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Recent Advances and Applications of Machine Learning in Experimental Solid Mechanics: A Review

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For many decades, experimental solid mechanics has played a crucial role in characterizing and understanding the mechanical properties of natural and novel artificial materials. Recent advances in machine learning (ML) provide new opportunities for the field, including experimental design, data analysis, uncertainty quantification, and inverse problems. As the number of papers published in recent years in this emerging field is growing exponentially, it is timely to conduct a comprehensive and up-to-date review of recent ML applications in experimental solid mechanics. Here, we first provide an overview of common ML algorithms and terminologies that are pertinent to this review, with emphasis placed on physics-informed and physics-based ML methods. Then, we provide thorough coverage of recent ML applications in traditional and emerging areas of experimental mechanics, including fracture mechanics, biomechanics, nano- and micromechanics, architected materials, and two-dimensional materials. Finally, we highlight some current challenges of applying ML to multimodality and multifidelity experimental datasets, quantifying the uncertainty of ML predictions, and proposing several future research directions. This review aims to provide valuable insights into the use of ML methods and a variety of examples for researchers in solid mechanics to integrate into their experiments. [DOI: 10.1115/1.4062966]

Keywords: experimental solid mechanics, machine learning, fracture mechanics, biomechanics, architected materials, nanoindentation, 2D materials, physics-informed neural networks (PINNs), neural operator

1 Introduction

Over the years, the field of experimental solid mechanics has kept evolving because of the continuous demand to characterize and understand the mechanical properties of natural and novel artificial metamaterials and structures [1,2]. There are two primary motivations for performing experiments in solid mechanics: (1) to provide experimental observations that can be used to advance universal mechanics laws; (2) to measure unknown mechanical properties of materials and structures, e.g., stiffness, strength, phase changes, inelasticity, damage, and fracture, under prescribed boundary or loading conditions. Measured fields and properties guide the construction of constitutive laws and interpretation of underlying physics. Throughout the history of experimental solid mechanics, various apparatuses have been invented to measure mechanical properties, from quasi-static testing (e.g., the universal tensile testing machine [3]) to high strain-rate testing (e.g., Kolsky bars [4] and plate impact facility [5,6]). In the past two decades, advances in nanomechanics tools like the nano-indenter and micro-electromechanical systems (MEMS) for in situ microscopy testing [7,8] have enabled nanoscale characterization of advanced materials [9–11]. Likewise, various experimental measurement techniques have been developed, from local methods, e.g., strain gages and displacement transducers [12], to full-field methods, such as high-resolution and high-speed imaging systems [13]. These technical innovations provide an extensive and ever-increasing amount of data collected during a single experiment. To analyze data from full-field measurement, new analysis techniques such as Moiré interferometry [14], digital image/volume correlations (DIC/DVC) [15,16], and electronic speckle pattern interferometry [17] have been developed to extract mechanical properties and deformation fields from experiments. Furthermore, inverse methods have been used to extract constitutive behavior and identify imperfections [18,19]. Indeed, the combination of experimental mechanics with fast and robust computational algorithms for inverse analysis has been growing in importance since it enables new approaches to mechanical property identification, from fracture properties under extreme conditions to anisotropic properties of biological tissues to superior mechanical properties of nano-architected and two-dimensional (2D) materials.

Recently, the concept of *materials by design* [20] has been advanced for the design of multifunctional architected materials [21] and 2D materials/devices [22,23] exhibiting unprecedented performance. Such progress was possible due to the rapid

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development of modern experimental mechanics techniques, which include fabrication processes, e.g., additive manufacturing (AM) [24], chemical vapor deposition, as well as the development of high-throughput testing methodologies [25–27]. In such research strategy, experimental solid mechanics plays an essential role in providing valuable training and validation of experimental data for extracting physically inspired reduced-order models as well as advancing understanding of fabrication process-mechanical property relationships. Therefore, combining novel and intelligent algorithms together with advances in fabrication and experimental characterization methods has the potential to achieve a paradigm shift in discovering multifunctional and architected materials and structures.

Recent advances in machine learning (ML) [28], in particular, deep learning (DL) [29], offer the opportunity to expand the field of experimental solid mechanics when combined with rapid data processing and inverse approaches. ML has played a significant role in computer science applications and technologies like computer vision [30], natural language processing [31], and self-driving cars [32]. In engineering and applied physics disciplines, ML has been widely used in various areas of materials science, including material microstructure design [33], microscopic imaging detection [34], and force-field development [35]. Several comprehensive reviews [36–40] have thoroughly surveyed the potential of ML in materials science. In solid mechanics, ML has been successfully employed in a wide range of applications, such as constructing surrogate models for constitutive modeling [41,42], advancing multiscale modeling [43,44], designing architected materials [45], extracting unknown mechanical parameters [46], or obtaining the internal material information from externally measured fields [47–49]. In these applications, most ML frameworks were trained on synthetic data from computational methods. Therefore, applying these ML frameworks to train and validate *sparse and noisy* experimental data with high fidelity and modality require cautious quantification of uncertainty [50,51], from both experimental data and ML architectures like hyperparameters, optimization method, and overparameterization. For this purpose, uncertainty quantification methods like Bayesian methods and deep ensembles can be employed. Moreover, employing ML in the experimental design data process could not only potentially identify material properties, which could not be revealed otherwise, but also inspire experimentalists to develop new experimental techniques with metrology capable of big-data generation with high information content. With broad community interest, as reflected by the increasing number of publications in this field, it is timely to conduct a contemporary and thorough review of recent advances in the use of ML in experimental solid mechanics. Though this review will be focused on experimental aspects, multidisciplinary approaches, including computational and theoretical mechanics, as well as materials science, are needed to address engineering applications.

This review is dedicated to Prof. Kyung-Suk Kim, on his 70 s birthday, to celebrate his seminal contributions to the fields of experimental and theoretical mechanics. The review is planned as follows. In Sec. 2, we will briefly review some key ML algorithms that can be employed in experimental mechanics. Then, in Sec. 3, we will review some recent progress of ML applications in experimental solid mechanics, covering the broad areas of fracture mechanics, biomechanics, nano- and micromechanics, mechanics of architected materials, and fracture toughness of 2D materials. In Sec. 4, we will discuss how to properly select ML models for experimental data with multifidelity and multimodality. We will also discuss possible solutions to estimate and reduce ML uncertainty. Finally, in Sec. 5, we will close our review with a discussion of potential future research directions. Please note that ML has also been extensively applied to AM and full-field optical measurement, which are two other important fields in experimental solid mechanics. Since extensive state-of-the-art reviews have been conducted in these two fields (see Refs. [52–54] for AM and Ref. [55] for full-field optical measurement), we will not cover these topics extensively in this review.

2 Machine Learning Framework for Experimental Solid Mechanics

Machine learning methods use algorithms mimicking human intelligence to perform optimization tasks for particular goals [28]. Since the early development of neural networks (NNs) and back-propagation algorithms [56] in the 1980s, the research field in ML has evolved significantly, leading to the discovery of various network architectures with distinct operational principles. Therefore, before applying these ML algorithms to experimental solid mechanics, it is crucial to understand their architectures, working principles, and potential limitations. Such fundamental knowledge will enable researchers to effectively understand these algorithms and utilize them appropriately in specific applications. In principle, ML methods can be divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning (RL). In supervised learning, the algorithm learns the mapping between the input dataset and their ground-truth labels, while in unsupervised learning, the algorithm aims to identify patterns and features in the data without being explicitly trained on labeled examples. In reinforced learning, an agent receives feedback in terms of reward or punishments for each action and then uses this feedback to improve future decision-making capabilities. In addition, there are other ML methods, such as semisupervised learning. In semisupervised learning, the ML algorithm is trained with both labeled and unlabeled datasets. The labeled data first train the model, and then the model is used to label the unlabeled data. Examples of supervised learning algorithms include linear regression, decision trees, and NNs. Examples of unsupervised learning algorithms include principal component analysis, K-mean clustering, and spectral clustering. Examples of RL include policy gradient and Q-learning. Examples of semisupervised learning include generative models like generative adversarial networks (GANs). For more details on the fundamentals of ML methods, readers are referred to textbooks, see, e.g., Ref. [57] and online courses.

Machine learning methods are typically data-driven, that is, the model is trained/informed by large datasets consisting of images, texts, audio, and so on [28]. For example, the revolutionary AI chatbot software, CHATGPT [58], was trained based on a transformer language model [59] that uses self-attention mechanisms, allowing the model to weigh input words at different positions to predict the following words. In engineering and physics disciplines, however, many problems can be well-defined by some underlying physical laws such as partial differential equations (PDEs). For example, in solid mechanics, the equilibrium, compatibility, and constitutive equations (a set of PDEs) define the kinematics of continuum bodies. Moreover, the physical laws themselves provide valuable a priori temporal or spatial information, which can be integrated into the ML framework during training. To this end, the concept of *physics-informed neural networks* (PINNs) [60] has been proposed by the Karniadakis group at Brown University. This framework has paved a new pathway to solving physical-law-governed forward and inverse problems, reducing the need to collect a large dataset. Based on the notion of data-driven and physics-informed ML methods, we may interpolate between these two ends, formulating a spectrum of scientific ML methods that may be developed for experimental solid mechanics. Depending on the size of the dataset we could obtain, and how much physics is embedded in the algorithms, the scientific ML approaches can be categorized into three scenarios depicted in Fig. 1: (I) physics-informed learning method [60,61], (II) physics-based data-driven method, and (III) purely data-driven method. The second scenario, i.e., the physics-based data-driven approach, is typically employed when a problem is too complex to be completely described by a set of PDEs. An example is the cohesive fracture of solids, where the training dataset can be relatively easily obtained from massive computer simulations incorporating the physics of the problem, e.g., finite element analysis (FEA) or molecular dynamics (MD).

In the following subsections, we will briefly review some existing ML algorithms and introduce terminologies that are useful for

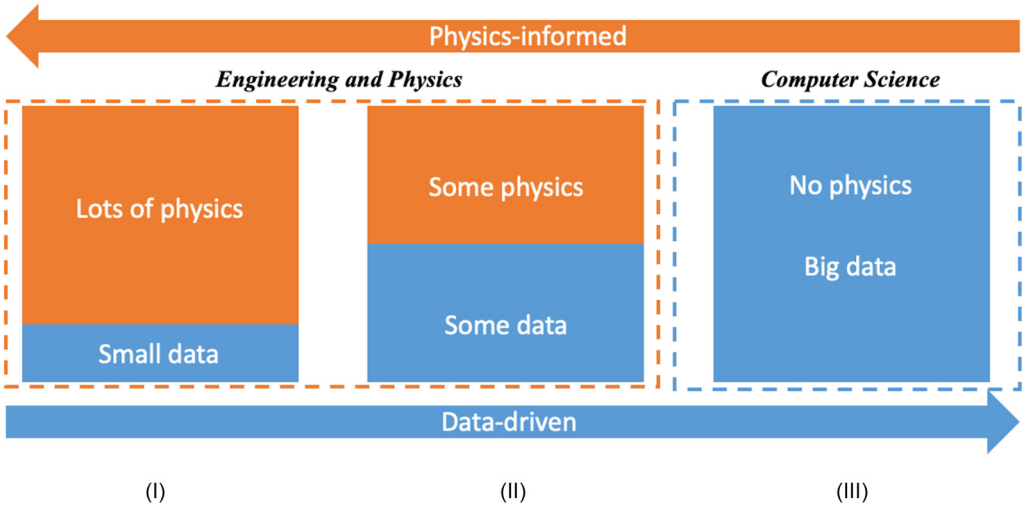

Fig. 1 Schematics of three ML approaches based on available physics and data: (I) PINNs; (II) physics-based data-driven; and (III) purely data-driven (Reproduced with permission from Ref. [62]. Copyright 2021 by Hanxun Jin). Figure idea from Karniadakis et al. [61].

applications in experimental solid mechanics. In Sec. 2.1, we will discuss one of the unsupervised ML methods, the clustering method. We will then introduce various types of NNs in Secs. 2.2–2.6. Then, in Secs. 2.7 and 2.8, we will discuss RL and Bayesian inference. Lastly, methods used in the scientific ML community will be discussed in Secs. 2.9 and 2.10.

2.1 Clustering. Clustering is an unsupervised ML technique that identifies data structure and grouping similar datasets into several clusters. The most common clustering algorithm is the K-means method, which groups the total dataset into K clusters by minimizing the total distance between the data and computed cluster centroids. When K-means algorithm fails to cluster the data due to data nonlinearities or complexity, the spectral clustering algorithm [63], which uses the spectral properties of the dataset to determine clusters, can be employed. The principle of spectral clustering is to transform a complex dataset into a low-dimensional representation by using the spectrum (eigenvalues) of the similarity matrix of the data. Then, the low-dimensional dataset can be clustered using traditional clustering techniques, such as K-means clustering. In experimental solid mechanics, spectral clustering particularly applies to acoustic signals such as acoustic emissions from mechanical response [64]. For example, Muir et al. [65] applied the spectral clustering technique to identify the damage mechanisms of SiC/SiC composites based on frequency information of acoustic emission signals.

2.2 Neural Networks. Neural networks are an ML algorithm inspired by the function and structure of the human brain. They consist of an input layer, interconnected layer(s), and an output layer. These layers are interconnected with nodes, which are like neurons. Through passing information by interconnected layers with activation functions [57] (such as Sigmoid, Softmax, and rectified linear unit (ReLu) functions [66]), the NN can learn a nonlinear mapping between inputs and outputs. There is a variety of NNs, including dense neural networks, convolutional neural networks (CNN), GANs, graph neural networks (GNNs), recurrent neural networks (RNNs), transformers, and autoencoders, which are useful in inverse problems and data generation for solid mechanics. Among these structures, the simplest architecture of NNs is the fully connected NNs, where all neurons in every layer are connected to all neurons in the adjacent layers. In the next subsections, we will briefly overview these NN structures and their current and potential applications in experimental solid mechanics.

