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Bridging Nature and Technology: A Perspective on Role of Machine Learning in Bioinspired Ceramics

Hamidreza Yazdani Sarvestani, Aditi Singh, and Behnam Ashrafi**

Nature has long inspired scientific and engineering advancements, particularly in the development of bioinspired ceramics. However, replicating nature's intricate structures through subtractive manufacturing techniques remains a significant challenge due to the limitations of precise and controlled material removal while maintaining structural integrity and complexity. This perspective article explores the transformative potential of machine learning (ML), particularly advancements in generative artificial intelligence (generative adversarial networks, transformer models) and multimodal learning, in accelerating the discovery of high-performance bioinspired ceramics. ML offers an avenue to optimize material behavior beyond the constraints of traditional experimental methods. Recent advancements have shown ML's effectiveness in predicting mechanical properties and refining material designs, often surpassing conventional approaches. ML excels at identifying complex relationships even with incomplete data during training. The integration of cutting-edge experimental data, cross-scale simulations, and ML facilitates high-fidelity multiscale modeling for predicting intricate phenomena like crack propagation paths in bioinspired ceramic structures. This article emphasizes the significant potential of ML to propel the field of bioinspired ceramics forward, paving the way for the discovery of ceramics with superior and tailored properties.

1. Introduction

Throughout human history, nature has served as an abundant source of inspiration, nurturing our growth and progress. It is only logical to turn to the natural world for solutions, especially when faced with challenges that continue to confound the scientific community. In the realm of material science, the field of bioinspiration has emerged as a triumph, resulting in materials with highly sought-after properties (see **Figure 1**a).[1–3] These materials often arise from the fusion of organic and inorganic components, forming intricate structures through hierarchical arrangements. Organic building blocks, such as proteins, collaborate with inorganic elements like ceramic particles (e.g., silica and calcium salts), often in composite forms.[4,5]

Notwithstanding their potential as high-temperature, impact-resistant, lightweight structural materials for various applications, synthetic ceramics are hindered by their inherent brittleness. Realizing their practical potential requires strategic modifications from their original states. Drawing inspiration from the remarkable designs found in natural structures such as teeth, crustacean shells, bones, and fish armors provides a promising avenue to enhance specific properties tailored to distinct needs[5–8] (see Figure 1b).

These structures exhibit a similar chemical composition but distinguish themselves through the arrangement of their fundamental building blocks and their intricate multilevel organization. For example, both teeth and bones consist of hydroxyapatite and collagen, forming mineralized collagen fibrils at the nanoscale. Teeth possess dentin microstructures with tiny fluid-containing channels known as dentinal tubules, while cortical bone features a lamellar structure.[9] While cortical tissue contributes overall strength to bones, the underlying dentin imparts toughness, compensating for the inherent brittleness of enamel in teeth. This remarkable adaptability within bioinspired designs opens the door to crafting multifunctional materials customized for specific fields or a wide range of applications.[10,11]

Efforts to replicate natural structures synthetically have posed a significant challenge, despite their striking similarities. Finding a universally effective manufacturing method for hierarchical structures remains elusive. Various manufacturing techniques have fallen short of achieving the substantial mechanical improvements observed in nature.[12–15] For instance, nacre-inspired ceramics have achieved only a fraction of the remarkable 40-fold enhancement in fracture toughness found in natural nacre.[9] The sheer complexity of multidimensional combinations involving material selection, features, hierarchy levels, loading conditions, and processing parameters makes it nearly impossible to establish a single optimal approach. Manufacturing constraints further impede the precise realization of simulated models.[14]

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In response to these challenges, the burgeoning field of machine learning (ML) has emerged as a powerful trend. ML, a subset of artificial intelligence (AI), leverages computer algorithms to optimize material performance without the time and cost associated with traditional experimentation. ML has found widespread application across diverse domains, from

