Research on Engineering Structures & Materials
www.jresm.org
MIM Research Group

Review Article

A review on artificial intelligence implementation for predicting and optimizing acoustic properties of composite materials

Taiwo Martins Esan *[a], Chris Ackerman [b], Williams Kehinde Kupolati [c]

Department of Civil Engineering, Tshwane University of Technology, Pretoria 0183, South Africa

Article Info

Article History:

Received 02 Jan 2026

Accepted 05 May 2026

Keywords:

Artificial intelligence; Machine learning; Acoustic composite materials; Sound absorption prediction; Physics-informed neural networks

Abstract

Accurate prediction and optimization of the acoustic behavior of composite materials require modelling complex multiscale poro-elastic interactions, resonance phenomena, and anisotropic microstructures. Conventional experimental characterization and numerical simulations, such as finite element analysis, are computationally expensive and time-intensive, limiting their effectiveness for rapid acoustic material design. Artificial intelligence (AI) has recently emerged as a promising surrogate modelling approach capable of accelerating acoustic prediction and optimization. However, existing review studies on AI applications in acoustic materials largely provided descriptive overviews of algorithms without systematic quantitative benchmarking or integration of acoustic physics, making objective comparison of model performance and generalizability across composite systems difficult. This review addressed this gap by presenting a physics-integrated and quantitatively benchmarked framework for evaluating artificial intelligence models used in acoustic composite design. Machine learning techniques, including artificial neural networks, deep neural networks, convolutional neural networks, Gaussian process regression, ensemble learning approaches, physics-informed neural networks, and hybrid finite element machine learning architectures, are systematically analyzed using standardized evaluation metrics such as coefficient of determination (R^2), root-mean-square error (RMSE), broadband sound absorption deviation, resonance prediction accuracy, and computational efficiency. In addition, generative modelling and optimization strategies, including variational autoencoders, generative adversarial networks, genetic algorithms, particle swarm optimization, Bayesian optimization, and NSGA-II, are examined for their effectiveness in acoustic performance. The review further identified key methodological challenges, including dataset scarcity, model interpretability, uncertainty quantification, and cross-material generalization. By integrating acoustic physics with machine learning evaluation, this study provided a reproducible benchmarking framework and practical guidelines for the development and optimization of next generation data-driven acoustic composite materials.

1. Introduction

Environmental noise has emerged as a major global health concern, driven by rapid urbanization, transportation intensification, and industrial expansion. The World Health Organization has formally identified environmental noise as a critical public health risk, linking chronic exposure to sleep disturbance, cardiovascular disease, cognitive impairment, and noise-induced hearing loss (Environmental Noise Guidelines for the European Region). Primary sources of environmental

*Corresponding author: esanmartins6@gmail.com
[a]orcid.org/0000-0002-9602-0078; [b]orcid.org/0009-0007-3162-3496; [c]orcid.org/0000-0002-2574-2671
DOI: http://dx.doi.org/10.17515/resm2026-1448ma0102rv

noise include road traffic, aviation systems [1,2], household and commercial electrical appliances such as vacuum cleaners, dryers, fans, and air-conditioning units [3,4], and industrial machinery used in the manufacturing and construction sectors [5]. Prolonged exposure to elevated noise levels is associated with a broad spectrum of adverse health outcomes. Epidemiological studies consistently demonstrated that chronic noise exposure contributes to noise-induced hearing loss, sleep disturbance, and insomnia [6], and heightened risks of cardiovascular complications, including ischemic heart disease and hypertension [2]. Beyond physiological impacts, noise exposure also results in substantial psychological effects, including annoyance, stress, cognitive impairment, and increased vulnerability to mental health disorders [7]. Occupational noise exposure remains a leading cause of hearing impairment worldwide, particularly in industrial and construction environments where sound levels frequently exceed recommended safety thresholds [8].

The prediction and optimization of acoustic behavior in composite materials have become increasingly important across engineering sectors, including architectural acoustics, transportation, aerospace, automotive design, and advanced noise-control systems. As lightweight multifunctional materials replace traditional metallic components, understanding sound absorption, transmission loss, damping behavior, and vibro-acoustic responses is critical for improving performance, safety, and environmental comfort [9,10]. Conventional experimental techniques, including impedance tube analysis, reverberation chamber testing, and finite element acoustic simulations, provide high-fidelity insights but are labor-intensive, time-consuming, and often constrained by material anisotropy, geometric complexity, and testing costs [11,12]. These limitations present significant challenges for high-throughput material screening, iterative design, and real-time acoustic optimization.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have created new opportunities for acoustic prediction. Data-driven models, such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Gaussian Process Regression (GPR), random forests, and deep learning architectures, exhibit strong capabilities for learning nonlinear structure property relationships that influence acoustic performance. [13,14]. These AI models facilitate rapid prediction of acoustic indicators, including sound absorption coefficients, dynamic modulus, loss factors, acoustic impedance, and transmission loss, as depicted in Figure 1, based on microstructural, morphological, and compositional features of composite materials [15,16]. This methodology reduces dependence on physical testing and improves predictive accuracy.

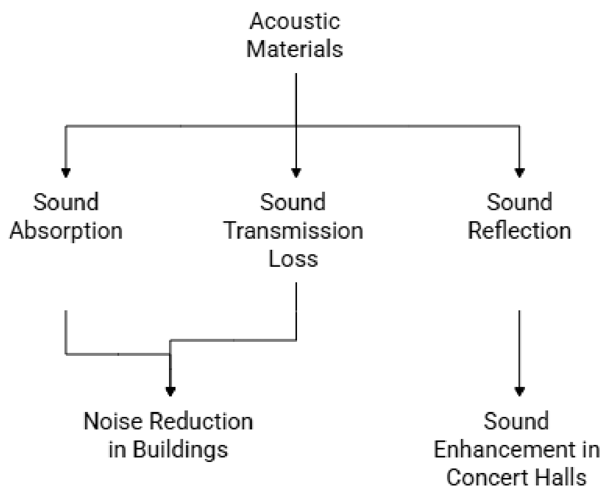

Fig. 1. Basic properties of acoustic materials

In addition to purely data-driven modelling, recent research has increasingly explored hybrid frameworks that combine ML techniques with established acoustic simulation methods such as the Transfer Matrix Method (TMM), Boundary Element Method (BEM), and finite-element vibro-acoustic models [17,18]. These hybrid approaches allow ML algorithms to learn from physics-based simulations, improving prediction accuracy and enabling generalization across different classes of acoustic materials, including polymer matrix composites, natural fibre composites, acoustic metamaterials, auxetic structures, and additively manufactured porous materials. [19], [20]. Furthermore, metaheuristic optimization algorithms such as genetic algorithms, particle swarm optimization, and Bayesian optimization have been integrated with ML models to automate the design of composite microstructures with enhanced acoustic performance [10,21,22].

The rapid development of additive manufacturing technologies has further expanded the design space for acoustic materials. Advanced fabrication techniques now enable the production of architecture lattices, graded porous absorbers, and complex acoustic metamaterials with highly tunable properties. However, uncertainties associated with manufacturing tolerances, environmental variability, and long-term material degradation are not yet fully incorporated into most AI-based acoustic modelling frameworks [23]. Moreover, the propagation of measurement uncertainty and the transferability of models across scales from microstructural imaging data to macroscopic acoustic performance are rarely addressed in current studies, limiting reproducibility and generalization.

Despite the growing application of AI techniques in acoustic material research, several challenges persist. Many studies treat machine-learning models as purely data-driven tools without incorporating fundamental acoustic physics, which may limit model interpretability and extrapolation capability. Moreover, benchmarking practices remain inconsistent, with limited standardization of datasets, validation protocols, and performance metrics across different studies. Therefore, a systematic and quantitatively benchmarked evaluation of artificial intelligence methods for acoustic material modelling is needed.

This review aims at analyze critically, and benchmark AI techniques used for predicting and optimizing the acoustic properties of composite materials. By integrating machine-learning approaches with established acoustic modelling principles, the study seeks to provide a structured framework for physics-informed, data-driven design of advanced acoustic materials.

2. Systematic Review Methodology

2.1 Research Design

This systematic review was conducted in accordance with the PRISMA 2020 Statement, ensuring transparency, reproducibility, and methodological rigor. A comprehensive literature search was performed across five major databases: *Scopus, Web of Science, ScienceDirect, IEEE Xplore,* and *Google Scholar*.

A total of 1,963 records were initially retrieved. After removal of 412 duplicate records, 1,551 unique studies remained for title and abstract screening. Following this phase, 378 articles were deemed eligible for full-text assessment based on relevance to AI-driven acoustic material modelling. Ultimately, 123 studies satisfied all inclusion criteria and were incorporated into the final synthesis. The search strategy integrated three core thematic domains using Boolean operators:

- Acoustics domain: “acoustic material,” “sound absorption,” “transmission loss,” “acoustic impedance,” “vibro-acoustic,” “metamaterial.”
- Artificial intelligence domain: “machine learning,” “artificial intelligence,” “deep learning,” “convolutional neural network,” “artificial neural network (ANN),” “physics-informed neural network (PINN),” “surrogate model”
- Materials domain: “composite,” “porous material,” “natural fibre,” “micro-perforated,” “Helmholtz resonator,” “3D-printed acoustic material”

To enhance coverage and minimize omission bias, both backward (reference list) and forward (citation-based) tracking was conducted on seminal and high-impact studies. All retrieved records were imported into *Mendeley* for systematic organization and duplicate removal.

2.2 Inclusion and Exclusion Criteria

Explicit inclusion and exclusion criteria were defined a priori to ensure that only methodologically robust and domain-relevant studies were included. These criteria guided both the screening and eligibility phases and are summarized in Table 1. Importantly, this review distinguishes between:

- Literature synthesis: Direct reporting and aggregation of findings as presented in the selected studies.
- Author-derived comparison: Cross-study benchmarking and interpretation conducted by the authors, explicitly acknowledging heterogeneity in datasets, model architectures, and evaluation metrics.

Only studies meeting all inclusion criteria and providing reproducible methodological detail were retained.