2.3 Convolutional Neural Networks. Convolutional neural network is a type of DL algorithm commonly used for image classification and feature extractions [67,68]. The input images are processed through convolutional layers, subsequently passed through the polling layer, and fully connected layers for feature reduction and filtering. Multiple convolutional layers can be applied to increase the complexity of the feature extraction. CNN can be useful for both regression and classification of image-based experimental data. For example, CNN can be used for material property identification and microstructure characterization from experimental images [69]. Furthermore, CNN can analyze images obtained from full-field measurement techniques like interferometric and DIC data. Using CNN for feature extraction from interferometric fringes can bypass the need for a conventional fringe unwrapping process while also increasing the feature extraction accuracy. For example, Jin et al. [70] employed a CNN-based DL framework to extract dynamic cohesive properties and fracture toughness of polyurea directly from image-shearing interferometric fringes. Kaviani and Kolinski [71] developed a CNN-based DL framework to convert fringes from Fizeau interferometry with a low resolution into frustrated total internal reflection images with high resolution while studying droplet impact. Another important application for CNN in experimental mechanics is to analyze DIC data. DIC is a powerful full-field measurement tool to analyze local displacement and strain distribution [15]. Many advanced DIC techniques like q-factor-based DIC [72] and augmented-Lagrangian DIC [73,74] were developed to increase the accuracy, efficiency, and robustness of strain field calculation. Recently, Yang et al. [75] showed the pretrained CNN-based DL algorithms from synthetic data can accurately predict end-to-end measurement of displacement and strain fields from experimental speckle images. CNNs were also used by Espinosa and coworkers in the study of cell morphology upon biomolecular delivery into cells using localized electroporation [76] and the localization of single cells within a population for single-cell gene editing [77].

2.4 Recurrent Neural Networks. Recurrent neural networks are a type of NNs that have been successfully used for processing sequential datasets such as natural language [57]. Unlike feedforward NNs, RNNs can retain information about previous inputs. One of the seminal RNNs models is long short-term memory (LSTM) networks [78], which were developed to solve the vanishing gradient problem for simple RNNs. RNNs have been widely applied in a variety of applications, such as speech recognition, machine translation, and natural language processing. In solid mechanics applications, RNNs have been used in structural health monitoring, such as crack path detection. For example, in Buehler's group,

LSTM models were trained based on atomistic simulations to predict the fracture patterns of crystalline solids [79] and 2D materials [80,81]. Furthermore, RNNs have been successfully applied to model solids with plastic behaviors due to their capability to deal with time-dependent data. For example, Mozaffar et al. [82] applied RNNs to model path-dependent plasticity for complex microstructures.

2.5 Graph Neural Networks. Graph neural networks [83] are a type of ML method that is usually employed on graph-structured data, which can be considered as a collection of nodes and edges. The nodes represent entities, and the edges represent the relationships between the entities. Therefore, GNNs are well-suited for handling problems where the relationships between entities are abstract, nonsequential, and highly interconnected. GNNs have been successfully applied to a broad range of applications, including recommender systems [84], social networks [85], drug discovery [86], material property prediction [87], and protein nature frequency prediction [88]. In solid mechanics, GNNs have been employed to characterize and design complex mechanical materials and structures based on the graph representation of their microstructure and/or crystallography. For example, Guo and Buehler [89] applied GNNs to design architected material through a semisupervised approach. Xue et al. [90] developed a GNNs-based framework to predict the nonlinear dynamics of soft mechanical metamaterials. Hestroffer et al. [91] applied GNNs to predict mechanical properties like stiffness and yield strength of polycrystalline materials. Thomas et al. [92] employed GNNs to represent fatigue features in polycrystalline materials and predict high-cycle fatigue damage formation.

2.6 Generative Adversarial Networks and Conditional Generative Adversarial Networks. Generative adversarial networks and conditional generative adversarial networks are ML algorithms initially used in the field of computer vision, like image generation. GANs consist of two NNs, a *generator*, and a *discriminator*, trained simultaneously in a game-theory-based framework to generate new synthetic datasets that mimic the original datasets [93]. First, the generator creates new data from random Gaussian noise. Then, the discriminator evaluates if the generated data is true or false. The training finishes when a Nash equilibrium [94] is reached, where the generator produces authentic data that the discriminator could not identify as fake. Therefore, GANs can be a promising ML algorithm for training data generation and augmentation in solid mechanics, such as generating synthetic structures of metamaterials, which can be used for simulations and experiments. For example, GANs were applied to generate complex architected materials, among which many of them have extreme mechanical properties without prior knowledge [95]. Similarly, GANs were used to generate three-dimensional (3D) microstructures from 2D sliced images, which are as authentic as real microstructures of battery electrodes [96]. While GANs have shown tremendous success in data augmentation, there are some common limitations, such as mode collapse and training instability [97], which need attention to generate high-quality synthetic data. Besides careful hyperparameter tunning, one possible solution is to introduce physics-informed constraints during training. For instance, in the context of microstructural generation, incorporating statistical information, such as geometry descriptors [98], as a constraint can help ensure that the generated structures adhere to certain physical properties.Conditional generative adversarial networks are an extension of GANs where data generation is conditioned on additional inputs or labels [99]. Beyond its data generation capability, cGANs can also be used for image-based end-to-end mapping and inverse problems, such as topology optimization [100]. Applying cGANs to inverse problems enables the generation of solutions that are consistent with the desired properties. cGANs have been applied to image-to-image transitions like image inpainting [101] or image semantic segmentation [102]. In Solid Mechanics, cGANs have been employed to inversely identify the material modulus map while employing strain/stress images [47] or predict strain and stress distributions in composites [103,104]. Furthermore, cGANs have been successfully applied to experimental data inpainting when partial experimental data is missing [70].

2.7 Reinforcement Learning. Reinforcement learning is a type of ML technique in which an agent learns to make the optimum decisions by interacting with its environment to achieve a specific goal [105]. During the training, the agent receives feedback in the form of rewards or penalties based on its actions, enabling it to adjust its time-dependent behavior to maximize the cumulative reward. Therefore, there are three important aspects of RL: agent, environment, and reward. The RL methods can be categorized into value-based methods, policy-based methods, and actor-critic methods. Recent advances in deep reinforcement learning (DRL) [106] have further expanded the capability of RL for sophisticated optimization tasks. Common DRL algorithms include deep Q-networks [107] and deep policy gradient [108]. DRL has been widely used in game playings, such as AlphaGo [109], autonomous robotics [110], chemical design [111], and fluid flow optimization [112]. As its application in solid mechanics, RL has been employed in a wide range of optimization tasks, such as materials design and structural optimization. In materials design, the geometry and material parameters can be considered as the agent, and the desired mechanical responses, like the stress–strain relationship, can be considered as the environment. By sampling the design space, the agent can receive a reward when the structure reaches the desired properties. For example, Sui et al. [113] applied deep Q-networks to design biphasic materials based on desired homogenized properties. More recently, Nguyen et al. [114] developed a DL method by combining GANs and RL to generate realistic three-dimensional microstructures with user-defined structural properties.

2.8 Bayesian Inference. Bayesian inference, named after Thomas Bayes, is a statistical method that allows us to quantify the uncertainty of unknown parameters based on observed data [115]. The fundamental concept of Bayesian inference involves integrating prior knowledge about an unknown parameter with the likelihood of the observed data given that parameter to generate the posterior probability distribution. In contrast to ML methods that focus on identifying the optimal model parameters, i.e., the maximum likelihood estimate, Bayesian inference provides a comprehensive description of the uncertainty surrounding the parameters, allowing for robust uncertainty quantification. However, Bayesian inference also has certain drawbacks. First, the selection of prior distribution can be subjective and may influence the results, especially in the case of limited data. Second, computational cost can be intensive, especially for high-dimensional spaces, as it involves sampling and computing likelihood across the entire parameter space. Despite these challenges, Bayesian inference has been widely used in various fields, such as finance, environmental science, signal processing, and healthcare. In solid mechanics, Bayesian inference has been widely used to identify material parameters and quantify their uncertainty from various experimental data, such as uniaxial stress–strain data [116], force-indentation depth data from nano-indentation [117], and resonance frequency data from resonant ultrasound spectroscopy [118,119].

2.9 Physics-Informed Neural Networks. Since the landmark paper [60] published by the Karniadakis group in 2019 (arXiv preprint in 2017 [120]), PINNs have played a significant role in scientific ML in engineering and physics disciplines [61]. The fundamental idea of PINNs is to apply a NN to approximate the solution to a physical problem, where the governing physical principles (mathematically expressed by PDEs) are enforced as prior knowledge by penalizing the residuals of PDEs, similar to Refs. [121] and [122]. PINNs have been successfully employed to solve scientific problems in a wide span of engineering disciplines

such as heat transfer [123], fluid dynamics [124–126], wave propagation [127], nano-optics [128], AM [129], and biomaterials [130]. Due to the injection of physical laws into the learning algorithm, PINNs require substantially less amount of data than data-driven neural network approaches to achieve similar predictive capability. For example, in the study on PINNs for fluid dynamics [125], by exploiting several snapshots of the concentration field of passive scalars, PINNs are capable of predicting the velocity and pressure fields. To fulfill the same task in a data-driven approach without integrating fluid mechanics, one may need at least hundreds of paired snapshots of concentration, velocity, and pressure fields as training data. To facilitate the usage of PINNs in the research community, Lu et al. implemented various PINN algorithms in an open-source Python library called DeepXDE [131].

As for the applications in solid mechanics, PINNs have been successfully applied to both forward problems (i.e., solving boundary- and initial-value problems) and inverse problems (e.g., material characterization and defect detection). For example, Henkes et al. [132] employed PINNs to model micromechanics for linear elastic materials. Haghighat et al. [133] applied PINNs to build surrogate models for elastostatics and elastoplastic solids. Bastek and Kochmann [134] employed PINNs to model the small-strain response of shell structures. Zhang et al. [48,49] demonstrated that PINNs could effectively identify the inhomogeneous material and geometry distribution under plane-strain conditions. Though most of the current PINNs frameworks in solid mechanics were demonstrated using generated synthetic data as proofs of concept, these frameworks can be applied to experimental mechanics seamlessly where continuum mechanics theories apply.

2.10 Neural Operators. Neural networks are not only universal approximators of continuous functions [135], but also nonlinear continuous operators [136]. Neural operators are neural network models that learn operators, which map functions to functions, such as differential operators, integral operators, and solution operators for parameterized PDEs. Learning operators is especially important in engineering and physics since many problems involve relationships between functions rather than between parameters. Within the scope of solid mechanics, examples of functions include displacement fields, stress fields, load distributions, stiffness distributions, crack propagation paths, and so on. The Karniadakis group proposed a neural operator architecture called deep operator network (DeepONet) [137]. DeepONet consists of two parts: a branch net to encode the discrete input function space and a trunk net to encode the domain of the output functions. Since then, some other neural operators have been developed [138,139]. For detailed explanations, adequate comparisons among these algorithms, and comparisons between neural operators and PINNs, the readers can refer to the original papers and recent reviews [137,140,141]. It is worth noting that while the original versions of these neural operators are data-driven, physical principles may also be incorporated in a similar way as PINNs, making the neural operators informed by physics in addition to data [142,143]. In the past few years, neural operators have been extensively applied to diverse engineering problems. In solid mechanics applications, neural operators have been successfully used for elastoplasticity [144], fracture mechanics [145], multiscale mechanics [43], and biomechanics [146–148].

3 Applications of Machine Learning in Experimental Solid Mechanics

In this section, we will review recent advancements and applications of ML in experimental solid mechanics, covering a wide range of fields such as fracture mechanics, biomechanics, nano- and micromechanics, architected materials, and 2D materials. Table 1 provides an overview of some detailed applications in these fields, including relevant ML algorithms and representative references.

3.1 Machine Learning For Fracture Mechanics. Since the landmark paper from Griffith in 1921 [179], the century-old discipline of fracture mechanics has been established in advancing a wide range of technological advancements, from airplane structural integrity to novel materials with microscale architectures to biomimicry of natural materials. From an experimental viewpoint, there are applications of material failure we summarize here. The first deals with quantifying material intrinsic fracture properties such as fracture toughness or cohesive laws that enable the transfer of knowledge obtained from laboratory tests to engineering applications, e.g., designing new devices, machines, and structures with unprecedented fracture resistance. The second addresses the identification of nonvisible crack-like defects by providing information such as their location and geometries from non-destructive evaluation data. This enables failure and reliability analysis, carried out to prevent catastrophic failure in service.

Interestingly, ML methods can estimate fracture toughness when it cannot be easily measured using traditional methods, e.g., fracture toughness testing, under quasi-static loading, based on the American Society for Testing and Materials standard. Readers specializing in this subject are referred to a dedicated previous review [180]. Typically, testing samples are machined into specific geometries and dimensions, and a load is applied to the sample to propagate a crack. Then, experimental data such as load, displacement, and crack-tip opening distance are recorded to obtain the fracture toughness based on analytical solutions. Recently, these methods have also been extended to measure the fracture toughness of soft materials like hydrogen [181,182]. However, such analytic solutions are not applicable when testing samples with more complex or irregular geometries and/or material nonlinearities. For example, Liu et al. [149] proposed two ML approaches, decision trees and NNs, to obtain the fracture toughness for microfabricated ceramic cantilevers. The ML models mapped geometry descriptors of cantilevers to their fracture toughness calculated from FEA. As shown in Fig. 2(a_i), when the analytical solution is not accessible due to geometry and material complexity, an ML solution trained from representative and sufficient FEA datasets can overcome these weaknesses and provide accurate fracture toughness with a mean error of 1% (Fig. 2(a_{ii})). Furthermore, with knowledge extraction and transfer techniques, the fracture toughness of samples with 3D complexity can be efficiently predicted from simpler 2D simulations [150].