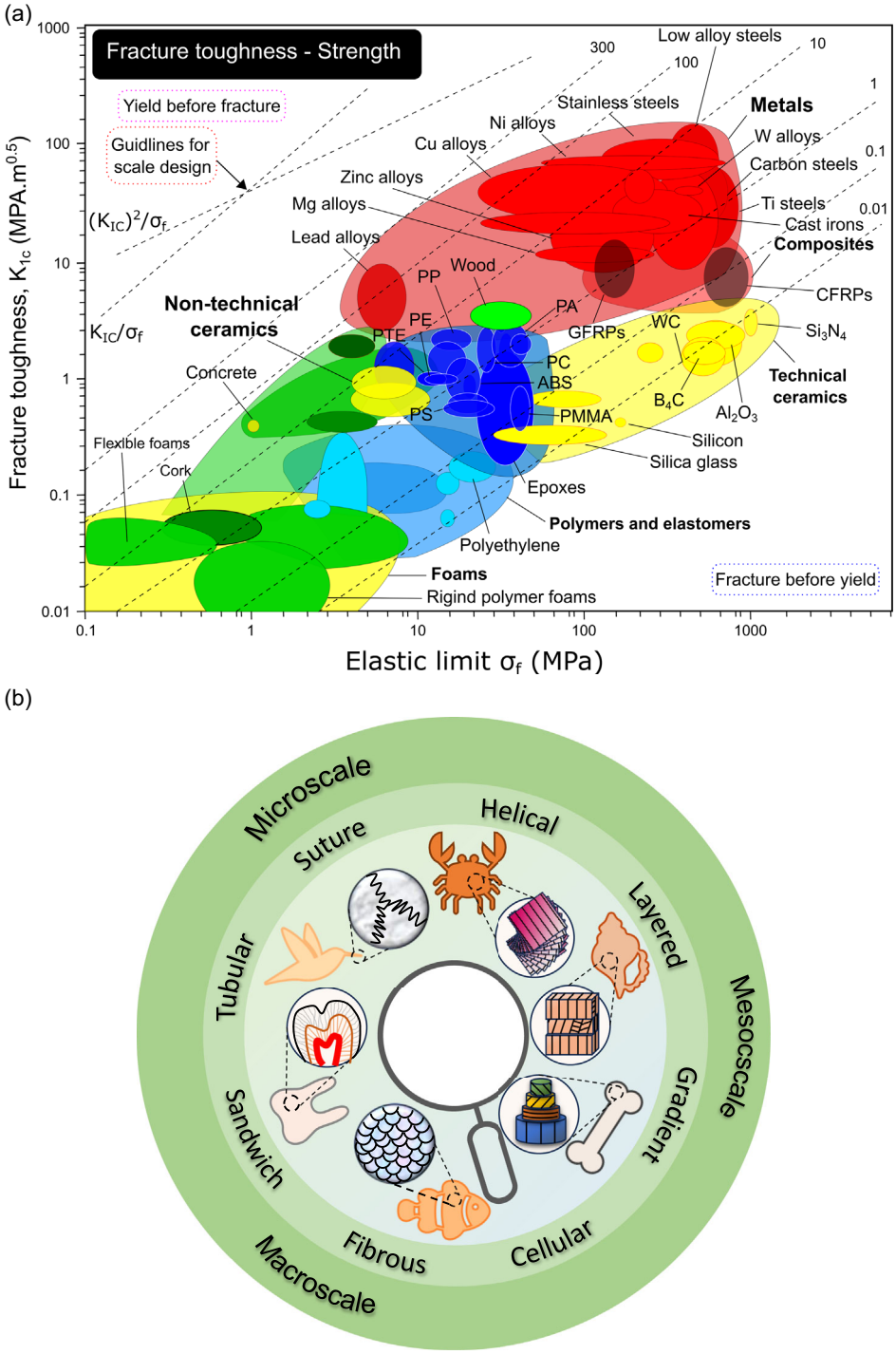

Figure 1. Bioinspired ceramics: a promising approach. a) Fracture toughness and elastic limit (strength) are two key mechanical properties in structures. b) Architectural and design features observed in biological materials offer a wealth of inspiration for bioinspired ceramics. These features include helical, sutured, tubular, sandwiched, fibrous, cellular, gradient, and layered configurations. c) Various biomicrostructures found in natural materials, such as shells, enamel, bone, and fish scales, exhibit diverse patterns with potential applications in aerospace, high-temperature environments, biomedical engineering, and other fields. These structures include helicoidal and Bouligand arrangements, nacreous design, as well as suture and stochastic features.

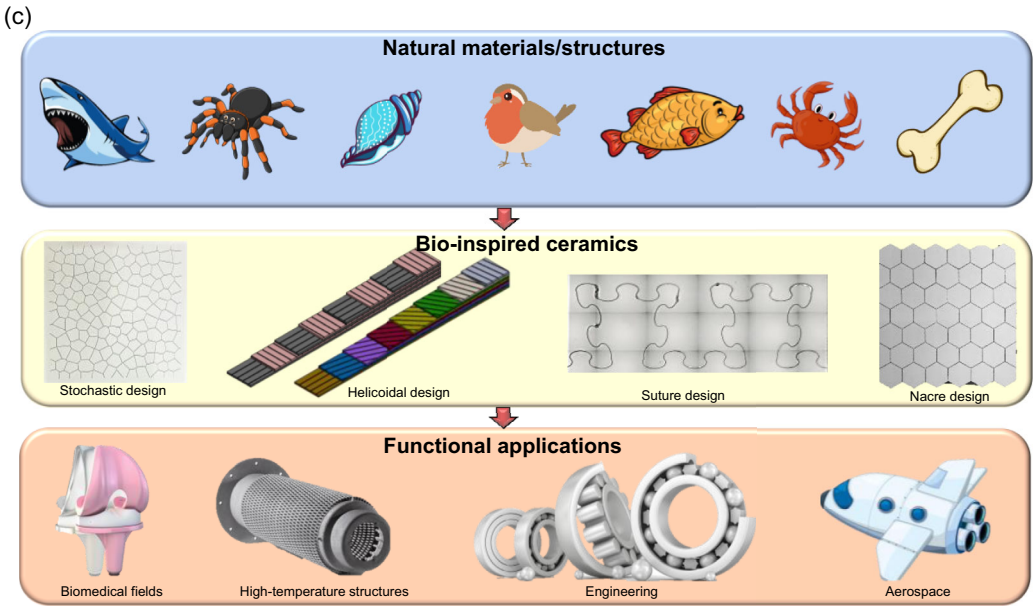

Figure 1. Continued.