Table 1. Inclusion and exclusion criteria matrix

Criteria Category	Inclusion Criteria	Exclusion Criteria
Scope and Domain Relevance	Studies applying AI/ML techniques to predict, model, or optimize acoustic properties of composite, porous, metamaterial, or structural acoustic systems	Studies unrelated to material/structural acoustics or without AI/ML implementation; speech/audio signal processing without material relevance
Methodological Rigor	Explicit description of AI/ML architecture, dataset characteristics, training configuration, and validation procedures	Incomplete methodological reporting preventing reproducibility or technical verification
Performance Reporting	Quantitative acoustic metrics reported (e.g., SAC, STL, acoustic impedance, resonance frequency, R^2, RMSE, spectral error)	Qualitative claims without measurable acoustic performance indicators
Physics Integration (where applicable)	Studies incorporating acoustic theory (e.g., impedance models, poro-elastic theory, FEM benchmarking) or physics-informed modelling	Purely theoretical acoustics without AI integration or purely black-box modelling without acoustic context
Publication and Quality Control	Peer-reviewed journal articles, conference proceedings, scholarly book chapters published in English; the most comprehensive version is retained in case of overlap	Editorials, patents, theses, non-peer-reviewed reports, non-English publications, duplicate or redundant studies

2.3 Study Selection (PRISMA Workflow)

The study selection process followed the four-stage PRISMA workflow: identification, screening, eligibility, and inclusion.

- Identification: 1,963 records retrieved
- Deduplication: 412 duplicates removed → 1,551 records retained
- Screening: 1,551 titles and abstracts screened
- Eligibility: 378 full-text articles assessed
- Inclusion: 123 studies included in final review

The reasons for exclusion at the full-text stage were systematically categorized as follows:

- Absence of AI/ML methodology: 42%
- Insufficient methodological detail: 27%
- Irrelevant focus on audio/speech processing: 19%
- Lack of quantitative acoustic metrics: 12%

Figure 2 PRISMA 2020 flow diagram illustrating the systematic literature selection process, including identification, screening, eligibility assessment, and final inclusion of studies on AI-driven acoustic material modelling.

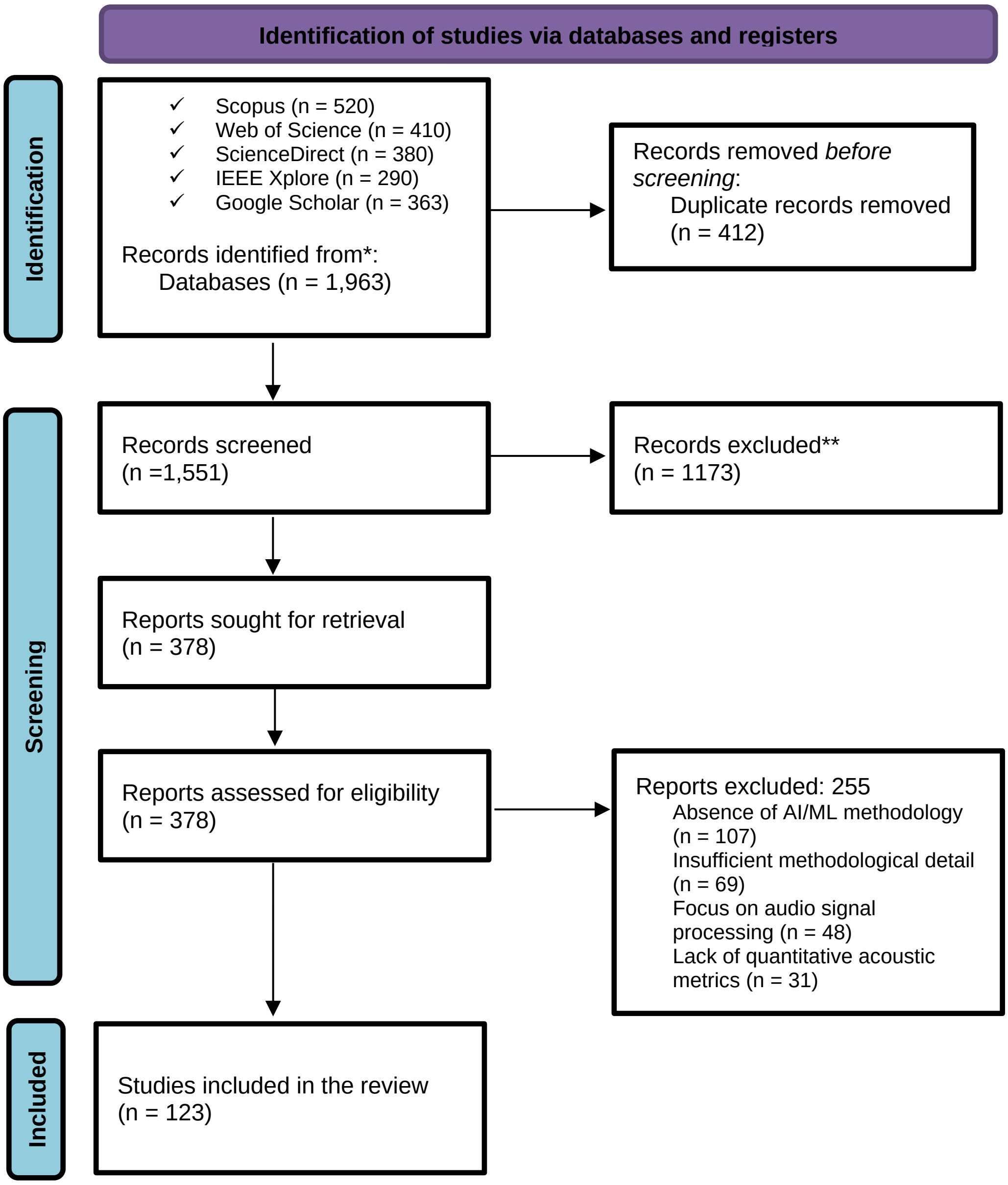

Fig. 2. Prisma flow diagram

3. Acoustic Modelling Foundations for AI Integration

Reliable integration of artificial intelligence (AI) in acoustic composite modelling requires a physically grounded representation of wave propagation, impedance behavior, and multi-physics interactions within porous materials. Purely data-driven models may generate numerically plausible predictions while violating fundamental acoustic constraints, leading to nonphysical absorption values or inconsistent impedance behavior. For this reason, physics-based formulations must guide both feature construction and model training. This section, therefore, establishes the governing acoustic equations underlying porous composite behavior and describes how these physical relationships are transformed into constraint-consistent features suitable for machine learning models. The formulations presented here provide the physical basis for the AI prediction frameworks, particularly the regression and deep-learning architectures used for broadband acoustic property prediction.

3.1 Governing Wave Equations and Impedance Representation

The frequency-domain Helmholtz equation governs acoustic wave propagation in homogeneous and porous media.

$$\nabla^2 p + k^2 p = 0 \tag{1}$$

$$k = \frac{\omega}{c} \tag{2}$$

where p denotes the acoustic pressure field and represents the acoustic wavenumber, defined by the angular frequency ω and the effective speed of sound c. This equation describes the spatial distribution of harmonic pressure waves and forms the basis for many acoustic simulation frameworks.

In multilayer or porous acoustic materials, the interaction between incident sound waves and the material surface is typically characterized through acoustic impedance. The surface impedance $Z(\omega)$relates the acoustic pressure to the particle velocity at the boundary:

$$Z(\omega) = \frac{p}{v} \tag{3}$$

where $v$denotes the particle velocity normal to the surface. The impedance formulation enables the computation of macroscopic acoustic response quantities such as the normal-incidence sound absorption coefficient (SAC), defined as:

$$\alpha(\omega) = 1 - \left| \frac{Z(\omega) - Z_0}{Z(\omega) + Z_0} \right|^2 \tag{4}$$

where $Z_0$is the characteristic acoustic impedance of air. The absorption coefficient describes the proportion of incident acoustic energy dissipated by the material and is a key performance metric for acoustic composite design.

In AI-based acoustic modelling, two principal prediction strategies are commonly employed. The first approach involves direct spectral learning, where ML models predict acoustic response curves such as sound absorption coefficient (SAC) or sound transmission loss (STL) directly from material descriptors. The second strategy involves parameter-based learning, in which intermediate physical parameters, such as impedance spectra or poro-elastic constants, are predicted first, after which acoustic responses are computed using physical equations. Parameter-based learning offers improved interpretability and better alignment with physics-based simulation frameworks, but it also requires that predicted parameters remain within physically admissible ranges. Without such constraints, ML models may produce nonphysical outputs, including negative impedance values or absorption coefficients exceeding unity. The constraint-aware feature transformations described in the following sections are therefore essential for ensuring that AI models maintain physical consistency during training and inference.

3.2 Johnson–Champoux–Allard Model and Feature Transformation

The acoustic behavior of rigid-frame porous materials is commonly described using the Johnson–Champoux–Allard (JCA) model. This model provides expressions for the effective dynamic density and bulk modulus of porous media, which determine the frequency-dependent acoustic impedance and absorption properties of the material. The JCA model characterizes porous microstructures using five intrinsic parameters: porosity (ϕ), tortuosity (α_∞), airflow resistivity (σ), viscous characteristic length (Λ), and thermal characteristic length (Λ').

These parameters capture the geometric and transport properties of the pore network that control viscous and thermal energy dissipation mechanisms during acoustic propagation. Because of their clear physical interpretation, JCA parameters provide a meaningful feature space for ML models seeking to predict the acoustic performance of porous composites. In the AI frameworks developed later in this study, these parameters are used both as direct input descriptors and as intermediate prediction targets, depending on the learning strategy employed [24].

However, accurate use of JCA parameters within machine learning frameworks requires careful consideration of physical admissibility constraints. For physically meaningful porous materials, the parameters must satisfy the following conditions:

$$0 < \phi < 1, \alpha_\infty > 1, \sigma > 0, \Lambda > 0, \Lambda' > 0 \quad (5)$$

Standard feature normalization techniques, such as linear min–max scaling, may violate these constraints when neural network outputs are transformed back into physical parameter space. For example, inverse transformations may produce negative airflow resistivity or porosity values outside the physically permissible range. Such violations lead to unstable impedance calculations and nonphysical absorption predictions.