Beyond the prediction of fracture toughness, ML can be employed to inversely extract cohesive law parameters (assuming its validity) from experimental measurements consisting of load–displacement curves [151,152] or full-field measurements. As previously articulated, the prediction performance can be significantly improved by integrating physical governing laws like equilibrium equations into ML training. For example, Wei et al. [153] proposed a Green's function embedded neural network to extract mixed-mode cohesive zone properties using only far-field displacement data measured from experiments. This method integrates Green's functions as a physical constraint, hence, reducing the amount of training data and increasing the local model accuracy. Furthermore, ML frameworks were developed to model and characterize interfacial behaviors. For example, Liu [183] proposed a deep material network with cohesive layers, which enables accurate modeling of the material interface in heterogeneous materials. Wang and Sun [184] proposed a metamodeling method that employs deep reinforcement learning to model constitutive behaviors of interfaces.

Another important application of ML in fracture mechanics is the crack path prediction, given the crack propagation history. Knowing the crack path is helpful in preventing catastrophic material failure by toughening the material along the path. For example, LSTM-based ML models were trained based on atomistic modeling to predict the fracture patterns of crystalline solids [79] and 2D materials [80,81]. The LSTM model is capable of learning the spatial-temporal relations from an atomic resolution of fracture, hence, it is effective in predicting the crack path. In another application, Goswami et al. [145] developed a physics-informed variational formulation of DeepONet to predict the crack path in

Table 1 Summary of ML applications in experimental solid mechanics

Areas of experimental mechanics	Detailed applications	ML algorithms	Selected references
Fracture mechanics	Fracture toughness	NN, decision trees	Liu et al. [149,150]
		CNN	Jin et al. [70]
	Cohesive parameters	CNN	Jin et al. [70]
		NN	Su et al. [151], Ferdousi et al. [152]
		PINN-based deep-green inversion	Wei et al. [153]
	Crack/flaw detection	PINNs	Zhang et al. [49]
		CNN	Niu et al. [154,155]
	Crack path prediction	LSTM	Lew et al. [80,81]
		DeepONet	Goswami et al. [145]
	Predict fracture instability	Gaussian process regressions	Athanasiou et al. [156]
Biomechanics	Human motion	NN	Komaris et al. [157]
		CNN	Eerdekens et al. [158]
	Constitutive parameters	ResNet, CNN	Holzapfel et al. [159]
		NN	Liu et al. [160]
		PINNs	Yin et al. [130], Kamali et al. [161]
	Surrogate constitutive model	Thermodynamics-based NN	Masi et al. [41]
		Constitutive artificial NN (CANN)	Linka et al. [42]
		DeepONet	Zhang et al. [147], Goswami et al. [162]
		Neural operator	You et al. [148]
	Cell manipulation and analysis	CNN	Espinosa and coworkers [76,77,163,164]
Micro-and nano-Mechanics	Nano-indentation	NN	Muliana et al. [165], Huber et al. [166,167]
		MFNN	Lu et al. [46]
		Bayesian method	Zhang et al. [117,168], Fernandez-Zelaia et al. [169]
	AFM	data-driven NN	Chandrashekar et al. [170]
	Microstructure characterizations	CNN, U-Net	Herriott et al. [171], Sepasdar et al. [172]
		Random Forest statistical algorithm	Bulgarevich et al. [173]
		cGAN	Ni et al. [47], Yang et al. [103]
Architected materials	Verify computational design	CNN, Auto-encoder	Alderete et al. [174]
		CNN, ResNet	Ma et al. [175]
	Training data generation	GAN	Mao et al. [95], Hsu et al. [176]
		GNN	Guo et al. [89]
2D materials	MD force-field parameterization	Multi-objective optimization algorithm	Zhang et al. [177]
	Fracture toughness	Integrated experiment-simulation framework	Zhang et al. [178]

quasi-brittle materials by mapping the initial crack configuration to the damage and displacement fields. More recently, Worthington and Chew [185] applied NNs to predict the crack path of heterogenous materials by mapping the crack process zone information to the possible crack growth directions based on FEA training employing a micromechanics fracture model. It is also important to mention that current ML applications for crack path prediction are primarily trained and validated using computational datasets obtained from FEA or MD simulations. Thus, it remains uncertain how these methods would perform when applied to real experimental data. In the future, it is necessary to obtain high-fidelity crack propagation data from advanced diagnostic imaging techniques such as in situ computed tomography [186,187] or in situ electron microscopy experiments [188–192]. This approach will enable researchers to validate and improve the current ML framework for crack path prediction.

When predicting dynamic fracture toughness under ultrahigh loading rates, the conventional experimental measurement of load–displacement is not accessible. To this end, Jin et al. [70] proposed an ML-assisted big-data-generating experimental framework that can accurately measure the dynamic fracture toughness and cohesive parameters of samples from plate impact experiments. As shown in Fig. 2(b_i), a cohesive law identification experiment was developed using plate impact, a target polyurea sample containing a half-plane midcrack, and a novel spatial-temporal interferometer that generates fringes associated with the sample rear surface motion history. By employing a physics-based data-driven method, using FEA, a CNN was trained to correlate the fringe images with corresponding cohesive law parameters. After the CNN was well-trained, polyurea's dynamic fracture toughness and cohesive parameters were successfully identified from the experimental fringe image (Fig. 2(b_{ii})). This big-data-generating experiment framework can be easily extended to other mechanics problems under extreme conditions, such as stress wave-induced phase transformations, shear localization, and others where conventional measurement methods are not applicable. Furthermore, uncertainty quantifying of dynamic fracture properties in inhomogeneous materials, e.g., composites, is crucial. Sharma et al. [193] developed an ML framework bridging limited experimental data from advanced experimental techniques and data-driven models like Monte Carlo simulation to quantify the uncertainty of the dynamic fracture toughness of glass-filled epoxy composites.

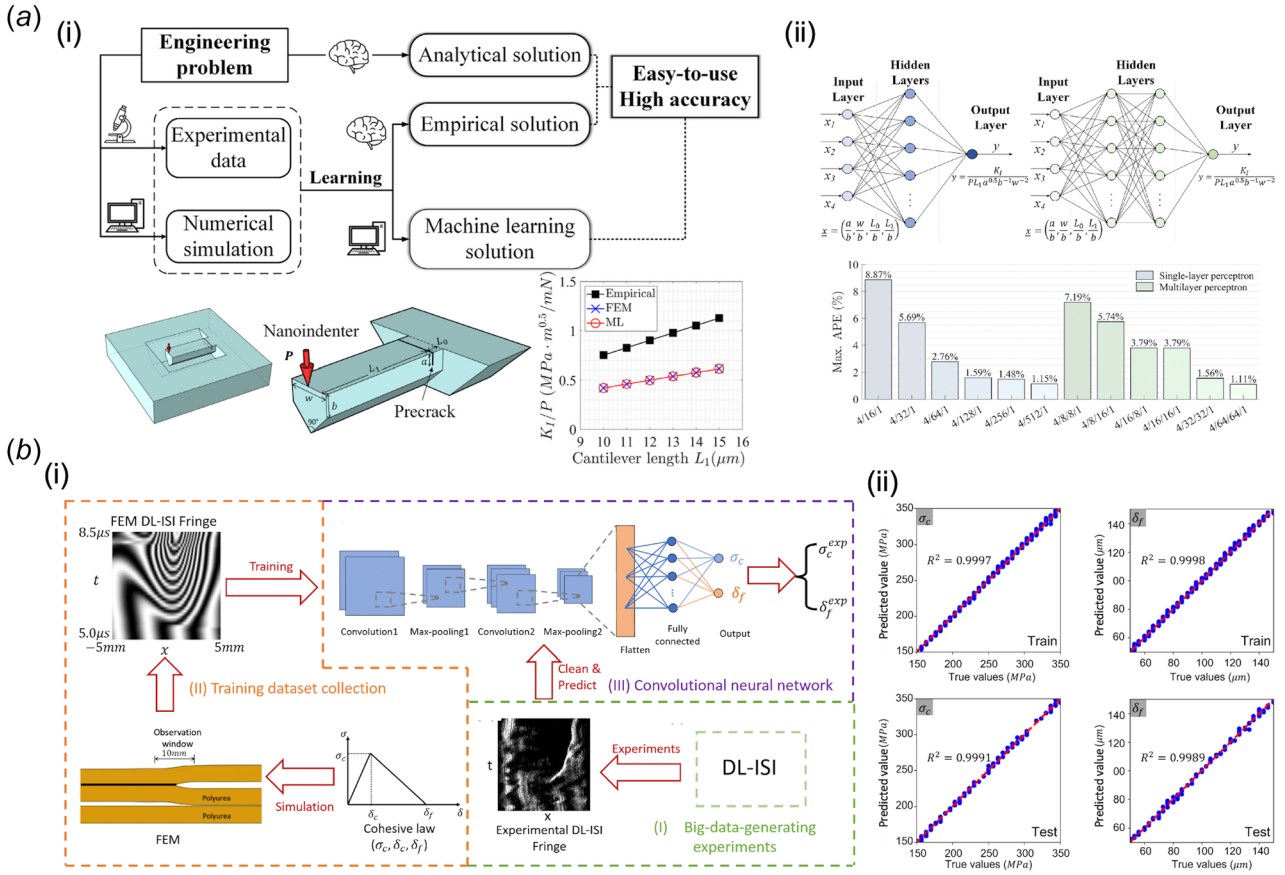

Fig. 2 Applications of ML in characterizing fracture cohesive properties. (*a*) ML solutions can predict accurate fracture toughness comparable to simulations when an analytical solution is not available due to sample complexity: (i) ML framework for engineering problems; (ii) NNs-based prediction of fracture toughness (Reproduced with permission from Ref. [149]. Copyright 2020 by Elsevier). (*b*) A CNN-based DL algorithm can accurately determine dynamic fracture toughness and cohesive parameters under ultrahigh strain rate loading: (i) DL framework for cohesive parameter inversion from dynamic *big-data-generating* plate impact experiments; (ii) comparison between predicted cohesive parameters and ground-truth. (Reproduced with permission from Ref. [70]. Copyright 2022 by Elsevier).

Beyond fracture properties identification, ML is also effective in predicting internal crack/flaw geometry and locations from experimental measurements. For example, Zhang et al. [49] applied PINNs to identify internal cracks in linear and nonlinear solids (Fig. 3(*a*)). As shown in Fig. 3(a_i), the framework uses the external boundary conditions as "sensors" to inversely identify internal cracks in the presence of deformation. More importantly, the PINNs framework directly integrates the underlying physics, such as material compressibility and equilibrium equations, into the loss function (Fig. 3(a_{ii})), hence, significantly reducing the amount of data required during training while achieving high prediction accuracy (Fig. 3(a_{iii})). Using this PINNs method, the cracks in nonlinear solids, e.g., exhibiting elastoplastic behaviors, can also be accurately identified [194]. Moreover, by employing a similar PINNs framework, other material properties like modulus distribution were inferred [48]. To predict material strength in solids with microcracks, Xu et al. [195] trained an ML framework that maps the crack distribution morphology to the strength calculated from micromechanics theory. This framework can effectively predict the strength of solids with randomly distributed microcracks. ML can also be used with nondestructive measurement methods to characterize internal cracks without the application of deformations. For example, Niu and Srivastava [154,155] used FEA-trained CNN to accurately identify internal cracks from ultrasonic measurements (Fig. 3(b_i)). Impressively, the simulation-trained CNN can make predictions of crack shape and locations, based on experimental data, with a mean average percentage error of about 5% (Fig. 3(b_{ii})). The accuracy of the prediction can be attributed to the fact that FEA can effectively simulate ultrasonic wave propagation processes. There is evidence that the method could potentially be extended to biomedical engineering applications, e.g., the identification of cancer tumors in soft breast tissue.

3.2 Machine Learning For Biomechanics. Biomechanics is an important research field addressing the mechanics of biological systems, including organs and tissues [196]. One important research topic in biomechanics is the understanding of human movement by analyzing motion data from sensors. Comprehensive and massive data have been collected over the past decades, including videos of human motion kinematics, force/displacement data from wearable devices like flexible electronics, and images obtained from computed tomography and magnetic resonance imaging. Understanding these data and developing applicable biomechanical models can guide the design of new devices and technologies to address body-related issues, e.g., predicting injury risk in sports and developing advanced medical devices. Recently, ML has been widely applied for data analysis from wearable sensors [197]. For example, Komaris et al. [157] successfully trained NNs based on a public dataset of 28 professional athletes to estimate the runner's kinetics. Eerdekens et al. [158] employed a CNN-based ML model trained from accelerometer data to understand equine activity. Recent reviews [198–201] have extensively surveyed the application of ML in this area. Therefore, in this subsection, we focus on reviewing ML applications in experimental biomechanics for characterizing and modeling biological materials such as tissues.

Another important ML application in biomechanics is cellular manipulation [202], the readers are referred to a recent review paper [163] for details.