image and speech recognition to healthcare, finance, marketing, and quality control. In material science, it offers the potential to enhance bioinspired structures, particularly architectured ceramics, through subtractive manufacturing methods.[16,17] This perspective article explores how ML can enrich the field of bioinspired ceramics by unlocking new possibilities and focuses on architectured ceramics as a prime candidate for reproducible, advanced structures.

2. Current Trends

2.1. Bioinspired Ceramics

Researchers frequently draw inspiration from staggered structures like those found in nacre. The exceptional toughness of nacre is attributed to its unique microstructure, which promotes controlled microcrack formation. These microcracks help dissipate energy and prevent catastrophic failure. Huang et al.[18] detailed how specific microcrack patterns contribute to the mechanical strength in biocomposites, which can be pivotal for developing bioinspired ceramic materials. A study by Valashani and Barthelat[19] employed precise laser engraving to mimic nacre's microstructure in a ceramic, resulting in a remarkable 700-fold increase in toughness. Mechanisms such as crack deflection, bridging, sliding, and interlocking contributed to this enhancement. Another investigation[20] focused on larger scale staggered hexagonal tablets (2.5–10 mm) to explore impact toughness. This study considered factors like frictional energy dissipation and viscous damping.

Examining conch shells, another study[21] sought to understand failure modes in a cross-ply structure, revealing valuable insights into material behavior under tensile loading. Findings included rotational failure at lower angles and tablet sliding at higher angles, illustrating the dynamic interplay of forces. In a quantitative comparative study, researchers bonded Bouligand and shell-like structures with Surlyn interlayers, favoring the resilience of hexagonal footprint ceramics even postyield.[22] An inverse Bouligand multilayered structure was introduced,[23] maintaining bulk strength while enabling high-temperature applications. Drawing inspiration from marine life's scaled skins, a team developed a puncture-resistant ceramic armor backed by silicone. This design ensured damage at one scale did not propagate to others, ideal for scenarios involving multiple impacts.[24]

Research on bioinspired architectured ceramics often relies on finite element methods (FEMs) and numerical simulations, often coupled with fracture mechanics analyses.[20,22,25] These techniques are crucial for validating experimental findings, exploring micromechanical intricacies, and predicting material behaviors under diverse loading conditions. For instance, transient nonlinear dynamics FEM was used to simulate high-speed impacts on a Boron carbide/polyurea laminated armor, achieving superior ballistic protection through microstructural optimization.[26] In another study, Johnson–Cook fracture models and Hashin-Damage material models were employed to investigate the ballistic impact process in ceramic composite armors.[27]

To address computational costs, some researchers have proposed discrete element modeling for simulating fracture and crack propagation in staggered composites, revealing the impact of microstructural variation on toughness.[28–30] Surprisingly, introducing stochasticity into material architecture has yielded favorable outcomes, possibly due to its presence at a higher length scale.[31] Additionally, discrete element models have been instrumental in gaining insights and simulating the influence of structural features on mechanical properties across various systems, enabling exploration of the design space.[32,33] This integration of diverse modeling techniques enhances our

understanding of bioinspired architectured ceramics, supporting their application across a spectrum of domains.

In conclusion, the study of bioinspired ceramics reveals innovative strategies inspired by nature's designs.[34–36] From mimicking nacre to emulating conch shells and marine life's scaled skins, researchers enhance traditional structures and introduce novel architectures (see Figure 1c). The utilization of FEM and numerical simulations validates findings and predicts behaviors under diverse loads. This approach deepens our understanding and broadens applications, marking a significant stride in biomimicry and materials science (see Figure 1c).

2.2. ML-Based Ceramic Design

Here, we have only scratched the surface of the extensive literature available on bioinspired ceramics. Although computational models enable us to ascertain and scrutinize closed-form relationships between key system parameters and overall material behavior, attempting to navigate the entire design space within a realistic timeframe is a monumental challenge. ML, with its capacity to process millions of test cases in mere seconds, presents interesting prospects for the evolution of architectured ceramics. This field is primarily categorized into supervised, unsupervised, and reinforcement learning, each designed for specific types of tasks or data. ML-based research in mechanical structures typically starts with a well-defined research problem that stands to benefit from the superior capabilities of ML-based approaches. A material dataset is then defined, sourced either from existing literature and databases, or generated through experiments and simulations, followed by implementation of ML algorithms to facilitate the analysis and extraction of meaningful insights from the dataset (see **Figure 2**b). Subsequently, the model undergoes rigorous training and validation processes to ensure its accuracy and generalization capabilities. Once validated, the ML model can be applied to predict material behaviors, guide targeted designs, and even discover novel structures with enhanced properties.