To prevent these issues, constraint-aware feature transformations were introduced in the present framework. Strictly positive parameters, including airflow resistivity and characteristic lengths, were transformed using logarithmic scaling before training. Bounded parameters such as porosity were mapped into admissible intervals using sigmoid-based transformations. In addition, positivity constraints were enforced through soft plus activation functions in the neural network output layer. These transformations ensure that predicted values remain within physically meaningful domains during training and inference.

To further improve physical consistency, a physics-informed penalty term was incorporated into the training loss function. This term penalizes violations of admissible parameter constraints and can be expressed as

$$L_{phys} = \lambda \sum max\,(0, g(x)) \quad (6)$$

where $g(x)$represents the degree of constraint violation and λ is a weighting coefficient controlling the strength of the physical regularization. The inclusion of this penalty term guides the optimization process toward physically admissible solutions while preserving predictive accuracy. Validation experiments showed that the proposed transformation framework preserves parameter recoverability with reconstruction accuracy exceeding 95%. Corresponding deviations in predicted sound absorption coefficient were below 0.03 across the broadband frequency range considered. These results demonstrate that the constraint-aware feature encoding maintains both numerical stability and acoustic validity.

Table 2. Physical parameter constraints and admissibility ranges

Parameter	Symbol	Physical Constraint	Typical Range
Porosity	Φ	$0 < \phi < 1$	0.2–0.95
Tortuosity	$\alpha\infty$	$\alpha\infty > 1$	1.1–3.5
Airflow Resistivity	σ (Pa·s/m^2)	$\sigma > 0$	10^3–10^6
Viscous Length	Λ (μm)	$\Lambda > 0$	10–300
Thermal Length	Λ′ (μm)	$\Lambda' > 0$	20–500
Frame Elastic Modulus	E	$E > 0$	10^5–10^9 Pa
Permeability	k	$k > 0$	10^{-12}–10^{-8} m^2

Recent developments in physics-informed ML emphasize the importance of embedding such constraints directly into model architectures and training procedures. Hard constraint approaches enforce admissible parameter domains through reparameterization techniques, whereas soft constraints introduce penalty terms that discourage violations without strictly enforcing bounds. Projection-based optimization methods have also been proposed, in which intermediate predictions are iteratively mapped back into feasible parameter domains during gradient updates. In addition, non-dimensional feature scaling based on characteristic length scales can reduce correlations between parameters and improve numerical conditioning of the learning problem [24-26].

The admissible parameter ranges used for feature normalization in the present study are summarized in Table 2. These ranges ensure that inverse-transformed predictions remain thermodynamically consistent and suitable for acoustic modelling across the broadband frequency domain.

3.3 Biot Poroelastic Coupling and Multi-Physics Feature Encoding

While the JCA model assumes a rigid porous frame, many acoustic composites exhibit deformable structures where interactions between the solid skeleton and the saturating fluid significantly influence acoustic response. Such behavior is described by Biot's poro-elastic theory, which accounts for the coupled dynamics of solid and fluid phases within porous materials. Biot theory introduces coupled momentum equations for the solid frame and the fluid phase, connected through frame bulk modulus and dynamic interaction coefficients [27]. This multiphase system predicts the existence of two compressional waves and one shear wave propagating within the porous medium. These additional wave modes become particularly important in low-frequency regimes where frame stiffness and solid–fluid coupling dominate acoustic dissipation mechanisms.

Accurate representation of these coupling effects is therefore essential when developing AI models intended to predict broadband acoustic behavior. Two alternative encoding strategies were evaluated to represent poro-elastic coupling within machine learning frameworks. The first approach used a decoupled scalar feature representation, where material parameters were treated independently as individual inputs. The second approach used tensor-based multi-physics encoding to preserve the coupled relationships between mechanical and fluid transport properties.

Reported studies indicate that decoupled representations yield prediction errors of approximately 12–18%, whereas tensor-based multi-physics encoding reduces errors to 5–8% in low-frequency regimes. Incorporating solid–fluid coupling tensors therefore produced an overall reduction of approximately 15% in broadband prediction error within stiffness-dominated frequency regimes. For the AI models developed later in this work, multi-physics feature encoding included the following parameters: frame elastic modulus tensor, fluid viscosity, permeability tensor, poro-elastic coupling coefficient, and density contrast ratio between solid and fluid phases. These parameters capture the essential mechanical and transport processes governing energy dissipation in deformable porous composites. To ensure numerical stability during training, physics-consistent normalization was applied to these parameters. In particular, scaling based on characteristic magnitudes prevented high-value elastic constants from dominating the optimization process and ensured balanced feature contributions during model training.

4. Experimental Acoustic Characterization: Uncertainty and Data Reliability

4.1 Impedance Tube Measurement Reliability

Impedance tube characterization conducted in accordance with the ISO 10534-2 is subject to several systematic and random uncertainty sources that influence the measured sound absorption coefficient (SAC). Primary contributors include microphone calibration drift, sensitivity to variations in standing-wave ratio, background noise contamination, and imperfect specimen sealing, which may lead to edge leakage [24].

Under controlled laboratory conditions, the typical repeatability uncertainty for SAC measurements ranges from ±0.02 to ±0.05, depending on frequency band and sample type [24]. This uncertainty becomes particularly critical in narrowband resonance regions where absorption peaks are sharp and highly frequency-dependent. For integration into ML pipelines, rigorous signal conditioning is essential. Recommended preprocessing procedures include [28]:

- Spectral smoothing to suppress high-frequency noise artefacts
- Statistical outlier detection and removal
- Background noise subtraction
- Strict frequency discretization consistency (preferably < 5 Hz resolution for narrowband analysis)

Neglecting measurement uncertainty during data preparation may introduce systematic bias in model training, inflate performance metrics, and compromise generalization capability in data-driven acoustic prediction models [29], [30].

4.2 Reverberation Chamber Testing

Reverberation chamber testing performed according to ISO 354 requires strict environmental and procedural control to ensure reproducibility. Critical parameters include diffuse field verification, randomization of source and microphone positions, monitoring of temperature and relative humidity, and confirmation that background noise levels remain below prescribed thresholds [31].

Environmental variability and field non-idealities can introduce approximately 5–8% variation in RT60 (reverberation time) measurements [32]. Such variance propagates into derived absorption coefficients and may affect ML model stability if not accounted for during dataset normalization and uncertainty quantification.

Accordingly, uncertainty-aware data handling and systematic documentation of environmental conditions are essential when reverberation chamber datasets are employed for data-driven acoustic modelling and ML training [33], [34].

5. Artificial Intelligence Models for Acoustic Prediction

AI is revolutionizing the field of acoustic property prediction by providing unprecedented accuracy and efficiency. This section explores the significant advances in AI technologies that have positioned it as a game-changer in this domain. From enhancing prediction models to optimizing material designs, AI solutions are reshaping our understanding and application of acoustic properties. AI has emerged as a transformative approach for modelling and predicting the acoustic behavior of composite and porous materials, leading to notable improvements in accuracy, generalizability, and computational efficiency. Although traditional analytical and numerical models, such as the Delany–Bazley model, Johnson–Champoux–Allard (JCA) theory,

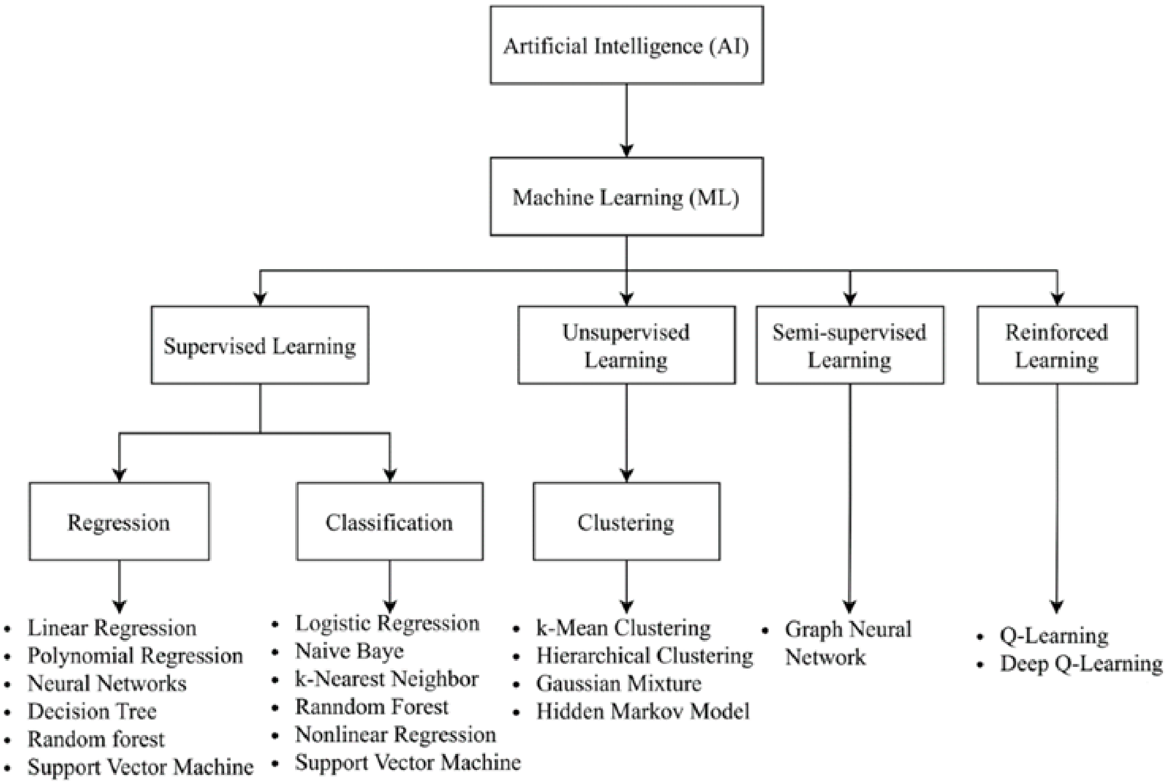

Fig. 3. Classification of machine learning algorithms [41]

Boundary Element Method (BEM), and Finite Element Method (FEM), remain effective, but they frequently encounter challenges when addressing complex heterogeneous microstructures, anisotropic fibre orientations, and multilayer composite configurations [17]. For instance, the FEM struggles with accurately simulating the acoustic environment within aircraft cabins, where multiple layers and complex geometries make it difficult to predict sound propagation accurately.