Most biological tissues, such as blood vessels and brain matter, are soft materials. Their surface can easily form multimode instability, i.e., *Ruga* morphologies [203–206], under external loading. For example, Jin et al. [204] performed FEA and experiments to systematically understand the surface instability and postbifurcation phenomenon of soft matter containing orifices, e.g., arteries, when subjected to external pressure. Furthermore, many of these materials are anisotropic, i.e., their mechanical responses are dependent on the loading direction. Therefore, characterization of these materials using well-planned experiments as well as identification of constitutive models are needed to understand and predict their mechanical behaviors. In turn, the information can be used in the investigation of disease and the

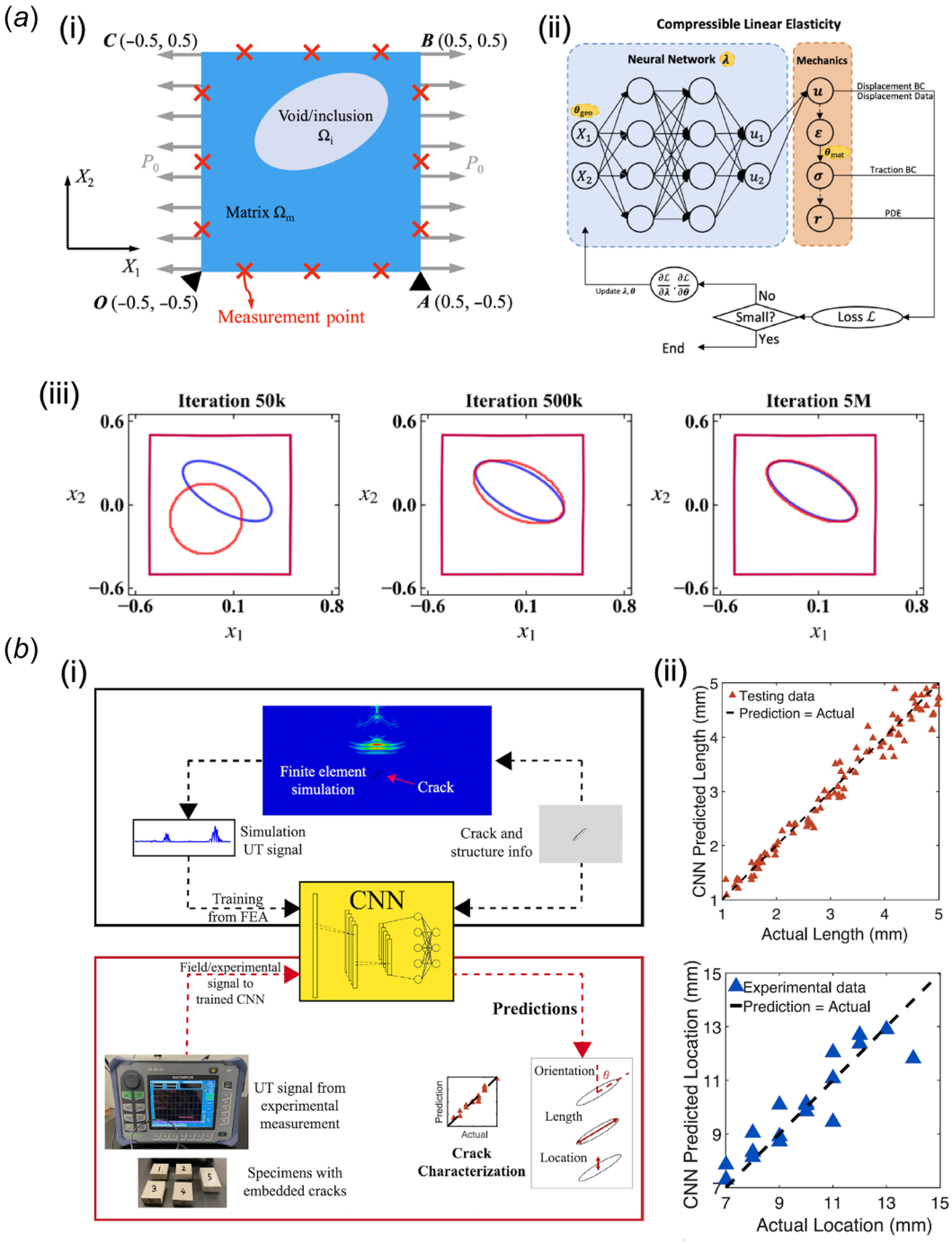

Fig. 3 Applications of ML in crack/flaw detection. (*a*) PINNs can identify internal voids/inclusions for linear and nonlinear solids: (i) general setup for geometric and material property identification; (ii) architectures of PINNs for continuum solid mechanics. (iii) inference of deformation patterns under different training epochs (Reproduced with permission from Ref. [49]. Copyright 2022, The authors, published by AAAS). (*b*) FEA simulation-trained CNN was used to determine crack locations and geometry in experiments: (i) proposed CNN architecture, (ii) CNN predicted crack property compared to ground-truth (Reproduced with permission from Ref. [154]. Copyright 2022 by Elsevier).

design of artificial organs. Many historical models have been developed to characterize various biomaterials, such as the neo-Hookean model [207], Ogden model [208], Fung-type model for blood vessels [209], and Holzapfel–Gasser–Ogden (HGO) model [210] for anisotropic biomaterials. However, identifying these constitutive parameters from experimental data typically requires extensive nonlinear FEA and sophisticated optimization algorithms [211–213]. ML can help infer material parameters from limited experimental data with multimodality, such as mechanical testing and microstructure data obtained from images. For example, Liu et al. [160] developed an ML framework to identify the HGO constitutive parameters of aortic walls based on synthetic microstructural data. Kakaletsis et al. [214] compared the parameter identification accuracy from an iterative optimization framework and a stand-alone NN for isotropic and anisotropic biomaterials. Results suggest that replacing FEA with Gaussian process regression or NN-based metamodels could accelerate the parameter prediction process while replacing the entire optimization process with a stand-alone NN yielded unsatisfactory predictions. Recently, Holzapfel et al. [159] developed a hybrid DL model based on a residual network (ResNet) and CNN to infer three unknown material parameters for a modified HGO model [215] (Fig. 4(a_i)). This ML model maps second-harmonic generation microstructure images, representing the orientation and dispersion of collagen fibers, to their mechanical stress–strain data for a total of 27 artery samples. By employing this hybrid ML model, the coefficient of determination, R^2, was 0.97, while conventional least square fitting gave $R^2 = 0.676$ with a much larger standard deviation (Fig. 4(a_{ii})). The exceptional high-accuracy prediction achieved from a limited biomechanics dataset can be attributed to two factors. First, the multimodal nature of the dataset allows for the inference of material parameters beyond the conventional stress–strain data. Second, a priori knowledge of theoretical constitutive laws also contributes to reducing the necessary dataset size. As the authors suggested, expanding the experimental datasets and incorporating biaxial extension experiments are required to validate these results. This research could have a transformative impact on soft tissue constitutive modeling, i.e., modeling soft tissues using prior physics laws and limited but multimodal experimental datasets.

Recent advances in PINNs provide a promising alternative in constitutive parameter identification for biomaterials by encoding the underlying physics. As shown in Fig. 4(b_i), Yin et al. [130] employed PINNs to infer the permeability and viscoelastic modulus of the thrombus. The interaction between thrombus and blood flow can be described by sets of PDEs like Cahn–Hilliard and Navier–Stokes equations. The parameters can be accurately identified by encoding these governing physics during the PINNs training (Figs. 4(b_{ii}) and 4(b_{iii})). Their results also demonstrated that PINNs could infer material properties from noisy data exhibiting complexity. Recently, Kamali et al. [161] implemented PINNs to accurately identify Young's modulus and Poisson's ratio for heterogeneous materials like brain matter. This method has potential clinical applications, e.g., noninvasive elastography.

Recently, a data-driven computation framework for constitutive modeling was proposed by Ortiz and coworkers [216–219]. In this framework, a data-driven solver directly learns the mechanical

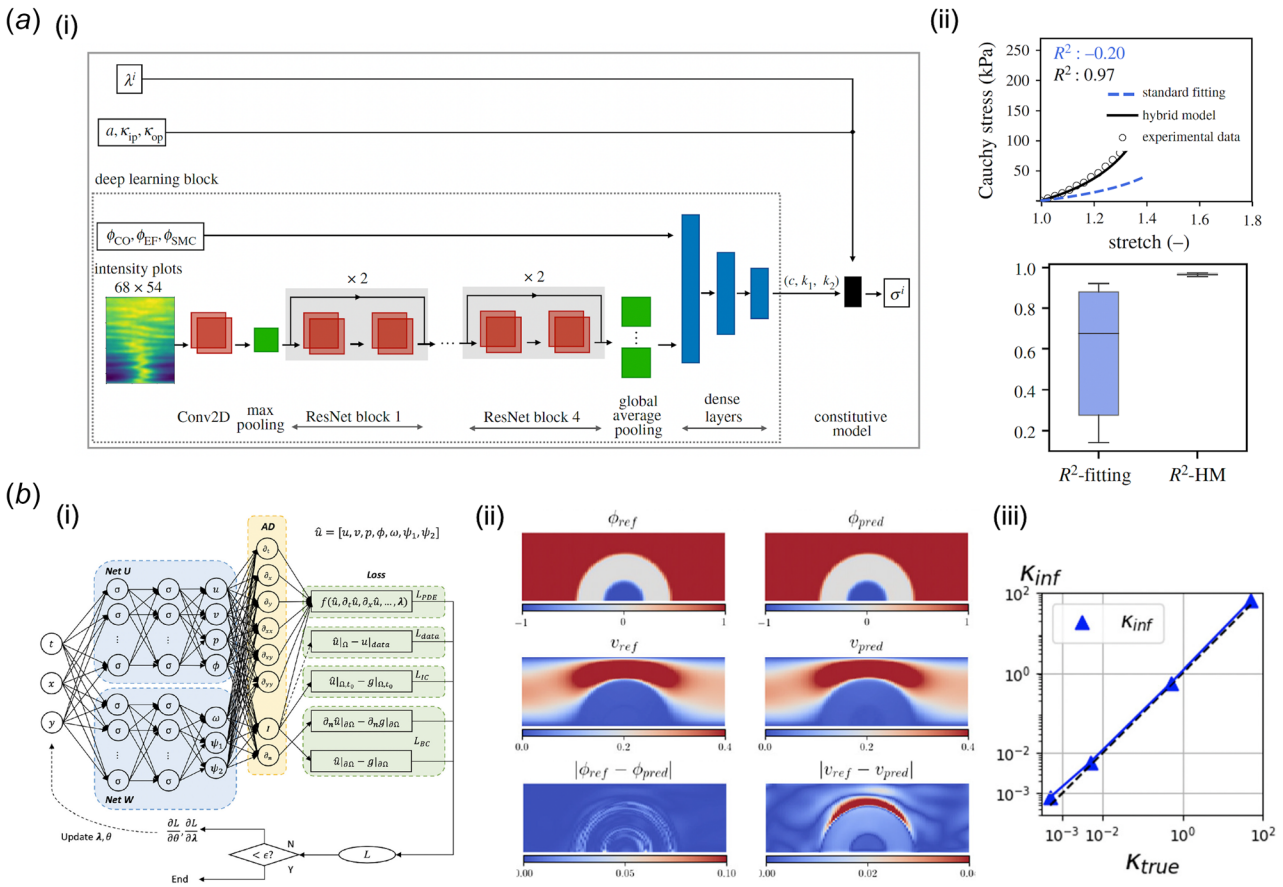

Fig. 4 Applications of ML in constitutive parameter inversion for biomaterials. (*a*) A hybrid DL framework to identify unknown material parameters of arteries with high coefficient of determination: (i) hybrid model architecture; (ii) predicted stress–stretch curves from standard fitting method compared to the proposed hybrid model. (Reproduced with permission from Ref. [159]. Copyright 2021, The authors, published by the Royal Society). (*b*) Noninvasive inference of thrombus material parameters using PINNs: (i) schematic of PINNs for solving inverse problem; (ii) prediction and ground-truth of 2D flow around a thrombus; (iii) comparison of the inferred permeability of 2D flow with the ground-truth. (Reproduced with permission from Ref. [130]. Copyright 2021 by Elsevier).

responses of materials from experimental data, which eliminates the need for complex empirical constitutive modeling. In this approach, NNs can be employed to build surrogate models of biomaterials for constitutive modeling [220,221]. For example, Linka et al. [42] developed a constitutive artificial NN to learn the constitutive models for hyperelastic materials directly from given stress–strain data. Masi et al. [41] introduced a thermodynamics-based NN for constitutive modeling by coupling thermodynamics laws as constraints during training. Li and Chen [222] developed an equilibrium-based CNN to extract local stress distribution based on DIC strain measurements performed in hyperelastic materials. Wang et al. [223] developed an ML algorithm based on singular value decomposition and a Gaussian process to build metamodels of constitutive laws for time-dependent and nonlinear materials. This metamodeling method can be used to determine sets of material parameters that are best fit for experimental data. In another investigation, Liu et al. [224] developed a physics-informed neural network material model to characterize soft biological tissues. Their model consists of a hierarchical learning strategy by first learning general characteristics for a class of materials and then determining parameters for each individual case.