Several recent studies have focused on the application of ML in predicting mechanical properties and developing high-performing ceramic composites[37–40] (see Figure 2). ML models excel at leveraging learned relationships between material features and mechanical behaviors to solve complex problems without the need for explicit modeling of physical laws. For example, an ML approach successfully estimated properties like toughness and strength for a 2D composite composed of stiff and soft building blocks, using geometric configurations as input parameters.[41] Despite being trained solely on binary information distinguishing "good" and "bad" designs, the ML model accurately ranked the geometries relative to each other, demonstrating remarkable proficiency. In a related study, one million high tensile strength brick-and-mortar geometries were determined and ranked within 6 s, using a combination of Statistical Analysis for feature selection, decision trees for class prediction, and Support Vector Regression for strength prediction.[42] Notably, this approach nearly matched the performance of FEM without explicitly solving the finite element equations. This illustrates the remarkable capability of ML models to discern intricate relationships and patterns in data, enabling accurate predictions even when certain critical information is not explicitly provided during the training phase. Furthermore, these models can overcome computational limitations in composite design and optimization, efficiently navigating the design space and reducing the iterations required to attain an optimal solution.

A significant focus of ML-based bioinspired architectured ceramics research is on interlocking structures.[43–45] For instance, a feed-forward neural network was utilized, trained, and evaluated through FEM to computationally discover high thermomechanical performance in interlocked panels.[43] This performance included factors such as energy dissipation, deflection, factor of safety, and reaction forces across combinations of panels with varying dimensions and interlocking angles. Additionally, researchers calculated covariance during preprocessing to elucidate the direction and strength of relationships between different variables. During preprocessing, especially in tasks like feature selection or dimensionality reduction, understanding which features exhibit high correlation with the target variable (or with each other) holds significance. Highly correlated features may offer redundant information and could be considered for removal, whereas features with low correlation may be deemed less crucial for modeling purposes and may be omitted or transformed. This streamlined approach not only simplifies the model but also mitigates the risk of overfitting. Remarkably, remarkable precision in predictions can be attained even with sparse training data, small batch sizes, and a restricted number of training iterations. Building upon their prior research, a comparative analysis of three distinct ML algorithms, extreme gradient parameters boosting, neural networks, and Gaussian process regression, was conducted based on interlocking panel designs.[44,46] This assessment was conducted with a relatively modest dataset comprising 99 observations. However, it is important to acknowledge that current ML approaches can be limited by the quality and quantity of training data, and may not always capture the full complexity of physical phenomena governing material behavior. When dealing with larger systems featuring a high number of parameters, ML models often necessitate extensive datasets to adequately represent the true distribution of the data and enhance model reliability. In such cases, data augmentation techniques can be applied during preprocessing to expand the datasets and eliminate any irrelevant data points that could potentially hinder performance.

The use of ML in laser removal of ceramics represents a transformative approach. Traditional methods often require manual adjustments, limiting adaptability to ceramic variations.[47–49] ML, particularly deep learning models, revolutionizes this process by enabling real-time optimization. By monitoring parameters like temperature and material response during removal, these algorithms adjust laser settings on the fly to ensure efficient material removal while reducing thermal damage risks. ML excels at recognizing unique characteristics in different ceramic compositions through diverse dataset training (see Figure 2b). This customization of laser removal strategies enhances accuracy and efficiency. Furthermore, the integration of ML minimizes errors and reduces rework, lowering manufacturing costs and waste. These models can even achieve high-accuracy predictions with limited training data, highlighting their robustness.