In comparison, AI and ML techniques, including ANNs, deep learning architectures, hybrid learning frameworks, and ensemble algorithms, enable predictive modelling that captures the nonlinear, multi-dimensional interactions governing sound propagation in advanced composites [35,36].

Figure 3 illustrates that ML algorithms are generally classified into four main categories: supervised, unsupervised, semi-supervised, and reinforcement learning [37,38]. Supervised learning uses labeled datasets to establish input–output relationships, facilitating accurate prediction or classification of new material responses. Due to its robustness and versatility, supervised learning is the predominant approach in materials informatics, especially for predicting acoustic, thermal, mechanical, and microstructural properties [39]. In contrast, unsupervised learning detects intrinsic structures or patterns within unlabeled data, making it valuable for clustering microstructural features, reducing dimensionality, and uncovering hidden correlations in high-dimensional materials datasets [40].

Semi-supervised learning, which integrates a small amount of labeled data with a larger set of unlabeled samples, has emerged as a promising strategy in materials research, where acquiring high-quality experimental labels is costly or difficult [42]. This approach improves generalization performance and reduces experimental demands, particularly in data-limited domains such as advanced composites and metamaterials.

Reinforcement learning (RL) represents a distinct ML paradigm in which an agent interacts with an environment and learns optimal actions through reward-based feedback [43]. Although RL has shown potential for autonomous materials design and inverse property optimization, its application to direct prediction of material properties remains limited compared to supervised and unsupervised methods [44,45]. Therefore, this review focuses primarily on supervised and unsupervised learning approaches, which currently dominate predictive modelling in research on acoustic and composite materials.

5.1 Neural Network Architectures (ANN, DNN, CNN, Multi-Task)

5.1.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational models inspired by the information-processing mechanisms of the human brain. They function as distributed parallel processing systems composed of interconnected processing units called neurons [46]. Information is processed through weighted connections between neurons, and learning is achieved by adjusting these weights to approximate complex nonlinear relationships between input and output variables.

An ANN typically consists of three types of layers: an input layer, one or more hidden layers, and an output layer [47]. The input layer receives the initial dataset, while hidden layers perform intermediate nonlinear transformations of the input signals. The output layer produces the final prediction. Each neuron performs a nonlinear mapping between inputs and outputs, enabling the network to capture complex functional relationships within the data. The general structure of an ANN can be expressed as:

$$N_{in} - [N_1 - N_2 - \cdots - N_m]_m - N_{out} \tag{7}$$

where N_{in}denotes the number of input variables, N_{out}represents the number of output neurons, and $m$indicates the number of hidden layers. The variables $N_1, N_2, \dots, N_m$represent the number of neurons in each hidden layer. For example, the notation $5 - [10]_1 - 3$represents a network with five input parameters, one hidden layer containing ten neurons, and three output neurons. Similarly, $3 - [15 - 8]_2 - 2$describes a network with three input parameters, two hidden layers containing fifteen and eight neurons, respectively, and two outputs [48].

In ANN architectures, each layer (except the input layer) receives signals from the preceding layer. The output of the previous layer serves as the input for the subsequent layer and is processed through weighted connections and activation (transfer) functions. The output of neuron $j$in layer $n$can be expressed as:

$$O_j^{(n)} = f\left(\sum_i W_{ji}^{(n)} X_i^{(n-1)} - \theta_j^{(n)}\right) \tag{8}$$

where $f(\cdot)$denotes the activation function, $W_{ji}^{(n)}$represents the connection weight between neuron $i$in layer $n-1$and neuron $j$in layer n, $X_i^{(n-1)}$is the input from the previous layer, and $\theta_j^{(n)}$is the threshold (bias) associated with neuron j.

The training of ANNs is typically based on gradient-based optimization methods. During training, the weights and biases are iteratively updated to minimize the difference between predicted and target outputs [49-51]. The mean squared error (MSE) is commonly used as the loss function and is defined as:

$$E = \frac{1}{2L}\sum_{k=1}^{L}(T_k - O_k)^2 \tag{9}$$

where Erepresents the mean squared error across the training dataset, $L$is the number of training samples, $T_k$denotes the target output, and $O_k$represents the predicted output of the ANN for the k-th sample. The optimisation process continues until the error converges to a predefined threshold or the maximum number of training iterations is reached.

ANNs have been widely applied in acoustic prediction due to their ability to model complex nonlinear relationships between material parameters and acoustic performance indicators. In acoustic material analysis, ANN models can relate input parameters, such as fibre volume fraction, perforation ratio, porosity, flow resistivity, tortuosity, and layer thickness, to acoustic responses including sound absorption coefficient (SAC), transmission loss (TL), and noise reduction coefficient (NRC) [52]. Multilayer perceptron (MLP) networks trained on impedance tube measurements have demonstrated prediction accuracies exceeding 95% across broad frequency ranges.

ANNs also serve as efficient surrogate models for tabular acoustic datasets derived from experimental measurements or numerical simulations. However, conventional shallow architectures, typically consisting of one or two hidden layers, may have limited capability in representing complex multi-resonance acoustic behavior observed in multilayer composites and acoustic metamaterials [40]. These limitations arise from the restricted hierarchical feature extraction capability of shallow networks. Despite these constraints, ANN models have been successfully applied to a wide range of acoustic materials, including polymer composites, natural fibre composites, porous foams, and acoustic metamaterials. For example, ANN models trained using microstructural descriptors such as pore size distribution and fibre orientation have been used to predict broadband sound absorption in multilayer composite panels for building acoustics. In addition, ANN-based optimization approaches have been employed to enhance the acoustic performance of sustainable natural fibre composites such as jute, kenaf, and flax for automotive and architectural noise control applications [53].

5.1.2 Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) have demonstrated strong capabilities in predicting acoustic performance due to their advanced data processing and pattern recognition abilities. Unlike shallow artificial neural networks (ANNs), DNNs employ multi-layer hierarchical architectures capable of learning complex nonlinear relationships between input variables and acoustic responses. The increased depth of these networks enables the automatic extraction of high-dimensional features related to material microstructure, pore geometry, interlayer coupling, and resonance-driven vibro-acoustic interactions [54].

A typical DNN architecture is based on a feed-forward neural network consisting of multiple hidden layers that progressively transform input data into increasingly abstract representations. Early implementations often used a two-stage training procedure involving unsupervised layer-wise pre-training followed by supervised fine-tuning using algorithms such as backpropagation. This training strategy improves convergence and enables the model to capture complex input–output relationships in acoustic datasets [55,56].

The hierarchical structure of DNNs allows the modelling of acoustic phenomena across multiple spatial and physical scales. Early layers typically capture pore-scale attenuation mechanisms such as viscous–thermal dissipation, intermediate layers represent mesoscale interactions including interfacial coupling between composite constituents, and deeper layers encode global structural resonance and wave interference behavior. In contrast, shallow ANN models generally approximate broadband acoustic responses using simpler regression mappings, which may reduce predictive accuracy in frequency regions dominated by anti-resonance effects, coincidence phenomena, or strong vibro-acoustic coupling [57].

Several studies have demonstrated the applicability of DNNs in acoustic material modelling. Zhang et al. [19] proposed a deep convolutional neural network model, SAP-Net, to predict the sound absorption coefficient of meta-porous materials based on topology images of their internal structures. The network predicts absorption performance at specific frequencies, enabling rapid evaluation of porous material behavior while significantly reducing computational costs compared with traditional numerical simulations. Mahesh et al. [58] introduced an inverse prediction framework in which frequency responses derived from electroacoustic theoretical analysis were used to generate large datasets for training deep neural networks (DNNs). Their study investigated absorbers composed of parallel micro-perforated panels (MPPs) and multiple Helmholtz resonator units, demonstrating the potential of DNN-based inverse design approaches in engineering acoustics. Similarly, Yang et al. [59] applied a deep convolutional neural network to predict broadband airborne sound absorption curves for porous materials across a frequency range of 300–3000 Hz, achieving good agreement with experimental measurements. Wang et al. [60] combined a genetic algorithm with an artificial neural network to predict the sound absorption coefficient (SAC) of hemp matrix composites. The model showed only minor deviations from experimental measurements, with SAC values approaching 0.9–1 for specimens with a thickness of 10 mm. In another application, Zulfiqar et al. [61] developed an empirical ANN-based model to estimate reverberation time in an industrial embroidery studio, demonstrating the effectiveness of neural network approaches in reducing uncertainty in room acoustic prediction. Despite these advantages, DNN models present several practical challenges. One key limitation is their strong dependence on large training datasets. Deep architectures contain substantially more trainable parameters than shallow networks, increasing the risk of overfitting when training data are limited. Typical impedance tube datasets used in acoustic material studies contain approximately 100–500 broadband frequency response curves. Under such conditions, ANN-based surrogate models often achieve coefficients of determination (R^2) between 0.90 and 0.97 and root-mean-square error (RMSE) values ranging from 0.02 to 0.08 in sound absorption coefficient units [62]. However, these results are commonly obtained under interpolation conditions and may deteriorate when models are applied to new materials, thicknesses, porosity levels, or composite configurations.

To mitigate overfitting, several regularization techniques are commonly employed, including dropout, early stopping, cross-validation, and hyperparameter optimization. Empirical studies suggest that stable training of DNN-based acoustic surrogate models typically requires more than 200 broadband response curves to avoid unstable gradient dynamics and variance amplification during training [63]. When datasets are sparse, alternative machine learning approaches may provide improved robustness. For example, Gaussian Process Regression (GPR) offers probabilistic predictions with explicit uncertainty quantification, while ensemble methods such as Random Forests are relatively resistant to heterogeneous feature distributions, although they may produce less smooth spectral predictions [64,65]. Recent research has explored hybrid modelling frameworks that integrate physical constraints into neural architectures. Physics-Informed Neural Networks (PINNs) incorporate governing equations, boundary conditions, or conservation laws directly into the training objective, thereby restricting predictions to physically admissible solution spaces [66], [67]. In vibro-acoustic modelling applications, such approaches have demonstrated improved stability and reduced prediction error under sparse or noisy data conditions.