Neural operators can also be employed to build data-driven surrogate models for constitutive modeling of biomaterials due to their advantage of generalizability and prediction efficiency for different inputs. For example, as shown in Fig. 5(a_i), Zhang et al. [147] developed a DeepONet-based model, genotype-to-biomechanical phenotype neural network (G2Φnet), to characterize mechanical properties of soft tissues and classify their associated genotypes from sparse and noisy experimental data. With a two-step training process consisting of a learning stage and an inference stage with an ensemble, G2Φnet could effectively learn the constitutive models from biaxial testing data for 28 mice with four different genotypes with an L2 error of less than 5% (Fig. 5(a_{ii})). Interestingly, it could also identify the correct genotype. This DL framework has important implications in biomechanics and related clinical applications, which is learning relationships between genotype and constitutive behaviors in biological materials from limited experimental data. Yin et al. [146] employed DeepONet to build a data-driven surrogate model that could predict the damage progression of heterogeneous aortic walls. Goswami et al. [162] developed a DeepONet-based surrogate model to identify pathological insults that could lead to thoracic aortic aneurysms from a synthetic FEA database. More recently, You et al. [148] employed a Fourier neural operator-based method to model mechanical responses of soft tissues under different loading conditions directly from experimental data (Fig. 5(b_i)). The proposed physics-guided implicit Fourier neural operator architecture is shown in Fig. 5(b_{ii}). This method learned the material deformation model from DIC measurements and could predict the displacement field under unseen loading conditions with errors smaller than those ascertained in conventional constitutive models for soft tissues (Fig. 5(b_{iii})).

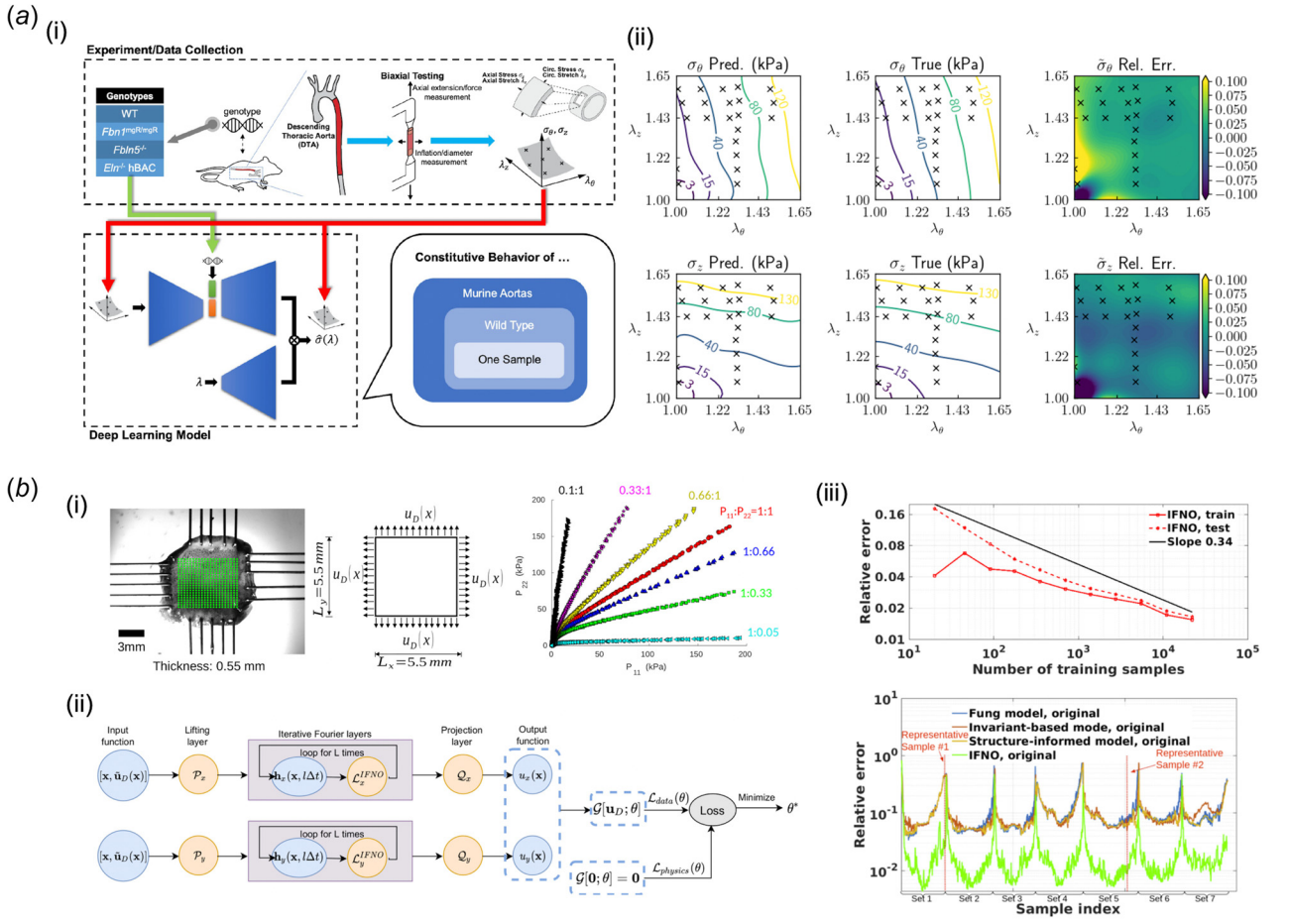

Fig. 5 Applications of neural operator in constitutive modeling of biomaterials. (*a*) A DeepONet-based DL framework to infer biomechanical response and associated genotype of tissues: (i) the DL framework; (ii) reconstructed stress–stretch relationships compared with their true values (Reproduced with permission from Ref. [147]. Copyright 2022, The authors, published by PLOS). (*b*) A neural operator model to construct the mechanical response of biological tissues from displacement data measured from DIC: (i) the biaxial experimental setup; (ii) the architecture of the physics-guided Fourier neural operator; (iii) error comparisons of proposed Fourier neural operator method and other mechanics models (Reproduced with permission from Ref. [148]. Copyright 2022 by ASME).

3.3 Machine Learning For Micro- and Nano-Mechanics. The emerging development of nanotechnology and biotechnology in recent decades continuously requires a new understanding of micro- and nanoscale material behaviors. For example, much research has been conducted on understanding the mechanical properties of nano-and micropillars [225–227], thin films [228–233], nanostructured metals [27,226,234–237], submicron-sized sensors [238], crystalline nanowires [188,239–241], 2D materials [178,242–246], origami [247], nanolattice metamaterials [248–250], and copolymers with nanoscale features [70,251–253]. Conducting precise experiments to characterize these materials with small-scale features is essential to understand their properties and underlining mechanisms and developing constitutive models. There are two major steps in this process. First, experimental measurements are taken from instrumentations with nanometer resolution. Advanced microscopes, including scanning electron microscope (SEM), transmission electron microscope (TEM), and atomic force microscope (AFM), have been developed to capture images with nanometer resolution. Furthermore, nanomechanical instruments, like nano-indenters and MEMS, have been developed for nano-mechanical characterization. Next, the properties of interest can be extracted from measurements via inverse algorithms. However, compared to macroscale samples, the interpretation between measurable data and material properties is not straightforward because the samples contain nanoscale features due to local inhomogeneity [254,255], size effect [231,256], or chemomechanical coupling [257]. For example, in instrumented indentation [258,259], identifying the material properties from measured load and indentation depth data is nontrivial and sometimes may not guarantee unique solutions when the material constitutive law is elastoplastic [260,261] or the indentation tip has a conical shape [262]. Therefore, there is a critical demand to identify material properties and quantify their uncertainty using nanomechanical experiments. Due to the popularity and accessibility of nano-indentation data, ML has been widely applied to such data. Hence, in this section, we review two methods used in interpreting nano-indentation data: the NN approach and the Bayesian-based statistical approach. We note that the methods are also applicable to other nanomechanical experiments, such as the membrane deflection experiments [263] and in situ, microscopy testing using MEMS technology [11], which provides direct measurement of stresses and strains. Finally, ML applications to other nano-and micromechanics features, e.g., microstructure characterization, will be briefly reviewed.

For using the NNs method to identify material properties in nanoindentation, most of the training is based on FEA due to its flexibility and efficiency. Indentation, a well-defined contact mechanics problem, can be accurately simulated in either commercial FEA software or in-house codes [264,265]. In 2002, Muliana et al. [165] trained a neural network with hidden layers based on 2D and 3D FEA simulations to map nonlinear material properties from simulated load–displacement curves. They found that the trained NN can accurately predict the load–displacement curves of materials with properties not included in the training dataset. This work demonstrated the potential of using NNs to inversely obtain unknown material properties from experimental data. Huber et al. [166,167] used FEA-trained NNs to identify the Poisson's ratio of materials exhibiting plasticity with isotropic hardening, something not easily obtained before. Since then, FEA-trained NNs have been widely applied as an inverse algorithm to identify material properties from nanoindentation [266–275]. However, in practice, these FEA-trained NNs could be cumbersome since they require a substantial amount of FEA training data to survey combinations of material properties within specific ranges. Such a training process is generally computationally expansive, especially when the unknown parameter space is large. Furthermore, the trained NNs usually have poor extrapolation performance, i.e., when material properties are outside the range used in the training dataset. Another issue in this approach is the lack of uncertainty quantification when identifying properties from datasets based on FEA. To overcome these challenges, Lu et al. [46] utilized a multifidelity NN (MFNN) [276], which trained low-fidelity FEA datasets together with a few high-fidelity experimental datasets together (Fig. 6(a_i)). As shown in Figs. 6(a_{ii}) and 6(a_{iii}), the MFNN can efficiently learn the correlations between these two datasets with different fidelities, hence significantly increasing the identification performance while reducing the size of FEA training datasets. The MFNN performance can be further improved by employing transfer learning when additional experimental data are obtained.

The NN method can identify unknown material parameters from indentation data as explained above. However, this method could not systematically quantify the uncertainty of identified parameters, i.e., yielding the likelihood that other possible parameter sets also minimize the cost function. The Bayesian method, which was derived based on Bayes' theorem [277], can be employed to quantify uncertainty in nanoindentation since it can provide a posterior probability for each set of parameters. For example, Fernandez-Zelaia et al. [169] utilized the Bayesian framework to identify unknown material parameters from an FEA-trained Gaussian process surrogate model using spherical indentation experiments. The Bayesian framework has also been employed to identify unknown properties from the spherical indentation of single crystal [278], plastic solids with exponential hardening laws [279], and plastically compressible solids with Deshpande–Fleck constitutive laws [168]. For the case of conical indentation, which is similar to experiments using a Berkovich indenter, the indentation force versus indentation depth (P-h) data sometimes could not yield unique sets of unknown parameters. To solve this issue, as shown in Fig. 6(b_i), Zhang et al. [117,280] employed a Bayesian framework to extract plastic properties and quantify the uncertainty from both P-h curves and surface profile datasets obtained from FE simulations (Fig. 6(b_{ii})). Furthermore, as shown in Fig. 6(b_{iii}), the posterior probability for possible material parameters could be calculated from both noise-free and noise-contaminated datasets. Later, Zhang and Needleman [281] applied the Bayesian framework to infer power-law creep constitutive parameters considering both the time-dependent indentation depth data and the residual surface profile. Though this framework was developed based on synthetic data from simulations, the parametric identification from the Bayesian approach offers valuable insights into uncertainty quantification resulting from nanoindentation experiments performed on materials with complex constitutive behaviors.

To understand the mechanical properties of soft materials such as biological tissues [282] and cells [163], one can conduct nano-indentation tests using AFM signatures based on high-resolution force detection and cantilever tip position obtained from a four-quadrant position-sensitive photodiode [283,284]. For example, Rajabifar et al. [285] trained a multilayer NN to predict surface viscoelastic and adhesive properties of samples based on load–displacement curves obtained from AFM tapping mode. They generated the training data from a rigorous contact mechanics model, known as the enhanced Attard's model [286]. Here also, ML can be employed to extract the nanoscale force without complex modeling. For example, Chandrashekar et al. [170] used a data-driven ML algorithm to capture the tip-sample force in dynamic AFM. The algorithm was also used to successfully identify the interaction forces for two-component polymer blends. Furthermore, the material parameter identification from AFM indentation data inherently involves uncertainty, which depends on the choice of contact mechanics model. To mitigate this uncertainty in modulus identification, Nguyen and Liu [287] employed five conventional supervised ML techniques (decision trees, K-nearest neighbors, linear discriminant analysis, Naïve Bayes, and support vector machines) to classify AFM indentation curves for different materials into appropriate contact mechanics models. By choosing the appropriate contact mechanics model, the uncertainty of modulus identification can be potentially reduced.