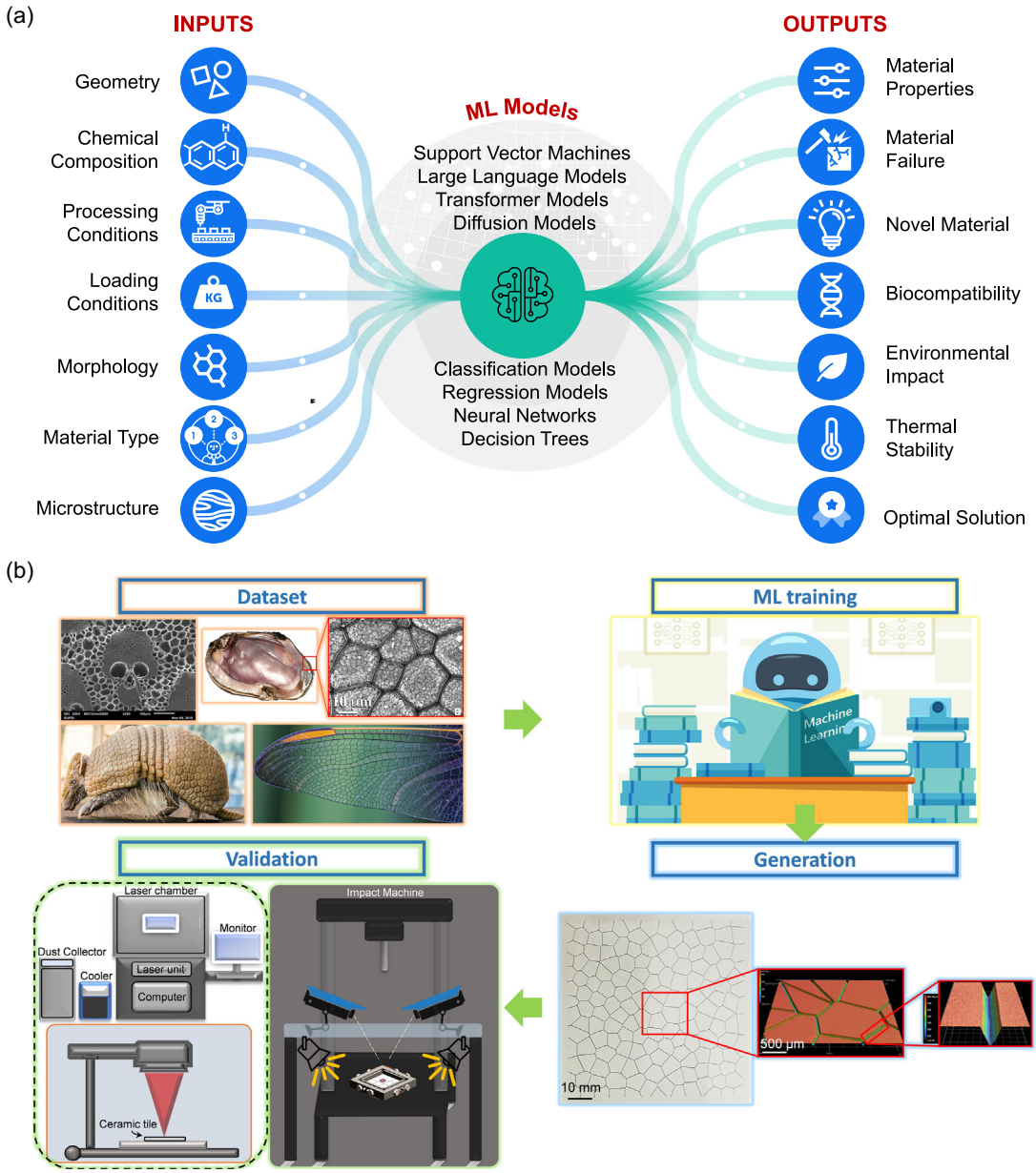

Figure 2. a) Flow of data in ML, encompassing input (geometry, chemical composition, processing conditions, etc.) and output (optimal solution, novel structures, material failure, etc.) selections. b) ML for bioinspired ceramics design: ML utilizes datasets found in nature, containing information on the structure and properties of biological materials (e.g., nacre, conch shells). After a training phase, the ML model develops novel bioinspired ceramic architectures. These proposed structures are then laser-manufactured to validate the ML model's effectiveness.

We have highlighted the diverse ways in which ML has significantly contributed to material discovery, taking advantage of limited resources and yielding substantial societal benefits. However, it is important to note that the full extent of ML's potential remains largely untapped. For example, beyond capturing underlying patterns and relationships, ML models have demonstrated the capacity to learn and predict symbolic expressions that represent fundamental physical laws. They can even unveil previously unexplored mathematical solutions to complex physical problems. This underscores the expanding role of ML techniques in deepening our comprehension of physical phenomena. Furthermore, advanced neural network structures hold promises in capturing the multiscale features commonly found in hierarchical structures. By combining state-of-the-art experimental data, cross-scale simulations, and ML, a path is opened toward achieving high-fidelity multiscale modeling. This methodology entails examining a material at a particular length scale, with the knowledge acquired proving valuable for understanding the material's properties at different length scales.[50] Through this method, it becomes possible to predict intricate behaviors such as crack propagation paths, material failure, biological properties, and chemical reactions. A

comprehensive overview of the diverse features of bioinspired structural materials was provided that can be explored across different length scales.[51] Moreover, a promising frontier lies in autonomous materials discovery, where emerging learning strategies such as active learning and reinforcement learning are integrated with automated experimentation. This integration enables autonomous exploration of vast design spaces.[50] The process commences with the collection and curation of extensive databases containing information on known materials, their properties, and their structures. These databases may encompass data from experiments, simulations, and literature. Thanks to progress in information retrieval and natural language processing, relevant data for a specific problem can be automatically extracted from the literature. It is worth noting that deep learning models, in contrast to traditional ML models, have the capability to directly acquire advanced features from image data. This significantly lessens the workload associated with preprocessing and feature extraction.[52] ML relies on model validation to ensure that ML models generalize well to new, unseen data, avoiding pitfalls like overfitting (see Figure 2b). It helps in selecting the best-performing model, evaluating its real-world performance, and identifying data issues or biases. It is crucial to acknowledge that these opportunities hinge on the expertise of domain professionals who provide critical insights for data preprocessing, feature selection, and model interpretation.