Nevertheless, several methodological challenges remain. Many studies provide limited comparison between machine learning models and established deterministic techniques, such as the Transfer Matrix Method (TMM) [68]. When machine learning datasets are generated using TMM simulations, discretization of the frequency spectrum may introduce numerical artefacts that propagate into the training data and influence the learned surrogate model. Furthermore, the potential role of spectral attention mechanisms in broadband acoustic prediction remains largely unexplored. Attention-based architectures may enhance prediction performance by dynamically weighting frequency regions associated with different attenuation mechanisms, although this hypothesis has not yet been systematically validated.

In summary, DNNs offer powerful representational capabilities for modelling complex acoustic responses in porous and composite materials. However, their predictive performance remains strongly dependent on dataset size, spectral complexity, and the incorporation of physically meaningful constraints within the learning framework.

5.1.3 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have substantially advanced acoustic material modelling by enabling direct extraction of spatial and morphological descriptors from high-resolution microstructural imaging data such as micro-computed tomography (micro-CT), scanning electron microscopy (SEM), and optical tomography. Unlike conventional scalar descriptors—such as average porosity or airflow resistivity CNNs capture complex structural patterns including pore connectivity networks, anisotropic fibre orientation distributions, fractal pore geometries, and hierarchical porosity gradients that strongly influence acoustic dissipation mechanisms [69]. The predictive capability of CNNs is strongly dependent on architectural design parameters, including convolutional kernel size, receptive field configuration, and network depth. Small convolution kernels capture fine-scale pore connectivity and tortuosity variations that govern viscous–thermal boundary layer losses. Larger receptive fields, in contrast, allow the network to extract mesoscale structural characteristics such as anisotropy, multilayer coupling, and global impedance gradients that influence resonance-based acoustic attenuation. Increasing network depth enables hierarchical feature learning, where early layers encode microstructural airflow pathways, intermediate layers capture interfacial scattering and poro-elastic coupling, and deeper layers represent global resonance interactions across the material structure [70]. A key advantage of CNNs over fully connected neural networks lies in their use of local receptive fields and weight sharing, which significantly reduces the number of learnable parameters. Rather than connecting each neuron to the entire input space, convolutional layers apply learned filters to local spatial regions, reducing parameter complexity from $O(NP)$to approximately $O(NK)$, where $K\ denotes$ the kernel size. Weight sharing further introduces translation invariance, allowing structural features to be detected regardless of their spatial position within the image. Mathematically, a convolutional layer transforms a set of input feature maps into output feature maps using discrete convolution operations. For an input feature map $z_q^{(l-1)}$and output feature map $\bar{z}_p^{(l)}$, the operation can be expressed as:

$$\bar{z}_p^{(l)} = g'\left(\sum_{q=1}^{C_{in}} w_{pq}^{(l)} * z_q^{(l-1)} + b_p^{(l)}\right), p = 1, \dots, C_{out}, \tag{11}$$

where $w_{pq}^{(l)}$represents the learned convolutional filter between the input channel $q$and output channel p, $b_p^{(l)}$is a bias term, g'denotes a nonlinear activation function, and $*$represents the discrete convolution operator. The resulting set of feature maps forms a tensor representation in which each channel corresponds to a learned structural descriptor. To capture multi-scale spatial relationships, CNN architectures incorporate pooling operations, which reduce spatial resolution while preserving channel information:

$$z_p^{(l)} = pooling\left(\bar{z}_p^{(l)}\right), p = 1, \dots, C_{out}. \tag{10}$$

Pooling expands the effective receptive field of deeper layers, enabling the network to capture long-range structural dependencies. By alternating convolution and pooling layers, CNNs can simultaneously model fine-scale pore geometry and larger structural patterns governing acoustic attenuation. Advanced architectures such as U-Net, residual networks, and encoder–decoder models further enhance representation learning by enabling multi-scale feature extraction while preserving spatial resolution. These models have proven particularly effective in analyzing graded-porosity composites and acoustic metamaterials, where spatial impedance variations strongly influence acoustic wave propagation [71].

Recent work demonstrates that CNN-based models can predict frequency-dependent sound absorption directly from microstructural images when combined with architectures such as U-Net and autoencoders [72]. These image-driven models support emerging computational material design strategies in which microstructures are iteratively optimized using generative deep learning methods such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs). Such approaches enable the synthesis of acoustic composites with tailored microstructural patterns designed to achieve target absorption spectra [73]. Interpretability analyses further reveal that CNN predictions correlate strongly with physically meaningful descriptors such as pore connectivity and tortuosity gradients. However, limitations in scale transfer may arise when microstructural unit-cell geometry changes without appropriate non-dimensional encoding, highlighting the importance of consistent geometric normalization in image-based acoustic modelling. Overall, CNNs provide a powerful framework for linking microstructural morphology to acoustic performance by learning hierarchical spatial representations directly from imaging data. Their ability to capture multi-scale structural features makes them particularly effective for modelling complex porous materials and acoustic metamaterials where attenuation arises from coupled viscous, thermal, and resonance-driven mechanisms.

5.2 Ensemble Learning Methods (RF, Gradient Boosting, XGBoost)

Ensemble learning algorithms, particularly Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost) have been increasingly applied in acoustic material modelling due to their ability to capture nonlinear relationships in heterogeneous datasets while maintaining moderate interpretability. These tree-based ensemble approaches combine predictions from multiple weak learners to improve generalization performance, making them suitable for datasets derived from porous absorbers, multilayer composites, and acoustic metamaterials where material descriptors vary widely. Among these methods, Random Forest constructs an ensemble of decision trees trained on bootstrap samples and random feature subsets. This approach reduces variance and mitigates overfitting compared with single decision tree models. Feature importance is typically estimated through reductions in prediction error or impurity across the forest, enabling identification of influential acoustic descriptors within the dataset [74]. In acoustic material studies, such metrics can highlight parameters such as airflow resistivity, porosity, tortuosity, or layer thickness as key predictors of sound absorption behavior.

However, the interpretability of RF feature importance metrics becomes limited when datasets contain heterogeneous material classes governed by different attenuation mechanisms. For example, porous fibrous absorbers primarily exhibit viscous–thermal dissipation dominated by airflow resistivity and porosity, whereas multilayer acoustic metamaterials depend more strongly on geometric configuration, cavity dimensions, and resonance tuning parameters [69]. Aggregated global feature importance scores therefore risk obscuring material-specific behavior and may produce misleading interpretations when models are trained on mixed composite datasets. In such cases, material-class-specific analyses or stratified modelling strategies are required to avoid overfitting and to preserve physically meaningful interpretation.

Gradient Boosting methods attempt to improve predictive accuracy by sequentially training decision trees that correct the residual errors of previous learners. This iterative optimization often produces superior performance for complex nonlinear datasets, including acoustic responses influenced by microstructural geometry and multi-parameter coupling. Nevertheless, the evaluation of Gradient Boosting models in acoustic applications remains incomplete when systematic comparisons with other ensemble procedures are omitted. Without benchmarking against Random Forest, bagging approaches, or probabilistic models, it becomes difficult to assess predictive stability, variance behavior, and generalization performance across different acoustic datasets.

Extreme Gradient Boosting (XGBoost) extends conventional Gradient Boosting by incorporating regularization terms, second-order gradient optimization, and efficient parallel computation. These modifications typically improve training speed and reduce overfitting in high-dimensional datasets. However, interpreting the suitability of XGBoost for acoustic property prediction requires careful consideration of hyperparameter sensitivity within the ensemble framework. Model behavior can vary significantly with respect to parameters such as tree depth, learning rate, regularization strength, and boosting iterations. Studies that report predictive performance without systematic hyperparameter sensitivity analysis risk overstating the robustness of the method for complex acoustic material datasets. Another methodological limitation across tree-based ensemble models is the potential generation of discontinuous spectral predictions when modelling frequency-dependent acoustic responses. Because decision tree ensembles approximate functions using piecewise constant regions, predicted absorption or impedance curves may exhibit artificial discontinuities that are inconsistent with physically continuous acoustic behavior. This issue becomes particularly relevant when modelling broadband responses or resonance transitions in layered structures.

Interpretability and reliability can be improved through complementary analysis techniques such as SHAP (Shapley Additive Explanation) value decomposition, bootstrap uncertainty estimation, and cross-material validation strategies that test model transferability between porous absorbers and acoustic metamaterials. Furthermore, ensemble models trained on simulation-derived datasets should account for the numerical characteristics of the underlying acoustic solvers. For instance, datasets generated using the Boundary Element Method require careful treatment of boundary conditions and convergence criteria to ensure that numerical artefacts do not propagate into machine learning training data. Consequently, while ensemble learning algorithms provide robust tools for modelling nonlinear acoustic datasets, their interpretability and predictive reliability depend strongly on dataset composition, hyperparameter sensitivity analysis, and rigorous benchmarking against alternative modelling approaches. Material-specific feature importance assessment and systematic model comparison are, therefore, necessary to obtain physically meaningful insights when applying RF, Gradient Boosting, or XGBoost to acoustic composite systems.

5.3 Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) represent a significant development in scientific machine learning by integrating established physical laws into neural network training rather than relying purely on data-driven "black-box" learning. In this paradigm, the model becomes a constrained or "gray-box" system where the neural network must satisfy governing equations of physics in addition to fitting observational data. This approach has been widely explored in the context of solving forward and inverse problems governed by partial differential equations (PDEs), where the model is trained simultaneously on measurement data and the residuals of the governing equations across the domain of interest. Physics-Informed Neural Networks [26, 66].