Another important ML application for nano-and micromechanics is microstructure characterizations [69,288–291]. Since the rapid advances of high-resolution imaging techniques, ML algorithms

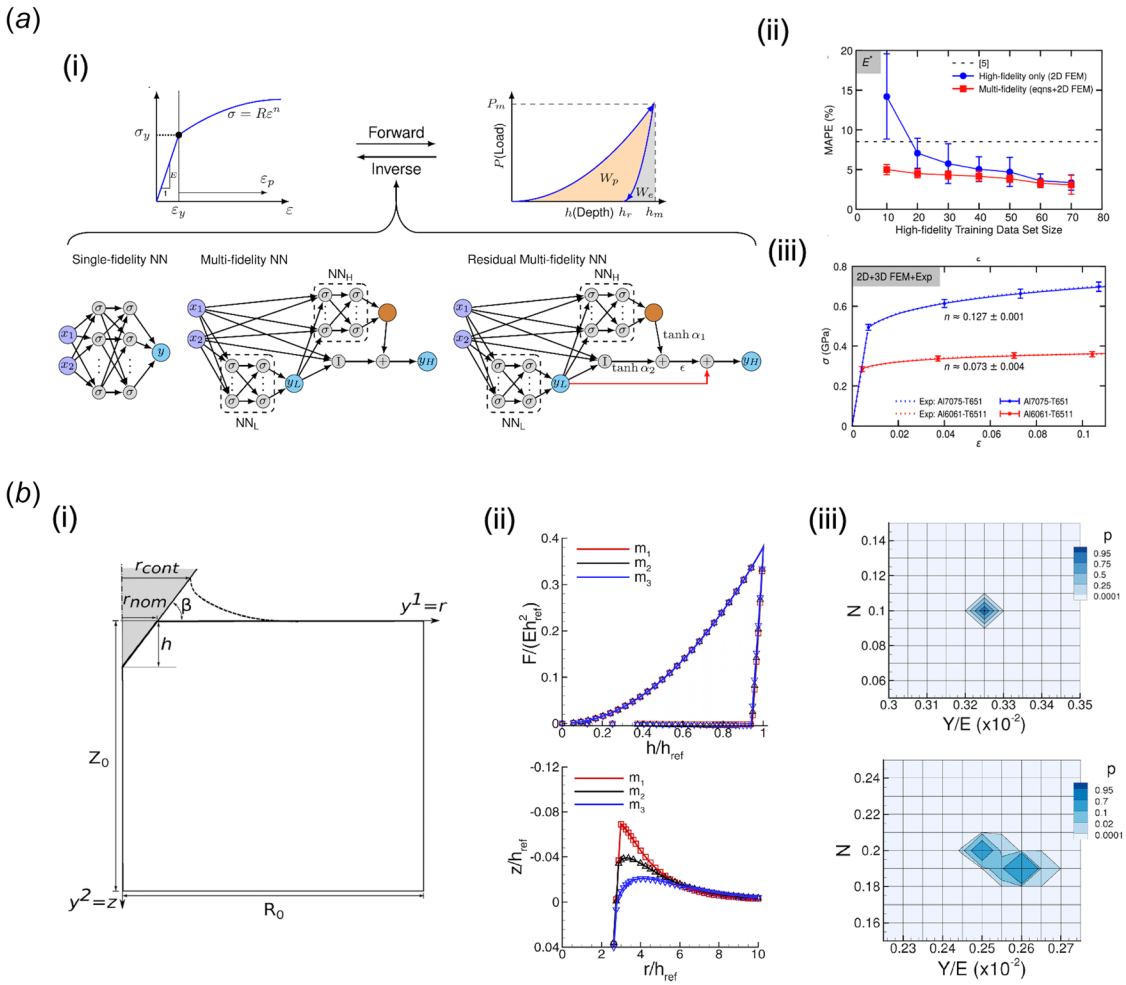

Fig. 6 Applications of ML in nano-indentation. (*a*) DL methods including single-fidelity NNs, multifidelity NNs, and residual multifidelity NNs to identify material parameters from instrumented indentation: (i) architectures of these NNs; (ii) Mean absolute percentage error as a function of training dataset size for multifidelity NNs; (iii) identification of hardening exponent for two aluminum alloys from 2D, 3D FEA simulations and three experimental data points (Reproduced with permission from Ref. [46]. Copyright 2020, The authors, published by PNAS). (*b*) A Bayesian-type statistical approach to identify material parameters and their uncertainty from conical indentation: (i) schematics of indentation configuration with conical tips; (ii) force-indentation depth curves and surface profiles for three different materials; (iii) posterior probability distribution of parameters with and without noisy data (Reproduced with permission from Ref. [117]. Copyright 2019 by ASME).

like CNNs have been increasingly applied to microstructure characterizations. For example, ML can be employed in microstructural image segmentation to identify individual grains or phases [292–295]. Additionally, ML can be applied to detect defects such as cracks based on microstructural images [173] as well as predict unknown material properties like yield strength [171] based on microstructure features such as grain size, orientation, and crystallographic features. Furthermore, ML can be applied to analyze evolving microstructure images to analyze time-dependent material behaviors during fracture [296,297], recrystallization [298], phase transformations [299], and cell morphology [76,77,163,164]. These ML applications in microstructure characterizations could enable rapid and accurate analysis of complex material microstructures, leading to developing of next-generation materials with desired properties.

3.4 Machine Learning For Architected Materials. Recently, the concept of *materials by design* has enabled us to design multifunctional materials with unprecedented properties. Such progress can be attributed to the rapid development of computational tools for structural design and experimental techniques for the synthesis and characterization of materials [21,300]. Among these novel materials, architected metamaterials, which combine the properties of material constitutes and architectural design, have demonstrated their superior mechanical properties like ultrahigh specific strength [301], excellent recoverability [250,302], and impact resilience [303]. Along this line, ML is becoming an important tool to systematically design these novel architected metamaterials with desired properties and functionality beyond laboratory trial-and-error [45,304–311]. Comprehensive review papers have been published in recent years that reviewed and discussed the methodology and applications of ML in architected material design [33,38,312,313]. Herein, in this subsection, we will focus on reviewing recent advances in experimental efforts in ML-enabled design of architected materials.

One significant aspect of experimental mechanics in architected materials is to verify the predicted power of computational methods used in the inverse design. Given the formidable challenges associated with cost and speed for the acquisition of large-scale experimental data sets, most of the current ML frameworks in material discovery were trained based on big datasets from reliable physically based computer simulations. Therefore, careful verifications from experiments are necessary to assess the ML framework's performance in producing real structures/materials with desired

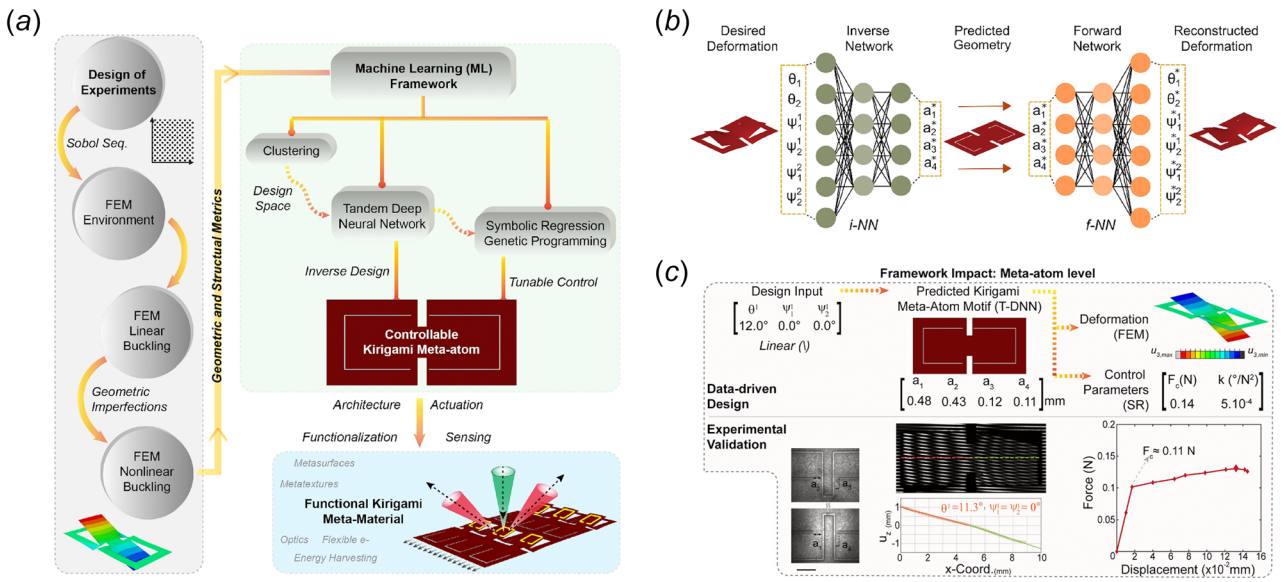

Fig. 7 Applications of ML in designing shape-programmable kirigami metamaterials. (*a*) The ML framework to inverse design kirigami metamaterials. (*b*) Schematics of the tandem network employed for inverse design. (*c*) Experimental verification of inverse design from shadow Moiré method (Reproduced with permission from Ref. [174]. Copyright 2022, The authors, published by Springer Nature).

properties. For example, as shown in Fig. 7(*a*), Alderete and Pathak et al. [174] have proposed an ML framework that combines the K-mean clustering methods for design space reduction and a tandem NN architecture to inversely design shape-programable 3D Kirigami metamaterials. The tandem NN architecture was employed to circumvent the nonuniqueness issue during the inverse design process (Fig. 7(*b*)). The framework was trained on finite element predictions of instabilities triggering 3D out-of-plane shapes and then validated by full-field experimental measurements using the shadow Moiré method [314] (Fig. 7(*c*)). A very good agreement between ML-designed cuts and predicted out-of-plane deformation and experiments was found under mechanical actuation (stretching). Moreover, using symbolic regression, the authors could predict the onset of actuation and needed stretching to achieve specific 3D shapes. These programable 3D kirigami metamaterials can be used in various engineering applications over a large range of size scales, from microscale particle trapping to macroscale solar tracking.

Likewise, ML can also assist in the inverse design of complex functional soft materials. For example, as shown in Fig. 8(*a*), Ma et al. [175] developed a ResNet-based model trained with FEA to inversely design tunable magnetomechanical metamaterials. The ResNet model was chosen due to its capability to preserve information between shallow and deeper layers (Fig. 8(*b*)) [315]. The predicted structures were printed and actuated in the magnetic field and found to be in good agreement with ML predictions (Fig. 8(*c*)). Moreover, GANs can also be employed to design architected structures without prior experience. For example, Mao et al. [95] used GANs to systematically design complex architected materials and found that some structures can reach Hashin–Shtrikman upper bounds. Experimental verification was also conducted by the authors to show the robustness of the framework. Furthermore, due to the stochastic deformation modes of metamaterials like buckling under compression, uncertainty quantification is necessary to design reliable structures. For example, Bessa et al. [316] demonstrated that a data-driven Bayesian ML framework could enable the design of super compressible metamaterials (Fig. 9(*a*)). Experiments on multiscale 3D printed structures (both macroscale and microscale) have also demonstrated the super compressibility predicted by simulations (Figs. 9(*b*) and 9(*c*)).

Another important feature in this field is the ability to conduct high-throughput experiments to generate high-fidelity data needed for ML training. Until now, most of the ML algorithms applied to the inverse design of architected metamaterials have been trained using computer simulations. However, such a computer data-driven approach assumes the model is accurate and readily obtainable. This may not be the case in more complex behaviors arising from material nonlinearities and rate dependencies for which accurate constitutive descriptions do not exist. A solution would be to run autonomous experiments based on a large number of additively manufactured structures/samples to obtain valuable representative data such as stress–strain curves or deformation patterns [317–319]. As such, there is a need to develop new ML frameworks for the inverse design of novel metamaterials directly from large and noisy experimental datasets. For example, Lew and Buehler [320] trained an ML framework called DeepBuckle that combines the variational autoencoder model and LSTM model to quantitatively learn buckling behaviors of polymer beams from simple and limited mechanical testing on 3D printed structures.

3.5 Machine Learning For Two-Dimensional Materials Fracture Toughness Characterization. In the past decades, significant progress has been made in the synthesis of 2D materials such as graphene, hexagonal boron nitride (h-BN), and transition metal dichalcogenides (TMDs), e.g., molybdenum disulfide (MoS_2), including fabrication, chemical functionalization, transfer, and device assembly [321–323]. Therefore, quantifying their mechanical properties, like fracture toughness, is crucial to ensure the durability and reliability of these 2D material devices. Ni et al. thoroughly reviewed the recent experimental, theoretical, and computational progress on quantifying 2D materials' fracture properties [324]. In addition, progress on ML prediction of 2D material fracture, including fracture pattern characterization, was previously discussed. Here, in this subsection, we will focus on reviewing the most recent experimental mechanics efforts from the Espinosa group to quantify fracture toughness via in situ high-resolution transmission electron microscopy experiments. Likewise, we will review ML-based parametrization of interatomic potentials for 2D materials and discuss the integrated experimental-computational framework advanced by the Espinosa group, not only to understand fracture (Fig. 10(*a*)). Such ML and atomistic experimentation frameworks are essential in advancing the predictive power of atomistic models employed in the exploration