2.2.1. Generative AI and Multimodal Learning

Recent advancements in generative AI, particularly in the realm of multimodal learning, have opened exciting avenues for designing bioinspired materials. This section delves into the potential of generative adversarial networks (GANs), transformer models, and their synergistic application through multimodal learning. 1) GANs: GANs, consisting of a generator and a discriminator, have proven instrumental in generating realistic and diverse samples from learned data distributions. In the context of bioinspired ceramics, GANs can be employed to design intricate microstructures that replicate the hierarchical organization found in nature. For instance, Chiang et al.[53] utilized a transformer-based GAN to generate 3D bioinspired microstructures, showcasing their potential in creating innovative designs that balance mechanical strength and toughness. 2) Transformer Models: Transformers, initially developed for natural language processing, have shown remarkable success in various domains due to their ability to model long-range dependencies and process sequential data. Transformer models can be used to predict material properties and design new materials by learning from large datasets. Their self-attention mechanism allows for capturing the intricate relationships between different components of a material, enabling the synthesis of bioinspired structures with optimized properties. One promising application of transformer models lies in "building block problems" encountered in bioinspired ceramics design. For instance, a transformer model could be trained on data consisting of various building blocks and their associated properties. The model could then be used to generate novel building blocks with desired characteristics, accelerating the design process for bioinspired materials. A recent study[54–56] exemplifies the application of transformer models in structural design.

Multimodal Learning for Bioinspired Ceramics: Multimodal learning goes beyond traditional approaches by integrating information from multiple sources or modalities, such as text, images, and structural data. This enriched data perspective leads to a more comprehensive understanding of materials, proving particularly valuable in materials science, where data from diverse experiments, simulations, and literature can provide complementary insights.

One emerging area within multimodal learning leverages large language models (LLMs) alongside other modalities. A recent study[57] exemplifies this approach. The authors developed an ontology and graph model to drive scientific discovery using a series of multimodal LLMs. Notably, their work explored the development of a mycelium-based bioinspired mineral-based material, demonstrating the potential of multimodal LLMs for creating novel bioinspired materials.

Ontologies play a crucial role in capturing universal design principles for bioinspired ceramics. These formal representations of knowledge can encode concepts and relationships related to microstructures, such as the ones depicted in Figure 1. By incorporating ontologies into the development of generative AI models, researchers can ensure that these models understand and utilize these fundamental design principles.

Furthermore, generative tools like MechGPT and graph reasoning can be employed for literature mining in materials science. These tools can process vast amounts of scientific text data to extract valuable knowledge related to bioinspired ceramics. This knowledge can then be integrated with other modalities, such as microstructural data, to inform the design of novel microstructures using generative AI models.

While similar methods have been employed for structural materials,[58] the unique challenges and opportunities presented by bioinspired ceramics necessitate further exploration of multimodal generative AI tailored to this specific field.

Applications in Bioinspired Ceramics: By leveraging the strengths of GANs, transformer models, and multimodal learning, researchers can unlock exciting possibilities in the design and optimization of bioinspired ceramics. 1) Design Optimization: By exploring a vast design space with the aid of advanced AI models, researchers can optimize the microstructures of bioinspired ceramics for specific applications. This opens doors to the discovery of novel material compositions and structures with superior performance. 2) Property Prediction: Multimodal learning enhances the prediction of material properties by combining experimental data with theoretical models. This integration allows for more accurate and reliable predictions, facilitating the development of materials with tailored properties. 3) Literature Mining and Knowledge Synthesis: Advanced AI models can mine vast amounts of scientific literature to extract relevant information and synthesize new knowledge. This capability is crucial for identifying trends, gaps, and opportunities in the field of bioinspired ceramics.

In conclusion, generative AI and multimodal learning represent powerful tools in the design and optimization of bioinspired ceramics. By harnessing these advanced technologies, researchers can push the boundaries of material science, leading to the

development of innovative materials with unprecedented properties.

2.2.2. Data Challenges and Opportunities in Bioinspired Ceramics

The development and utilization of effective datasets are crucial for advancing research in bioinspired ceramics, particularly when leveraging ML techniques. However, a significant challenge lies in the heterogeneity of data related to this field. Information on material properties, microstructures, processing techniques, and performance can be scattered across various sources, including scientific publications, databases, and experimental reports. This fragmented data landscape hinders the development of comprehensive datasets suitable for training and utilizing ML models effectively.