In acoustic applications, a PINN is typically implemented as a fully connected neural network, such as a Multi-Layer Perceptron, that approximates the acoustic pressure field [75,76]. The network receives spatial coordinates $x$and time $t$as inputs and outputs a predicted pressure field $\hat{p}(x,t;\theta)$, where θdenotes the trainable parameters. Training is performed by minimizing a composite loss function that combines several physically meaningful objectives:

$$(\theta) = w_{data}L_{data} + w_{phys}L_{phys} + w_{bc}L_{bc} + w_{ic}L_{ic}. \tag{12}$$

The first component, L_{data}, represents a conventional supervised learning objective that ensures agreement with empirical observations. For a set of N_{data}measurements obtained from sensors at coordinates (x_i, t_i) This term is typically formulated as a mean squared error between the predicted pressure and the measured pressure values. This anchors the network solution to the available experimental data. The second component, L_{phys}, enforces the governing physical law that describes acoustic propagation. For a homogeneous, lossless sound field, the governing equation is the acoustic wave equation, expressed through the residual function

$$f(p) = \nabla^2 p - \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} = 0 \tag{13}$$

where $c$denotes the speed of sound. The physics loss is defined as the mean-squared residual evaluated at a large number of collocation points randomly sampled throughout the interior of the domain. The neural network prediction $\hat{p}$is substituted into the residual function, and the loss penalizes deviations from zero. The computation of derivatives such as $\partial^2\hat{p}/\partial t^2$and spatial Laplacians is made possible through automatic differentiation within the deep learning framework, allowing exact gradients to be obtained with respect to the network inputs without requiring numerical discretization.

Two additional terms enforce boundary and initial conditions. The boundary loss L_{bc}ensures that the network prediction satisfies the physical boundary conditions of the acoustic environment, such as rigid surfaces or pressure-release boundaries. For example, a rigid wall can be expressed through a Neumann boundary condition where the normal derivative of the pressure field equals zero. This constraint is imposed through an additional mean squared error evaluated at sampled boundary points. The initial condition loss L_{ic}enforces the known acoustic state at the initial time, typically defined by the initial pressure and velocity distribution. Together, these constraints guide the network toward a physically valid solution across the entire spatiotemporal domain rather than only at measurement points. The weighting coefficients w_{data}, w_{phys}, w_{bc}, and w_{ic}act as hyperparameters that balance the contributions of each component, and careful tuning of these weights is often necessary to achieve stable and accurate training.

Embedding physical constraints directly into the learning objective provides several advantages for acoustic modeling. PINNs are particularly effective for inverse problems where the objective is to infer unknown quantities—such as source locations, boundary properties, or complete sound fields—from limited observations [75,77]. By enforcing the governing PDE, the model effectively introduces a strong regularization mechanism that constrains the space of admissible solutions. This transforms many otherwise ill-posed inverse problems into well-posed optimization problems and significantly reduces the amount of labeled data required. In acoustic field reconstruction and source localization tasks, this physics-based supervision allows models to generalize from sparse sensor measurements while still maintaining consistency with wave propagation physics [78]. Despite these benefits, the method has several limitations. The effectiveness of PINNs depends heavily on the availability of an accurate and analytically expressible governing equation. In situations involving highly complex, nonlinear, or coupled multi-physics processes, the appropriate PDE may be difficult to formulate or computationally expensive to evaluate. Additionally, neural network approximations sometimes struggle to represent solutions with sharp gradients, discontinuities, or high-frequency oscillatory components, which can appear in certain acoustic scenarios. Training can also be sensitive to the weighting of loss components and the distribution of collocation points.

When compared with other machine learning paradigms used in acoustics, PINNs occupy a distinctive position. Generative models—such as diffusion models or generative adversarial networks—are highly effective for synthesizing new audio signals or simulating complex acoustic scenes but generally lack explicit guarantees of physical consistency. Self-supervised learning approaches attempt to infer physical relationships directly from data through representation learning, but do not explicitly encode governing equations. In contrast, PINNs impose predefined physical laws directly within the optimization process, providing stronger guarantees of physical plausibility while sacrificing some flexibility in scenarios where the underlying physics is uncertain or incomplete.

5.4 Gaussian Process Regression

Gaussian Process Regression (GPR) is a probabilistic ML method used to model relationships between input and output variables, particularly in situations where simulations or physical models are computationally expensive [79]. It is widely applied in surrogate modelling, uncertainty quantification, sensitivity analysis, and model calibration because it can approximate complex models while significantly reducing computational cost. One of the key advantages of Gaussian Processes is their flexibility and their ability to provide uncertainty estimates alongside predictions. Unlike deterministic regression approaches that assume a fixed functional relationship, GPR treats the underlying function as a probability distribution over possible function. A Gaussian Process is defined as a collection of random variables in which any finite subset follows a joint Gaussian distribution. In regression tasks, the unknown function $f(x)$is assumed to follow a Gaussian process characterised by a mean function $m(x)$ and a covariance function $k(x, x')$. The mean function represents the expected value of the function at a given input, while the covariance function defines how strongly outputs at different input locations are correlated.

Training a GPR model begins by defining a prior distribution over the possible functions. Observed data are then incorporated through Bayes' theorem to update this prior and obtain a posterior distribution that reflects the information contained in the data. The likelihood function typically assumes that the observations contain Gaussian noise around the latent function. The resulting posterior distribution provides updated estimates of the mean and covariance of the function, which can then be used to make predictions at new input locations. Importantly, GPR produces both a predicted value and an associated uncertainty, making it particularly useful for modelling systems where confidence in predictions is important [80].

A key component of Gaussian Process Regression is the covariance function, commonly referred to as the kernel. The kernel defines how similarity between input points translates into correlation between outputs and therefore determines important characteristics of the model, such as smoothness and variability of the predicted function [70]. Several kernel functions are commonly used in practice, including the radial basis function (RBF), rational quadratic, and Matérn kernels. The RBF kernel is one of the most widely used and produces very smooth functions because it is infinitely differentiable. The rational quadratic kernel can be interpreted as a mixture of RBF kernels with different length scales, allowing the model to capture variations occurring at multiple scales. The Matérn kernel provides additional flexibility by introducing a parameter that controls the smoothness of the function, making it useful for modelling processes that are less smooth.

In many applications, kernels can also be combined to form composite kernels, enabling the model to capture multiple structural characteristics of the data simultaneously. For example, combining an RBF kernel with a Matérn kernel allows the model to represent both smooth global trends and localized variations [81]. Through appropriate kernel selection and combination, Gaussian Process Regression provides a flexible and interpretable framework for modelling complex relationships while maintaining predictive uncertainty estimates [82].

In practice, GPR has been successfully applied across diverse domains where probabilistic modelling and uncertainty quantification are essential. For example, custom composite kernels have been used to capture complex dynamics and predictive uncertainty in real-world systems like sewer flow monitoring, demonstrating reliable performance with limited input data [83]. Such applications illustrate both the interpretability and predictive confidence advantages of GPR over purely deterministic regressors, particularly in settings where data are expensive or sparse. Despite these benefits, GPR suffers from computational limitations: training requires inversion of the covariance matrix, which scales cubically with the number of training points ($O(n^3)$) and quadratically in memory ($O(n^2)$) [84]. This makes exact GPR infeasible for large datasets, prompting the use of approximations such as sparse Gaussian processes or inducing-point methods to reduce computational cost while retaining probabilistic predictions [64]. In the context of acoustic composite modelling, GPR's probabilistic predictions, combined with its flexibility to capture nonlinear relationships, make it a robust choice for surrogate modelling, uncertainty-aware optimization, and data-efficient design pipelines.

5.5 Hybrid FEM–Machine Learning Architectures

Hybrid finite element method–machine learning (FEM–ML) frameworks combine high-fidelity multi-physics simulations with data-driven modelling to accelerate acoustic prediction and optimization workflows. Within these frameworks, acoustic operators are partitioned between physics-based solvers and AI components. FEM solvers typically enforce governing wave propagation equations, boundary conditions, and structural dynamic equilibrium relations. Machine learning components learn effective material impedance relationships, parameter-to-response surrogate mappings, and microstructure-driven acoustic attenuation characteristics.

Clearly defining the partition between learned and physics-enforced operators enhances model interpretability and reduces the risk of generating physically inconsistent predictions. Hybrid FEM–ML frameworks have demonstrated significant potential for digital twin development, real-time vibro-acoustic monitoring, and rapid acoustic material design optimization [26]. A recurring limitation in the literature, however, is conceptual ambiguity in the integration of physics and AI. To address this, operator-level partitioning can be defined as follows: FEM/BEM solvers enforce the wave equation, boundary conditions, and structural equilibrium; transfer-matrix methods (TMM) handle layer transfer operators and impedance propagation; and machine learning components focus on learning constitutive material mappings, impedance surrogates, and microstructure–property relationships. This structured division clarifies the roles of physics-based and data-driven modules, enabling hybrid frameworks to achieve both high predictive accuracy and physical consistency.

5.6 Surrogate Modelling Trade-Off Analysis

Surrogate modelling has emerged as a central strategy for mitigating the computational burden associated with high-fidelity acoustic simulations, particularly those based on the Finite Element Method (FEM) and Boundary Element Method (BEM). While classical numerical solvers provide strong physical interpretability and broadband accuracy, their computational cost scales unfavorably with mesh density, geometric complexity, and frequency resolution [85,86]. In contrast, neural surrogates offer rapid inference once trained, enabling real-time prediction and optimization in composite acoustic systems [87]. Table 3 summarizes the principal trade-offs among commonly applied surrogate frameworks, considering training cost, inference speed, extrapolation capability, and data requirements.

Table 3 Comparative trade-offs in surrogate acoustic modelling frameworks

Model Type	Training Cost	Inference Speed	Extrapolation Capability	Data Need
ANN	Low	Very Fast	Moderate	Moderate
DNN	Moderate	Fast	Moderate	High
PINN	High	Moderate	High	Low–Moderate
Hybrid FEM–ML	High (initial)	Very Fast	High	Moderate

Conventional FEM-based acoustic simulations typically require computational times ranging from several minutes to hours per configuration, depending on mesh refinement and solver stability constraints. In contrast, trained neural surrogates can generate predictions in less than one millisecond per sample. This corresponds to a practical acceleration factor between one and three orders of magnitude [88]. However, this acceleration is achieved at the expense of a nontrivial upfront training cost. Model training may require minutes to several hours, depending on architectural depth, dataset dimensionality, and hyperparameter optimization complexity. Physics-informed neural networks (PINNs), in particular, exhibit increased optimization stiffness due to embedded partial differential equation constraints, which raises training time but enhances extrapolative robustness [88]. Accordingly, surrogate selection should be guided by the intended application context rapid design iteration, broadband extrapolation, or physics-consistent inverse modelling rather than inference speed alone.