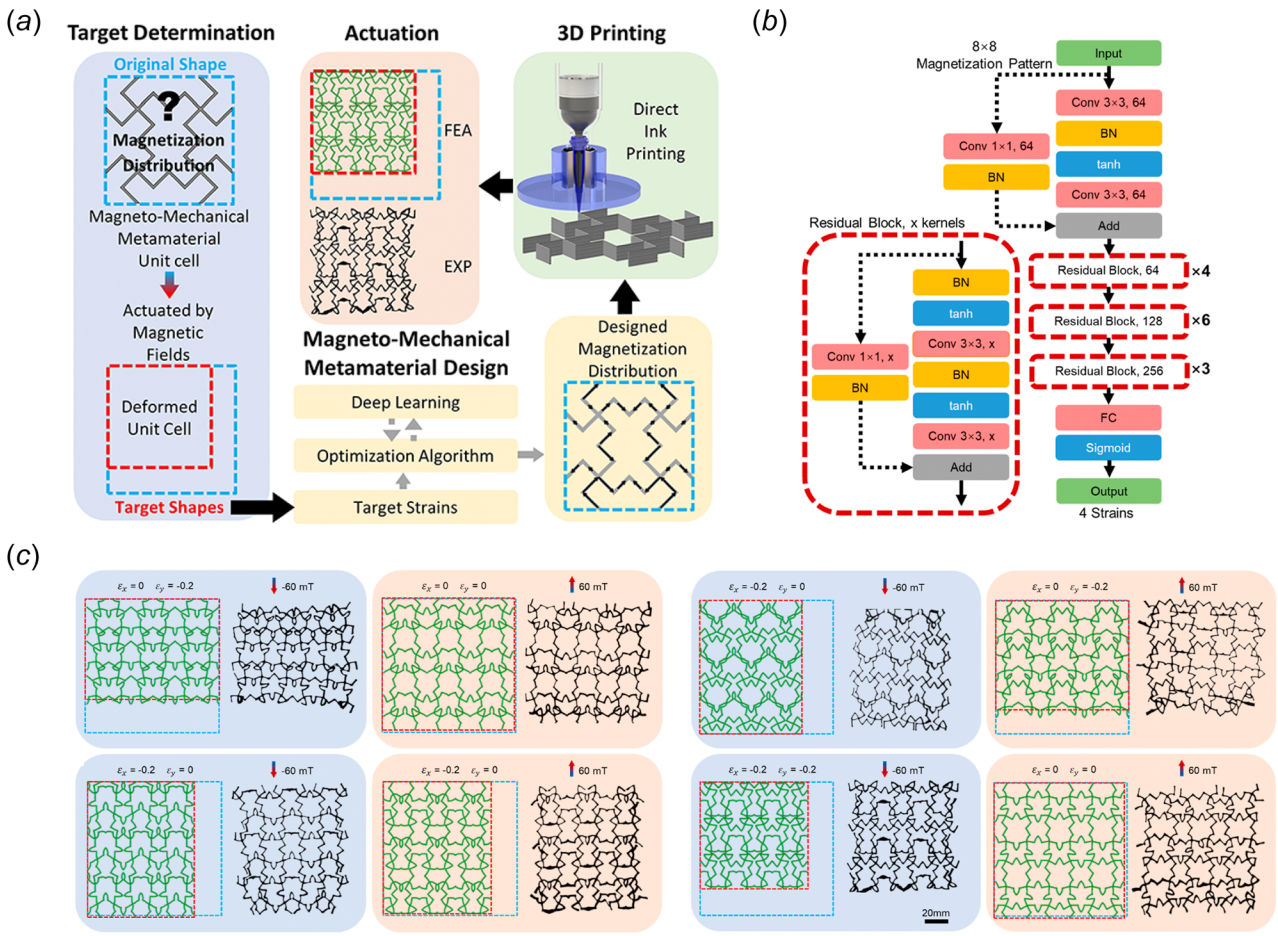

Fig. 8 (*a*) Applications of ML in the inverse design of magneto-activate mechanical metamaterials. (*b*) The deep residual network (ResNet) architecture. (*c*) Comparisons between FEA and experiments (Reproduced with permission from Ref. [175]. Copyright 2022 by ACS).

of families of 2D materials (e.g., TMDs and MXenes) in the spirit of the materials genome initiative.

The fracture toughness of monolayer graphene [325] and h-BN [245] have been measured using in situ SEM and TEM experiments. It was found that both materials obey Griffith's brittle fracture criterion [179]. Assisted by molecular dynamics simulations, researchers attributed their high toughness to different intrinsic toughening mechanisms like pre-existing grain boundaries for graphene and structural-asymmetry-induced crack branching and deflection for h-BN. However, the direct observations of atomistic information like internal defects and lattice deformation are absent due to the resolution limits of the previous experiments. To overcome these challenges, in our group, Zhang et al. [178] performed in situ high-resolution transmission electron microscopy (HRTEM) fracture experiments to investigate the fracture toughness of two TMDs, MoS_2, and $MoSe_2$ (Fig. 10(*b*)). The J-integral was computed from experimental stress–strain fields obtained from an affine transformation (deformation gradient) using HRTEM images of atomic structures surrounding the crack tip. The experimental measurements revealed a nonlinear region near the crack tip, where bond dissociation occurs, and confirmed brittle fracture and the applicability of Griffith's fracture criterion.

To verify the experimental observations, Zhang et al. also performed MD simulations with a newly developed ML-based parametrization framework [177]. Force-field accuracy in MD simulations plays a crucial role in studying large atomic deformation as they occur near the crack tip. Although several successful parametrizations have been developed for various 2D materials [326–328], a force field that can accurately predict phase transition and fracture toughness of 2D materials was not reported. While ML has immense potential for force-field parameterization directly from large datasets based on first principal calculation like density functional theory (DFT) [329,330], a suitable methodology that can incorporate atomic configurations far from equilibrium, essential to the prediction of fracture, is not common. Zhang et al. [177] proposed a parametrization framework trained from DFT datasets and an evolutionary multi-objective optimization algorithm (Fig. 10(*c*)). This parametrization was performed iteratively and consisted of three essential steps: training, screening, and evaluation. The force field was trained to capture both near-equilibrium properties like cohesive energy and nonequilibrium properties such as bond dissociation energy landscapes and vacancy formation energies. Therefore, the parametrized potential can accurately capture bond breakage during fracture. MD simulations with this potential gave similar fracture toughness as those obtained from experimental measurements. We anticipate that by integrating in situ experiments with atomistic resolution and MD simulations with force-field parametrized based on physical ML training, the fracture behaviors of other 2D materials beyond the TMDs family as well as other functional crystals can be identified. Moreover, MD simulations with ML parameterized force fields should accurately predict the effect of defects such as random vacancies, line vacancies, and grain boundaries, enabling the exploration of other constituents as well as thermomechanical properties.

4 Discussion

4.1 Selection of an Appropriate Machine Learning Model for a Specific Experimental Mechanics Application. Selecting an appropriate ML model for a given task in experimental mechanics

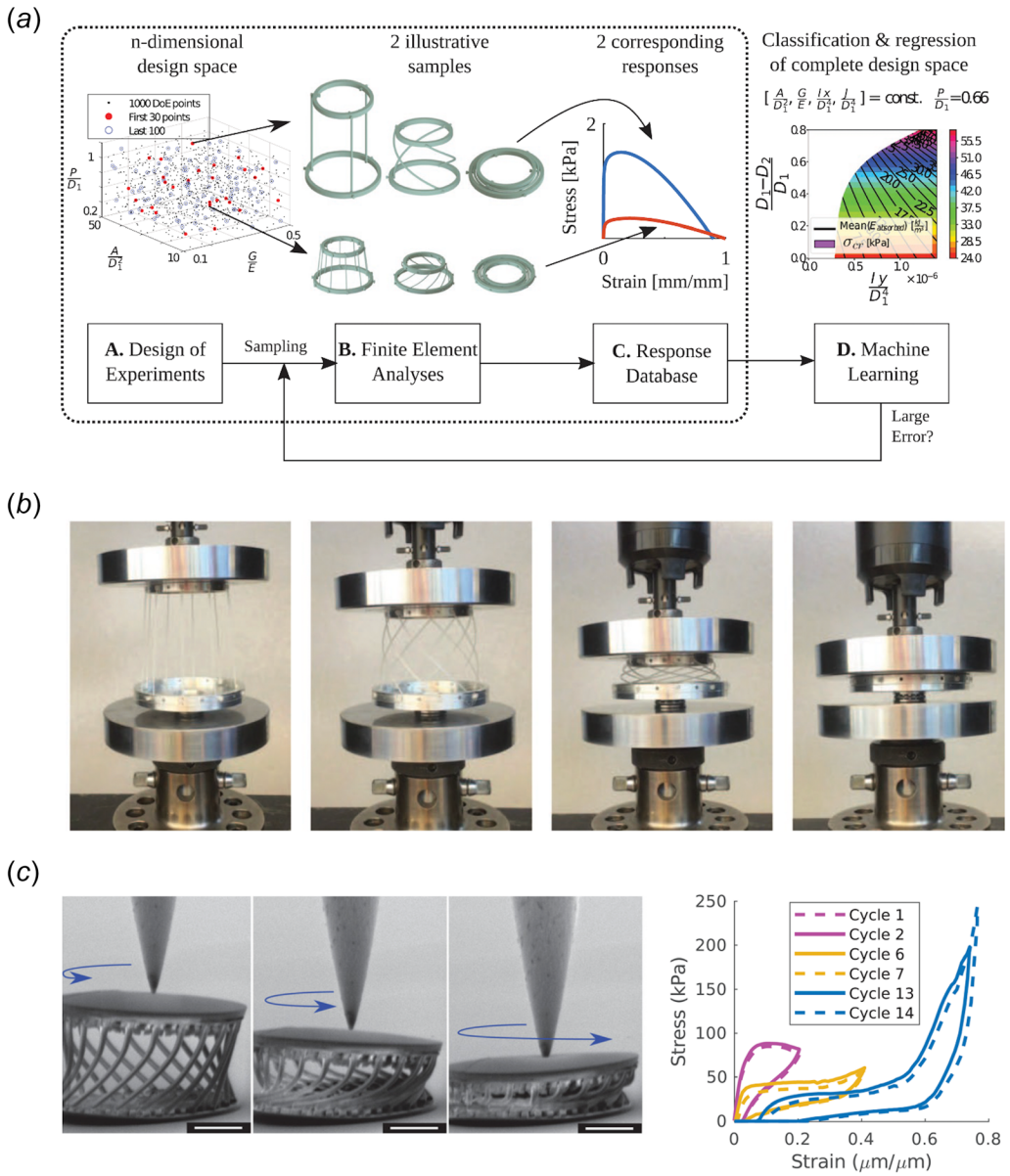

Fig. 9 (*a*) Data-driven Bayesian ML framework for supercompressible metamaterials design. (*b*) Experimental validation for designed structure from fused filament fabrication using polylactic acid. (*c*) Experimental validation for designed structure with microscale size from two-photon lithography. The scale bar in (*c*) is 50 μm. (Reproduced with permission from Ref. [316]. Copyright 2019, The Authors, published by WILEY).

can be challenging since the broad range of ML algorithms and the complexity of experimental data. Here, we provide some practical guidelines on ML model selection based on the type and amount of available data, as well as the underlying physics of the problem. Before searching for a specific ML model, researchers and practitioners should ask themselves a crucial question: is ML necessary for the problem at hand? It is important to avoid the unnecessary use of ML when conventional methods and techniques are sufficient. For instance, using ML for constitutive parameter fitting for simple models like neo-Hookean solids from stress–strain data is not necessary. In such a case, nonlinear regression is preferred instead.

Next, it is important to properly define the types of problems that the user wishes to tackle. Are we using ML for an inverse problem like predicting unknown material parameters from experimental data? Or is it an optimization problem like the optimal design of architected materials subject to specific constraints? Having these questions and others answered before searching for suitable ML algorithms is important. Furthermore, one should be aware of the quantity and quality of available information before choosing an appropriate ML model. What forms of experimental data are available (e.g., stress–strain curves, images, full-field displacement)? What is the precision of these data? Is there any prior knowledge or simulation tool that may enrich the data? When a large amount of experimental data can be collected, a complex ML model like NNs can be applied. On the other hand, when there is data scarcity due to experimental constraints, the user may opt for employing PINNs or Gaussian Processes to embed additional physics and quantify uncertainty.

When experimental data is not adequate, possible data augmentation techniques can be employed. One common approach is to interpolate among the original datasets. For image-based data, methods such as rotation, flipping, or noise injection can be employed [331]. It is crucial to exercise caution when applying these data augmentation methods, ensuring the key characteristics of the original data are maintained while increasing its quantity.

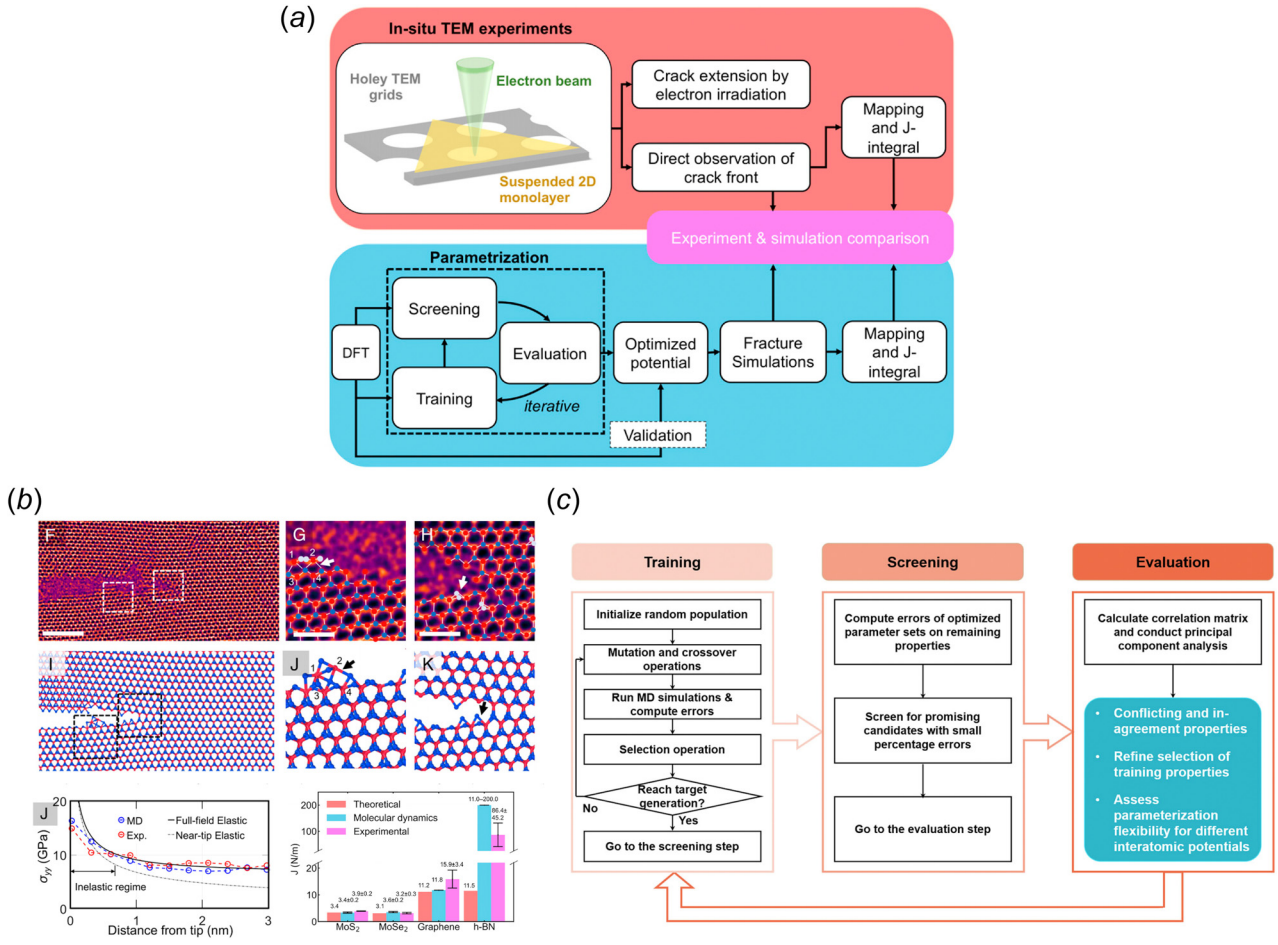

Fig. 10 Applications of ML in fracture toughness characterization of 2D materials. (*a*) An integrated experiment-simulation framework to quantitively measure intrinsic fracture toughness of 2D materials. (*b*) In-situ HRTEM experiments of $MoSe_2$ compared with MD simulations (Reproduced with permission from Ref. [178]. Copyright 2022 by National Academy of Sciences). (*c*) Schematic of ML-based interatomic potential parametrization approach consisting of three steps: training, screening, and evaluation (Reproduced with permission from Ref. [177]. Copyright 2021, The authors, published by Springer Nature).

