to studying and use. This computational burden becomes particularly prohibitive when attempting to scale CVNNs to the size required for modeling large-scale brain networks, directly limiting their applicability to complex cognitive models.

3.2.3. Lack of standardization in evaluation systems and benchmark data

The field of CVNN research lacks unified evaluation standards and baseline datasets. Different studies use varying task settings, data preprocessing methods, and evaluation metrics, making direct comparison of results difficult. Particularly in cognitive modeling tasks, there is a lack of specifically designed complex-valued baseline datasets. Researchers often have to convert real-valued data into complex form, a practice that may lead to unnecessary bias. Simultaneously, current evaluations overly focus on task performance metrics, such as accuracy, but neglect the assessment of the model’s cognitive plausibility. Researchers need to establish a standard evaluation structure that includes various cognitive tasks, such as working memory, attention allocation, and decision-making, and develop evaluation metrics that can quantify the similarity between models and neural activity, thereby comprehensively measuring the progress and shortcomings of CVNNs in cognitive modeling.

3.2.4. Lagging development in hardware support and ecosystems

Both hardware and ecosystem levels limit the development of CVNNs. Current mainstream AI acceleration hardware, such as GPUs and TPUs, is primarily optimized for real-valued computations, with low efficiency support for complex calculations. It may be possible that the

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efficiency of using complex matrix multiplication on the same hardware is less than that of real-valued operations. On the software ecosystem side, although major deep learning frameworks provide basic complex number support, there is a lack of high-level libraries and tools specifically designed for CVNNs. Researchers need to spend significant effort implementing basic components rather than focusing on algorithmic innovation. This ecosystem incompatibility severely hinders the rapid development of CVNN research and affects the reproduction and promotion of research results [14].

4. Suggestion

To address the challenges faced by CVNNs in cognitive modeling applications, this part will propose optimization strategies.

4.1. Establish an interdisciplinary collaboration framework to enhance model interpretability

To tackle the "black box" nature of CVNNs and their unclear mapping to neural mechanisms, one of the effective strategies is to promote the deep collaboration between computational science and neuroscience. This necessitates the formation of interdisciplinary teams comprising neuroscientists, psychologists, and AI researchers. Their core task is not merely improving the function of the model. Instead, they need to endow the mathematical operations of CVNNs with biological significance. For example, they can design experiments to verify whether phase changes in complex weights correspond to communication delays between neuronal populations, or whether magnitude changes reflect the modulation of synaptic connection strength. By directly testing the internal representations of CVNNs, it is possible to transform CVNNs from a powerful tool into a testable, computational theory of cognition, thereby truly bridging the gap between computational models and the biological brain. This transformative approach would elevate CVNNs from mere pattern-recognition tools to computationally grounded theories of brain function.

4.2. Develop efficient specialized optimization algorithms and lightweight techniques

To address the bottlenecks of high computational cost and training instability, the research focus needs to shift from simply adapting real-valued tools to developing solutions native to the complex domain. Specifically, three research priorities emerge: first, it is helpful to explore more efficient and stable complex network components, such as complex versions of batch normalization, dropout, and activation functions, to lay the foundation for building deeper complex networks; second, researching dynamic network techniques to enable networks to automatically computational load based on input complexity is also helpful; third, it is helpful to develop optimization algorithms to ensure the fluency in training.

4.3. Build unified standard and promote an open-source ecosystem with hardware support

To solve the problems of an unclear evaluation system and insufficient ecosystem support, leading academic institutions need to lead a joint construction of a standardized benchmark suite for complex-valued cognitive modeling. This benchmark should include standardized complex data, a series of well-defined cognitive tasks, and unified evaluation standards. At the same time, the open-source community should be developed to share core code, pre-trained models, and toolkits to lower the barrier to entry. Additionally, active collaboration with hardware manufacturers should be promoted to activate native hardware-level optimization for complex operations in the next

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generation of AI accelerator chips, solving the computational efficiency problem from the ground up. Furthermore, industry-academia collaborations should be fostered to pilot these technologies in high-impact domains such as healthcare and communications. This will provide real-world validation, drive iterative improvement, and create a pull for commercialization, complemented by robust intellectual property frameworks to incentivize innovation.

4.4. Promote industrial application and transformation

To ensure long-term viability, a clear pathway for the commercialization and industrial adoption of CVNN technologies must be established. It is recommended to establish collaboration relationships with related industries, such as healthcare and communications to explore application scenarios of complex-valued neural networks in specific fields. Meanwhile, technology transfer platforms should be established to provide technical support, accelerating the industrial process of research achievements. Additionally, attention should be paid to intellectual property protection to provide legal safeguards for technological innovation.

5. Conclusion

5.1. Key findings

This study reveals that while CVNNs hold unique advantages for cognitive modeling, their adoption is hindered by four core challenges: insufficient theoretical interpretability, computational complexity, and training stability issues limiting practical applications, and a lack of standardized evaluation systems and hardware support. To address these challenges, this paper formulates a strategic framework comprising interdisciplinary collaboration mechanisms, developing specialized optimization algorithms, constructing standardized evaluation systems, and promoting industrial applications. These recommendations provide clear pathways for advancing complex-valued neural networks.

5.2. Research significance

This study has theoretical importance and practical value in many fields. Theoretically, it advances understanding of how complex-valued representations can enhance artificial neural networks' capability to model biological cognitive processes. The research provides valuable mathematical insights and offers a novel paradigm for emulating brain-like processing in artificial systems. Practically, the finding is significant to many industries. Specifically, in healthcare, CVNNs can revolutionize medical imaging analysis, particularly in magnetic resonance imaging and functional magnetic resonance imaging data processing, leading to more accurate diagnostics and treatment planning; in telecommunications, CVNNs can enhance the efficiency and robustness of signal processing for next-generation networks; and in finance, CVNNs can be used in analyzing complex data.

5.3. Limitations and future studies

While this study provides a thorough analysis and recommendations, there are several limitations that offer some directions for future research. The main limitation is the theoretical nature of the study, which relies on existing literature and conceptual analysis rather than empirical data from practical experiments. Consequently, the proposed framework, while logically sound, requires

DOI: 10.54254/2753-8818/2026.HZ27831

empirical validation to assess its practical efficacy and scalability. Additionally, the broad scope of the research means that some technical details require further elaboration and specification. Further study should focus on experimental validation of proposed frameworks through case studies and pilot implementations. Researchers should develop a prototype system based on the recommendations, conduct rigorous testing across different application scenarios, and propose detailed technical specifications for the proposed standardization frameworks. Additionally, research exploring the commercial viability and market potential of CVNN-based applications would help bridge the gap between theoretical research and practical implementation. Finally, investigations into the ethical implications and broader societal impact of widespread CVNN adoption are another crucial area for future research. By addressing these multifaceted challenges and opportunities, this research contributes to laying a foundation for the next generation of explainable, efficient, and ethically grounded artificial cognitive systems.

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