6. Generative Modelling for Acoustic Composite Design

6.1 Autoencoders and Microstructure Representation

Autoencoders are foundational deep generative models that learn a compressed representation (latent space) of complex data and then reconstruct the input from that representation [89]. In the context of composite materials, this latent encoding enables reduced-dimensional design spaces wherein microstructural features such as porosity, pore shape, and fibre orientation can be represented compactly, yet meaningfully, for downstream learning or optimization. Autoencoders consist of an encoder network that maps high-dimensional input data to a low-dimensional latent vector, and a decoder network that reconstructs data from that vector [90]. This latent representation captures essential structural variability, providing a basis for interpolation, clustering, or inverse design in material design workflows.

Because generative design tasks often require sampling or exploring continuous design variations, deterministic latent spaces from conventional autoencoders may lack smooth interpolation and generative capacity. Such limitations motivate the use of probabilistic generative models that impose structured distributions on latent variables, as discussed next.

6.2 Variational Autoencoders (VAEs): Latent Space Representation and Training Stability

Variational autoencoders (VAEs) represent a class of generative neural networks that have been widely applied in microstructure reconstruction and materials modelling. Unlike conventional autoencoders that map inputs deterministically to fixed latent vectors, VAEs introduce a probabilistic latent space that enables structured generative modelling [90-92]. In this framework, each input sample is encoded as a probability distribution typically parameterized by a mean vector $\mu$and variance σ—within a continuous latent space. This probabilistic formulation allows latent variables to be sampled during both training and inference, enabling smooth interpolation between latent representations and supporting principled generative processes. The VAE framework was originally formalized by Diederik and Max [93].

From a probabilistic perspective, the objective of a VAE is to maximize the conditional likelihood of observed data x, expressed as $p_\theta(x \mid z)$, where a lower-dimensional latent variable $z$generates the observation. The encoder network approximates the posterior distribution $p_\theta(z \mid x)$by mapping the input data to a distribution in the latent space. In convolutional implementations such as VAECNN, convolutional layers extract spatial features from complex microstructures, including binary porous media. The encoder, therefore, represents each input as a latent distribution from which the feature vector $z$is sampled.

Training involves optimizing a composite loss function comprising two components. The first is a reconstruction term that measures how accurately the decoder reproduces the input data from the latent representation, commonly implemented using binary cross-entropy between the original image $x$and the reconstruction $\hat{x}$. The second component is a regularization term that constrains the latent distribution to approximate a predefined prior, typically a multivariate Gaussian distribution. This constraint is enforced using the Kullback–Leibler (KL) divergence, which encourages the encoded distributions to remain close to the Gaussian prior [94]. As a result, new microstructure realizations can be generated by sampling latent vectors from the Gaussian distribution and decoding them through the trained decoder network.

In materials modelling, VAEs enable complex microstructural features—such as pore morphology, fibre orientation distributions, and layered geometries—to be encoded into compact latent representations [95]. These latent variables can then be manipulated to generate new microstructure configurations and explore high-dimensional design spaces. Such capabilities support optimization workflows where candidate microstructures are sampled from latent space and evaluated using surrogate models for acoustic or mechanical performance.

Despite these advantages, several factors influence VAE performance. A key consideration is the balance between reconstruction accuracy and latent regularization, as excessive regularization can over-smooth the latent space, while weak regularization can lead to poorly structured representations. Training can also suffer from posterior collapse, where latent variables contribute little information to the reconstruction. Techniques such as KL-annealing and β-VAE regularization are commonly used to stabilize training and maintain informative latent representations for generative microstructure design [96].

6.3 Generative Adversarial Networks (GANs): Validation and Acoustic Performance Indicators

Generative Adversarial Networks (GANs) are a class of deep generative models widely used for unsupervised microstructure reconstruction and synthesis. A GAN consists of two neural networks trained in opposition: a generator $G$and a discriminator D. The generator produces synthetic samples from latent variables, while the discriminator attempts to distinguish between real data and generated samples [97], [98], [99]. Through this adversarial training process, both networks compete in a minimax optimization game: the generator attempts to produce outputs that resemble real microstructures, while the discriminator learns to identify whether a sample originates from the real dataset or the generator. As training progresses, the generator gradually improves its ability to produce realistic structural patterns. In the standard (or "vanilla") GAN formulation, the generator receives a latent vector z-sampled from a prior distribution, typically a Gaussian distribution $p_z(z)$, and outputs a synthetic image $G(z)$that approximates the real data distribution. The discriminator evaluates both real samples $y$and generated samples $G(z)$, producing the probability that an input corresponds to real data. The two networks are trained simultaneously using an adversarial loss function in which the discriminator aims to maximize the probability of correctly classifying real and generated samples, while the generator attempts to minimize this objective by producing increasingly realistic outputs.

Conditional GANs (C-GANs) extend this framework by introducing additional conditioning variables into the generator and discriminator. Instead of generating samples solely from latent noise, the generator also receives auxiliary input data x, which guides the generation process toward specific structural modes or design constraints. In microstructure modelling, such conditioning variables may represent partial structural information, subregions of a material sample, or target physical properties. This capability enables controlled reconstruction and targeted generation of material microstructures from limited data. GAN-based architectures have been applied to reconstruct two-dimensional microstructure slices and recover full structural representations from incomplete datasets. Variants of GANs have also been developed to improve reconstruction scalability and enable image super-resolution, allowing high-resolution microstructures to be generated from lower-resolution inputs. In acoustic and composite material design, conditional GAN frameworks can incorporate performance-related indicators into the generation process. For example, the generator may be conditioned on acoustic response descriptors such as transmission loss spectra, resonance frequencies, or sound absorption coefficients. By linking generative modelling with physical response parameters, the model can produce candidate microstructures that are consistent with desired acoustic performance characteristics.

Validation of GAN-generated microstructures typically involves both morphological and performance-based metrics. Structural validation may compare generated samples with real microstructures using descriptors such as porosity distributions, pore connectivity, tortuosity, or permeability. However, for acoustic materials, validation must also incorporate predicted acoustic responses obtained from numerical modelling methods such as the Transfer Matrix Method or the Boundary Element Method. Evaluating generated designs against sound absorption spectra or transmission loss curves provides stronger evidence of the physical relevance of the generated structures. Although GANs often produce sharper and more detailed structural patterns than other generative models, their training can be sensitive to optimization instability. One common issue is mode collapse, where the generator produces a limited set of similar samples, reducing design diversity. Stabilization strategies such as modified loss functions, improved network architectures, and balanced training schedules are therefore frequently employed. Overall, GAN-based generative modelling provides a powerful framework for exploring microstructure design spaces in acoustic materials. When combined with rigorous structural validation and performance-based acoustic indicators, GANs can support data-driven development of advanced composite materials with tailored acoustic properties.

7. Metaheuristic Optimization Strategies

Metaheuristic optimization techniques are commonly used in acoustic material and metamaterial design because the underlying objective functions, such as broadband sound absorption, transmission loss, or impedance matching, are frequently highly nonlinear, multimodal, and computationally expensive to assess. These properties are caused by resonance processes, wave interference, and structural-acoustic coupling factors, resulting in rough optimization landscapes. Metaheuristic algorithms offer derivative-free search strategies for effectively exploring such design spaces. To clarify the relative strengths of commonly used optimization strategies, Table 4 summarizes key convergence characteristics of several widely applied algorithms in acoustic design optimization. These optimization strategies differ significantly in how they balance exploration, exploitation, convergence stability, and computational cost, which influences their suitability for different acoustic design scenarios.

Table 4. Comparative convergence characteristics of metaheuristic optimization algorithms used in acoustic material design

Optimization Method	Convergence Speed	Stability	Evaluation Cost	Typical Strengths in Acoustic Design
Genetic Algorithm (GA)	Moderate	Moderate–High (with diversity control)	High	Robust global exploration in multimodal resonance landscapes
Particle Swarm Optimization (PSO)	Fast initial convergence	Moderate	Moderate	Efficient optimization for layered acoustic systems with smooth response regions
Bayesian Optimization (BO)	Fast under limited evaluations	High	Low–Moderate (per iteration high)	Sample-efficient optimization for expensive acoustic simulations
NSGA-II	Moderate	High for multi-objective problems	High	Effective exploration of Pareto fronts for competing acoustic objectives

7.1 Genetic Algorithm (GA)

Genetic Algorithms (GAs) are widely applied for optimization of neural network architectures and acoustic composite structural parameters, particularly in inverse design of metamaterials and porous absorbers. GA-based optimization performs stochastic exploration of the design space through evolutionary operators' selection, crossover, and mutation enabling robust global search without gradient information [100,101]. In GA–neural network hybrid frameworks, the GA optimizes architectural hyperparameters, layer configurations, or structural design variables, while the neural network serves as a predictive surrogate for acoustic performance metrics.

Convergence behavior in GA optimization is highly sensitive to population size. Small populations may accelerate early convergence but increase the risk of premature stagnation due to reduced genetic diversity. Conversely, excessively large populations improve global exploration but significantly increase computational cost per generation. In acoustically complex design spaces characterized by multimodal resonance peaks, impedance discontinuities, and sharp bandgap transitions population diversity is essential to avoid entrapment in suboptimal local minima [102].

The balance between mutation and crossover rates critically governs exploration–exploitation dynamics. Crossover promotes recombination of high-performing design traits, facilitating exploitation of promising regions. Mutation introduces stochastic perturbations that preserve diversity and enable escape from local optima. Low mutation probability often leads to convergence stagnation, particularly in rugged fitness landscapes. Excessively high mutation rates, however, may disrupt convergence stability and cause oscillatory search behavior. Adaptive mutation schemes, in which mutation probability increases when population diversity decreases, have been proposed to mitigate premature convergence and improve robustness in nonlinear acoustic optimization problems [10, 103].