Furthermore, if experiments are well-defined and can be simulated efficiently using some computational tools like FEA, MD, and DFT, we can generate synthetic data from these simulations. However, it is crucial to thoroughly examine and understand the differences and biases present in both computational and experimental datasets. We should ensure that the computational data accurately captures the experimental data's key features. During training, it is important to monitor the model's performance on both datasets during training to identify any overfitting to the synthetic data. Understanding the differences between the fidelity of computational and experimental data is another important aspect, which will be discussed in the subsequent subsection.

The selection of an appropriate ML algorithm is also based on the experimental data type. If the data consists of images or video-based datasets, CNNs could be the most efficient. If the problem involves time-dependent data, RNNs and transformers could be a better choice. When the problem can be framed in terms of physical laws, PINNs should be employed. Given the speed at which the field is evolving, literature searches should be performed to identify the most suitable ML models for the problem at hand. Once the ML algorithms have been selected, the user can start to build an ML pipeline using open-source ML platforms such as TENSORFLOW [332], PYTORCH [333], or JAX [334]. Iterative refinement of the ML model by hyperparameter-tuning based on testing and validation datasets is necessary to reach the desired accuracy. However, it is worth noting that over-tuning hyperparameters can potentially result in over-fitting. To address this issue, we can employ robust hyperparameter optimization methods such as k-fold cross-validation [335]. In k-fold cross-validation, the original dataset is split into k equal folds. During each iteration, one-fold is used as the validation set, while the other $k-1$ folds are used for training. After completing all iterations, we can compute the average performance metric, such as mean squared error, from all k validation sets. This method can efficiently reduce the risk of overfitting since it trains and evaluates the model on different subsets of the data. Furthermore, it is important to keep in mind that there may be more than one possible choice of ML model for a specific experimental mechanics problem. Therefore, it is practical to carefully evaluate the prediction accuracy and efficiency of each model and select the model that is the best fit for a specific application.

4.2 Integrating Multimodality and Multi-Fidelity Experimental Data Into Machine Learning Methods. Conducting mechanical experiments, particularly those utilizing cutting-edge facilities and techniques for extremely large/small time and length scales, can be both costly and time-consuming. In many cases, researchers need to combine different experimental methodsto gain a better understanding of mechanics problems. Furthermore, computer simulations may be employed to provide additional insight into the experiments. As a result, one may obtain experimental data with multimodality and/or multifidelity. Multimodal data refers to the data on an object comprising different forms and patterns, hence providing information from different channels

(e.g., language data in the forms of text and speech, data on the mechanical test sample in the forms of images, and stress–strain curves). Multifidelity data refers to the measurement data with different levels of accuracy (e.g., high/low-resolution images of a test sample; stress–strain curves measured with load cells of different accuracies; data from real experiments and from computer simulations). Typically, high-fidelity data are expensive and hence limited, while low-fidelity data are cheap and plentiful.

To maximize the available information injected into learning algorithms, it is important to propose ML models that are capable of handling data with multimodality [336] and multifidelity [276]. There have been some studies in applying such ML models to mechanics problems. For example, Holzapfel et al. [159] developed an ML method that combines microstructural information and biomechanical tests. Trask et al. [337] proposed a framework that is capable of conducting multimodal inference for lattice metamaterials, relating their lattice design, stress–strain curves, and microstructural images. Lu et al. [46] designed a multifidelity neural network for characterizing the mechanical properties of materials in instrumented indentation. While these studies, among others, have explored multimodality and multifidelity ML methods for solid mechanics problems, further investigation is still needed to better integrate data with multimodality and multifidelity from experiments and/or simulations to provide a deeper understanding of the mechanics of materials and structures.

4.3 Estimating and Reducing the Uncertainty of Machine Learning Predictions. Most ML applications in experimental solid mechanics provide a point estimation—that is, a single value as the best estimate. To further acquire information regarding the reliability and confidence of such an estimation, one sometimes needs to quantify and/or reduce the uncertainty of the ML predictions. In the context of experimental solid mechanics, there are diverse sources of uncertainties coming from data and models related to almost every component in the research workflow, including (1) experimental implementation, such as the uncertainty of material properties caused by the manufacturing of specimens, inaccurate enforcement of the experimental setup (e.g., boundaries that are not perfectly clamped, approximate fulfillment of plane strain/stress condition), representativeness and noisiness of data; (2) theoretical modeling, such as the misspecification/oversimplification of constitutive models, ignoring dynamic effects, ignoring length scale effects, typical in micro- and nanomechanics, as well as continuum assumptions, neglecting material and/or geometric nonlinearity, and stochasticity; (3) numerical modeling, such as finite element discretization, inaccurate force fields in molecular dynamics simulation. On top of these three aspects of uncertainty, ML methods (especially NN-based methods) introduce a few additional sources of uncertainty, including the choices of model architecture and hyperparameters, stochasticity in the training process, and transferability of the trained model, making the accurate quantification of total uncertainty a complex and time-consuming endeavor.

Uncertainty quantification (UQ) is a discipline of science focusing on identifying, quantifying, and reducing uncertainties associated with models, numerical algorithms, experiments, and predicted outcomes or quantities of interest [338]. It is a broad area that has been studied extensively and is not exclusively applicable to machine learning methods. For detailed UQ methods and their applications in ML, readers are referred to related textbooks and review papers [339–341]. Here, we briefly review a few UQ methods that are extensively applied to estimating and reducing uncertainty in the context of ML applications in experimental solid mechanics. To quantify the uncertainty of mechanics systems, one of the most widely adopted classes of methods is the Bayesian procedure. Built upon the well-established, century-old Bayes' theorem [277], the Bayesian procedure seeks to infer the posterior distribution of variables based on prior knowledge and measured data. Specific examples of methods involving the Bayesian approach include the use of Gaussian process regression for modeling the nonlinear behavior of solids [342], the creep behavior of concrete [343], and metamaterial design [316], as well as NNs for crystal plasticity [344] and multiscale modeling of nanocomposite [345]. These studies, by employing the Bayesian procedure, provide a distribution of the quantities of interest rather than a single output. Another prevalent technique is the ensemble method, which combines a group of base (weak) models, which differ by the algorithm, hyperparameter, training data, and/or random seeds, to provide more accurate, more robust predictions. They may be applied to machine learning models such as decision trees (random forests), support vector machines, and neural networks. Through this method, one may estimate the uncertainty of the prediction according to the spread among base models as well as reducing the uncertainty by combining these models into an ensemble for enhanced predictive capability.

After training a machine learning model, one often needs to validate it by testing the performance of the model on unseen data. Aside from the simplest way of the train-test split of the dataset, techniques including k-fold cross-validation, leave-one-out cross-validation, and bootstrapping are often employed. These techniques help to better assess the performance of the trained model and estimate the uncertainty of predictions by efficiently utilizing the available dataset. In addition to the foregoing methods related to uncertainty quantification, some other commonly invoked techniques and procedures include sensitivity analysis [346], Monte Carlo simulations [347], and computation of confidence interval [348]. Note that the field of UQ has developed for decades, with numerous methods proposed and investigated. In the foregoing context, we have only provided a very brief, nonexhaustive list of UQ methods that have been commonly used in mechanics. Finally, we comment that there are still a lot of problems related to the quantification of uncertainty associated with ML applications in mechanics. As we analyzed at the beginning of this section, there are different sources of uncertainty throughout the research workflow of experimental mechanics, many of which have not yet been well investigated. It is a challenging yet worthwhile task to quantify the total uncertainty of the experimental mechanics workflow addressing all relevant sources of uncertainty.

5 Outlook: Future Opportunities of Machine Learning in Experimental Solid Mechanics

5.1 Machine Learning For Experimental Mechanics Under Extreme Conditions. In recent years, there has been an emerging interest in characterizing material properties under extreme conditions like high strain rate, high pressure, and high temperature. However, such experiments are often considered laborious and costly, requiring significant experiment preparation time. For example, in conventional plate impact experiments, which characterize dynamic properties of materials under high strain rates, the experiment preparation time (e.g., sample preparation, optical alignment, triggering circuits connection, and interferometry) alone can take several days. Therefore, there is an increasing demand to design *big-data-generating experiments* where new high-throughput experimental techniques can be coupled with ML methods to improve the efficiency of data collection and analysis. One recent study by Jin et al. [70] demonstrated the benefits of *big-data-generating experiments* in the context of material dynamic fracture toughness and cohesive parameter determination. By leveraging a high-throughput optical interferometer and CNN-based ML model, the researchers were able to significantly increase the experimental efficiency, reducing the required number of experiments by orders of magnitude. These results highlight the potential for ML to transform the field of experimental mechanics, enabling researchers to characterize material properties more efficiently and effectively under extreme conditions. Moving forward, it will be crucial to continue to develop new experimental full-field measurement techniques for experiments under extreme conditions like spatial-temporal interferometer [70] or stereo DIC [349] that can be effectively coupled with ML to generate and analyze large volumes of high-fidelity data. By leveraging ML for

extreme mechanics, experimentalists will be capable of characterizing extreme material properties more efficiently and accurately, enabling new insights and applications in designing next-generation materials and technologies, e.g., earthquake protective coatings used in architectural design.

5.2 Design of Intelligent Architected Materials With In-Situ Decision-Making Capabilities. The design of materials with decision-making capability is a relatively new concept that has the potential to revolutionize material design by offering unprecedented properties. With the help of ML, architected materials can be programmed to respond to real-time stimuli based on external input. Here, we present some potential research areas in which experimental mechanics and ML can contribute to the development of these intelligent architected materials. One such area is the development of new fabrication techniques to build novel material systems with high resolution. For example, new high-throughput AM techniques, such as the hydrogel infusion AM method [350], can be employed to fabricate architected materials with complex geometries at a variety of scales. Furthermore, bottom-up approaches such as self-assembly can be employed to spontaneously organize nanoscale constituents into ordered structures through intermolecular forces. Recently, scaling-up fabrication techniques [351], like holographic lithography, were employed to build centimeter-size samples with nanoscale features. Another area of focus is the development of new actuation methods. Current actuation methods are mainly focused on passive actuation techniques like mechanical or electromagnetic actuation while designing materials with active actuation that can deform on demand according to local environmental stimuli would confer intelligence to these materials. Designing materials with active actuation would involve the development of ML algorithms capable of optimizing material structures and properties based on a set of design objectives and constraints. For example, reinforcement learning algorithms could be used to train materials to learn and respond to different loading scenarios, leading to enhanced structural performance and durability. Moreover, ML algorithms could enable materials to make intelligent decisions in real-time based on environmental conditions, such as changes in temperature, humidity, or mechanical loads. This opens a wide range of potential applications for intelligent architected materials in fields such as aerospace and robotics.

6 Conclusions

Recent advances in ML have revolutionized the field of experimental solid mechanics, allowing for efficient and accurate experimental design, data analysis, parametric or function identification, and inverse design. In this review paper, we highlight recent advances and applications of ML in experimental solid mechanics. We started by providing an overview of common ML algorithms and terminologies relevant to experimental mechanics, with a particular emphasis on physics-informed and physics-based scientific ML methods. Then, we reviewed recent applications of ML in traditional and emerging areas of experimental solid mechanics, including fracture mechanics, biomechanics, nano- and micromechanics, architected materials, and 2D materials. Furthermore, the review discussed current challenges in applying ML to problems involving data scarcity, multimodality, and multifidelity experimental datasets. It also advances several future research directions to address such challenges. It is hoped that this comprehensive and up-to-date review will provide valuable insights for researchers and practitioners in solid mechanics who are interested in employing ML to design and analyze their experiments. As the field continues to evolve, it will also be essential to build bridges across disciplines, with the most obvious being computational mechanics and materials sciences, to address challenges and opportunities.

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Data Availability Statement

The authors attest that all data for this study are included in the paper.

Author Contribution

H.J. and H.D.E. conceived the initial idea to write this review and defined its content. H.J. wrote the initial draft except for Secs. 4.2 and 4.3. E.Z. wrote the initial draft for Secs. 4.2 and 4.3 and revised other sections. H.D.E. supervised the project and revised the entire paper. All authors gave final approval for the publication.

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