Despite these challenges, exciting opportunities exist for leveraging advanced techniques to overcome them and enhance data quality for bioinspired ceramics research. 1) Literature Mining: Techniques similar to those employed in BioinspiredLLM can be adapted for literature mining in this context. By processing vast amounts of scientific publications, these methods can extract valuable knowledge on material properties, processing methods, and structure–property relationships. This extracted information can then be used to populate and enrich datasets specifically designed for bioinspired ceramics research. 2) Knowledge Graphs and Ontologies: Developing knowledge graphs or ontologies tailored to bioinspired ceramics presents another promising approach. These formal representations of knowledge capture key concepts, relationships, and rules governing the field. Knowledge graphs can integrate information from diverse sources, including literature, databases, and experimental data. This structured knowledge can then be used to query, analyze, and ultimately generate new hypotheses and research directions in bioinspired ceramics.

Moving Forward: By combining efforts in literature mining, knowledge graph development, and data curation, researchers can significantly enhance the quality and accessibility of data for bioinspired ceramics research. This, in turn, will pave the way for the development of more powerful and reliable ML models that can accelerate the design, discovery, and optimization of novel bioinspired materials.

2.3. Limitations of Current ML Approaches

While ML holds tremendous promise for accelerating the design and analysis of bioinspired ceramics, there are crucial limitations to consider. 1) Data Dependence: ML models are heavily reliant on the quality and quantity of data used for training. In the field of bioinspired ceramics, where complex material properties and intricate microstructures are involved, generating high-quality datasets can be challenging. Limited or noisy data can lead to inaccurate or misleading predictions by the ML model. 2) Black Box Issue: Many ML models, particularly powerful deep learning algorithms, are often referred to as "black boxes." This means their internal workings and decision-making processes are opaque, making it difficult to understand how they arrive at specific predictions. This lack of interpretability can hinder scientific understanding, material optimization, and debugging potential errors in the model.

2.3.1. Addressing the Challenges

Fortunately, there are ongoing efforts to address these limitations and enhance the effectiveness of ML in bioinspired ceramics research. 1) Data-Centric Strategies: Researchers are exploring techniques for data augmentation, which involves generating synthetic data or manipulating existing data to improve its quality and quantity. Additionally, active learning approaches can be employed to prioritize data collection efforts, focusing on areas where the model requires more information for accurate predictions. 2) Explainable AI: The field of Explainable AI is rapidly evolving, offering a suite of methods to make ML models more transparent. Techniques like Local Interpretable Model-Agnostic Explanations and SHapley Additive exPlanations can help identify the most influential features in an ML model's predictions, providing insights into the decision-making process.

By actively addressing these limitations, researchers can leverage the power of ML to its full potential in the design and development of novel bioinspired ceramics with superior properties and functionalities.

3. Future Perspective

Nature's brilliance has long inspired engineers, with materials like nacre showcasing exceptional strength and toughness. Bioinspired ceramics, drawing inspiration from these natural wonders, offer immense potential for various applications, including the aerospace, biomedical, and automotive industries. This potential lies in their distinctive blend of properties (see **Figure 3**). ML, a powerful form of data-driven automation, plays a pivotal role in unlocking this potential. In conjunction with advanced computational techniques like AI and multiscale simulation, ML helps reveal latent possibilities for crafting multifunctional bioinspired structures. These structures exhibit high strength and toughness, and their development can be expedited through sustainable routes, ultimately enhancing the efficiency of structures design and minimizing environmental impact.

One way ML facilitates the development of bioinspired ceramics is through advanced generative models like GANs and transformer models. These models excel at learning complex patterns and relationships from data. For example, the use of a transformer-based GAN to generate 3D bioinspired structures has demonstrated the capability to create materials with optimized properties that mimic the hierarchical organization found in nature. Such innovations can lead to the development of materials with superior mechanical properties, tailored for specific applications in the aerospace, biomedical, and automotive industries.

Multimodal learning, which involves combining information from various data sources such as text, images, and structural data, offers a holistic approach to material design. This method enhances the predictive power and design accuracy by providing a multi-faceted view that can inform the design of bioinspired ceramics with optimized properties for specific applications. Notably, multimodal learning can integrate information from

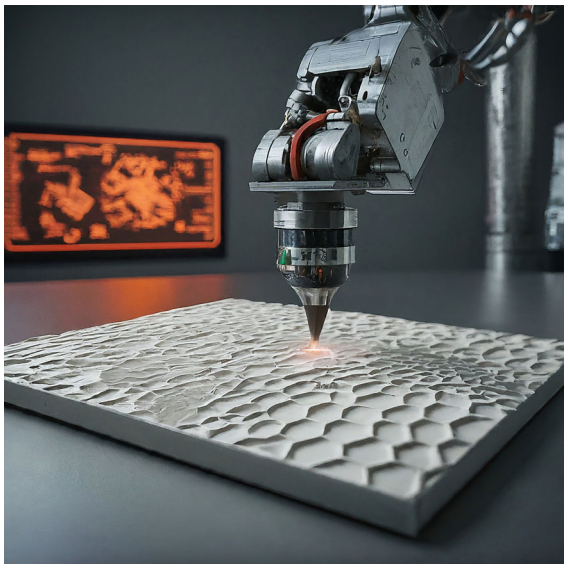

Figure 3. Integration of FEM and ML: This schematic depicts a smart method that combines the FEM with ML techniques to predict the thermomechanical responses of bioinspired ceramics. This strategy aims to identify high-performance ceramics under various thermomechanical loads with reduced computational costs. These structures could then be produced using a scalable subtractive manufacturing platform.[44]

various sources including microstructural data like those depicted in Figure 1.

3.1. ML in Design and Optimization

The future of ML in the design, subtractive manufacturing, and testing of bioinspired ceramics holds great promise. As ML continues to evolve and integrate further into material science, its impact on bioinspired ceramics will be transformative. 1) Enhanced Material Designs: ML algorithms increasingly enable researchers to optimize material compositions and structures for specific applications. For instance, imagine a scenario where ML analyzes vast datasets of bioinspired ceramics and their properties. By doing so, ML can identify novel designs that were previously unattainable, leading to ceramics tailored for diverse fields such as aerospace, biomedical, and automotive industries. These ceramics boast improved properties like enhanced toughness and heat resistance while potentially minimizing material usage through optimized designs. 2) Efficient Iterative Design Process: The iterative process of designing bioinspired ceramics will become more efficient and precise with ML. This efficiency will result in structures that outperform their synthetic counterparts, meeting the demands of various industries, and accelerating the discovery of sustainable material solutions.

3.2. ML in Subtractive Manufacturing of Ceramics

ML is finding applications in the laser removal of ceramics, revolutionizing this intricate process. Laser removal, particularly for ceramics, requires precise control to avoid cracking or damaging the material. 1) Precision through Real-Time Adjustments: ML models analyze real-time sensor data during the laser removal process, such as temperature and material responses. By processing this data, ML algorithms dynamically adjust laser settings, optimizing parameters like laser power, focal point, and scanning speed. This adaptability ensures effective ceramic removal while minimizing thermal damage or microcracks, potentially reducing wasted material. 2) Customized Removal Strategies: ML can identify unique characteristics and vulnerabilities of different ceramic compositions, allowing for tailored laser removal strategies. This technology enhances precision and quality while potentially reducing manufacturing costs and waste, making it a game-changer in laser-based ceramic processing.

3.3. ML in Testing and Predictive Modeling

In the realm of testing, ML algorithms can develop automated procedures, reducing time and costs associated with traditional investigations. 1) Automated Testing: ML can identify potential failure modes and weaknesses in bioinspired ceramics, refining designs and developing structures with superior mechanical properties. 2) Predictive Modeling: ML can simulate how these structures would perform under various real-world conditions. This capability ensures bioinspired ceramics are not only high-performing but also reliable in their intended applications, reducing the need for physical prototypes and associated material waste.

In conclusion, the integration of ML into bioinspired ceramics offers transformative potential across various stages of material development. Enhanced designs, precise laser removal, automated testing, and predictive modeling are just a glimpse into the possibilities. By embracing ML, the field of bioinspired ceramics is poised to deliver structures with unparalleled properties, impacting industries and society as a whole, while promoting sustainable practices through material optimization and reduced waste.

4. Conclusion

The convergence of nature's wisdom and cutting-edge technology, particularly through the fusion of bioinspired ceramics and ML, represents a remarkable stride in materials science. Bioinspired ceramics, characterized by their hierarchical structures and multifunctional properties, offer immense potential for diverse applications. However, the inherent complexities of replicating nature's designs, particularly in understanding the relationships between building blocks, have posed significant challenges. ML, as a powerful computational tool, is poised to expedite this field by optimizing material performance without the constraints of traditional experimental methods. Recent trends showcase the success of ML, including advancements in generative AI like GANs and transformer models, in predicting mechanical properties, optimizing material designs, and uncovering the intricate relationships between building blocks in bioinspired structures. The integration of data-driven automation and traditional material development efforts holds the promise of unlocking novel classes of bioinspired ceramics with unique and desirable properties. The future of bioinspired

ceramics lies at the intersection of nature's inspiration and AI. This marriage presents vast possibilities, facilitated by advancements in generative AI and the power of multimodal learning to integrate diverse data sources, from the development of high-strength and toughness ceramics to exploring sustainable design routes. As we embark on this exciting journey, the potential for groundbreaking discoveries and innovations in material science is brighter than ever. Through continued research, collaboration, and the application of advanced technologies like ML, we are poised to create a new generation of ceramics that not only meet but exceed the demands of various industries, paving the way for a more sustainable and technologically advanced future.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

H.Y.: Conceptualization; formal analysis; investigation; supervision; visualization; roles/writing—original draft; writing—review and editing. A.S.: Data curation; investigation; visualization; roles/writing—original draft. B.A.: Conceptualization; funding acquisition; resources; supervision; writing—review and editing.

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