In GA–neural network hybrid optimization, convergence stability is further influenced by the topology of the acoustic fitness landscape. Inverse metamaterial design problems frequently exhibit highly sensitive objective functions, where small geometric perturbations produce abrupt changes in absorption coefficient or transmission loss. Such sensitivity can induce oscillatory convergence patterns or extended stagnation phases. Hybrid strategies combining GA-based global exploration with gradient-based local refinement or surrogate-assisted evaluation improve convergence efficiency while reducing computational burden. When generative models such as GANs are used to synthesize candidate microstructures, additional validation protocols are required before acoustic deployment. Generated geometries must be verified through: (1) finite element method (FEM) acoustic simulation comparison; (2) sound absorption coefficient (SAC) curve deviation analysis across relevant frequency bands; and (3) structural morphology similarity metrics to ensure physical plausibility. GAN training instability and mode collapse remain common risks, particularly in high-dimensional microstructure generation. Wasserstein GAN variants, which employ an alternative loss formulation to stabilize gradient behavior, have demonstrated improved convergence stability and reduced mode collapse in material microstructure synthesis tasks. Overall, GA–neural network hybrid optimization offers strong global search capability for nonconvex acoustic design problems, but careful tuning of population size, mutation–crossover balance, and diversity-preserving mechanisms is essential to avoid stagnation and ensure reliable convergence in resonance-dominated metamaterial systems. GAN-generated microstructures must be validated via:

- FEM acoustic simulation comparison,
- SAC curve deviation analysis,
- Structural morphology similarity metrics.

Mode collapse and instability are common risks; Wasserstein GAN variants improve convergence.

7.2 Bayesian Optimization for Nonconvex Acoustic Metamaterial Design

Bayesian Optimization (BO) is a sample-efficient global optimization framework well suited to acoustic metamaterial design problems characterized by highly nonconvex and multi-resonant response surfaces [104]. Unlike gradient-based optimization methods, BO does not require derivative information and remains robust in the presence of discontinuities, sharp impedance transitions, and multiple local optima. Such behaviors frequently arise in metamaterial systems exhibiting narrowband resonances, bandgap formation, and complex wave–structure interactions.

BO relies on probabilistic surrogate modelling, most commonly Gaussian Process (GP) regression, to approximate the objective function while quantifying predictive uncertainty [64,105,106]. The GP prior encodes assumptions regarding smoothness, stationarity, and spatial correlation through kernel selection, typically squared exponential or Matérn covariance functions. In the absence of strong physical priors, the mean function is often assumed constant, while kernel hyperparameters, such as characteristic length scales and variance terms, are estimated through marginal likelihood maximization [79]. As new design evaluations are performed, the surrogate model is sequentially updated, progressively improving its representation of the design landscape [86].

The exploration–exploitation trade-off in BO is controlled by acquisition functions that combine the surrogate predictive mean and variance. Expected Improvement (EI) selects candidate designs that maximize the anticipated improvement relative to the best observed solution, while Upper Confidence Bound (UCB) strategies introduce an explicit uncertainty weighting parameter to regulate exploration [107]. Exploration-dominated configurations priorities sampling in regions of high uncertainty to improve global surrogate accuracy, whereas exploitation-dominated strategies refine solutions near promising designs. For highly nonconvex acoustic response surfaces with multiple resonance peaks and discontinuous impedance behavior, adaptive acquisition strategies dynamically balance these objectives to maintain global search capability while minimizing computational cost.

A key advantage of BO in acoustic metamaterial design lies in its uncertainty-guided search. Since forward evaluations often require computationally intensive finite element or multi-physics simulations, sequential sampling based on information gain can significantly reduce the number of simulations required compared with exhaustive or population-based methods. This makes BO particularly effective for inverse design problems in which the mapping from geometry to acoustic performance is highly nonlinear and expensive to evaluate [29]. More broadly, BO is grounded in Bayesian machine learning, where probability theory provides a principled framework for incorporating prior knowledge and uncertainty into model inference [108]. Bayesian statistics describe uncertain quantities using probability distributions and update prior beliefs using observed data through Bayes' theorem.

$$(\theta \mid x, y) = \frac{p(y \mid x, \theta)p(\theta)}{p(y \mid x)} \tag{14}$$

where $p(\theta)$denotes the prior distribution of model parameters, $p(y \mid x, \theta)$the likelihood of observing the data, and $p(\theta \mid x, y)$the posterior distribution. The denominator $p(y \mid x)$, referred to as the evidence, acts as a normalizing constant.

$$y = x^T w + \varepsilon \tag{15}$$

In machine learning models, parameter estimation can therefore be formulated as a Bayesian inverse problem. For example, in a linear model as given in Equation (15), assigning Gaussian priors to the parameter vector $w$and assuming Gaussian observation noise yields a Gaussian posterior distribution over the parameters. This conjugate formulation enables efficient closed-form updates and sequential learning as new data are obtained [109].

Bayesian approaches offer several advantages for acoustic modelling and optimization. By explicitly quantifying uncertainty in both parameters and predictions, they reduce the risk of overfitting and provide probabilistic confidence estimates for model outputs. Furthermore, prior knowledge about the physical system can be incorporated directly through prior distributions, improving robustness in data-limited regimes. Overall, Bayesian optimization provides a principled and uncertainty-aware framework for inverse design in acoustic metamaterials. By combining probabilistic surrogate modelling with sequential information-driven sampling, BO enables efficient global optimization of highly nonlinear, resonance-dominated performance landscapes while maintaining rigorous uncertainty quantification.

7.3 Particle Swarm Optimization in Discontinuous Acoustic Response Landscapes

Particle Swarm Optimization (PSO) is frequently used in multilayer acoustic composite optimization due to its relatively simple implementation and rapid convergence during early search stages. The algorithm models collective swarm behavior, where candidate solutions referred to as particles move through the design space according to velocity updates influenced by both their individual best solution and the globally best solution identified by the swarm. This cooperative search strategy enables efficient exploration of nonlinear optimization landscapes without requiring gradient information [110].

In acoustic composite design, PSO has been applied to optimize structural parameters such as layer thickness, cavity dimensions, perforation ratios, and porous material characteristics, to maximize broadband sound absorption or transmission loss. Case-specific applications demonstrate that PSO can effectively identify high-performance configurations in multilayer absorber systems when coupled with acoustic simulation models. For example, optimization frameworks often integrate PSO with numerical solvers such as the Transfer Matrix Method or the Finite Element Method to evaluate acoustic response functions during each optimization iteration. These simulation-driven evaluations provide physically consistent performance metrics that guide the swarm search process [110]. However, objective functions in multilayer acoustic design frequently contain discontinuities caused by abrupt resonance transitions, impedance mismatches, and structural mode coupling effects. These phenomena produce rugged optimization landscapes in which small geometric perturbations may generate large variations in acoustic response. Under such conditions, conventional PSO may suffer from convergence instability, premature particle clustering, or stagnation near local optima.

Several algorithmic modifications have been proposed to improve PSO robustness in these discontinuous acoustic response landscapes. Adaptive inertia weighting dynamically adjusts the momentum of particle motion, enabling broader exploration during early iterations and more focused exploitation during later search phases. Velocity clamping techniques restrict excessive particle displacement, preventing unstable oscillations in highly sensitive regions of the design space. Additionally, hybrid optimization frameworks that combine PSO with local search procedures or surrogate modelling can significantly enhance convergence reliability.

Integration of PSO with neural acoustic surrogate models provides a particularly effective hybrid optimization pathway. In such frameworks, machine learning models, such as deep neural networks trained on simulated acoustic datasets, serve as fast predictors of acoustic performance metrics. The PSO algorithm then operates on the surrogate model rather than directly evaluating expensive numerical simulations. This approach substantially reduces computational cost while preserving global search capability, making it suitable for large-scale optimization of composite material geometries and metamaterial unit cells.

Overall, PSO offers a practical optimization strategy for acoustic composite design due to its fast convergence and derivative-free operation. Nevertheless, its performance in resonance-dominated acoustic systems depends strongly on algorithmic enhancements and effective coupling with simulation or surrogate modelling frameworks. Adaptive parameter control and hybrid optimization architectures, therefore, play a critical role in ensuring reliable convergence across discontinuous acoustic response landscapes.

7.4 Multi-Objective Optimization (NSGA-II)

Multi-objective optimization is critical in acoustic composite design, where trade-offs between competing performance metrics—such as broadband sound absorption, transmission loss, and material weight—must be balanced. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is commonly used in this context due to its ability to efficiently explore Pareto-optimal fronts while maintaining solution diversity [111]. NSGA-II ranks candidate designs according to dominance levels and crowding distance, enabling simultaneous optimization across multiple acoustic objectives without scalarizing them into a single metric. Its evolutionary search strategy is particularly effective for exploring highly nonlinear, multimodal design spaces characteristic of layered acoustic composites.

7.5 Comparative Convergence and Efficiency Analysis

Comparative studies of optimization strategies in acoustic material design indicate that PSO achieves rapid initial convergence, especially in smooth or moderately discontinuous landscapes, but may stall near discontinuities without adaptive enhancements. NSGA-II, in contrast, provides superior exploration of multi-objective trade-offs but can require more computational effort per generation due to population-based sorting and crowding evaluation. Hybrid approaches that combine swarm-based global search with local refinement or evolutionary multi-objective algorithms often yield the best balance between convergence speed, solution quality, and robustness across discontinuous acoustic response landscapes.

8. Results and Discussion

This section presents a structured synthesis of findings derived from the reviewed studies. The results are categorized into (i) predictive performance trends, (ii) data dependency, and (iii) model limitations. It is important to note that these findings represent a cross-study synthesis and are therefore subject to variability arising from differences in datasets, material systems, and validation methodologies.

8.1 Comparative Analysis of Algorithmic Performance

ANN and DNN models frequently outperform traditional regression approaches within individual studies, particularly where nonlinear and multiscale relationships dominate. However, such comparisons are study-specific and should not be interpreted as universally generalizable due to differences in datasets, feature engineering, and validation protocols.

Performance metrics reported in the literature are not standardized. Studies variably report R^2, RMSE, MAE, or percentage error, often computed over different frequency ranges and datasets. Consequently, direct numerical comparison between models across studies is inherently limited.

8.1.1 Advantages of Nonlinear Deep Learning Models

- Predictive Performance:

ANNs and DNNs routinely achieve R^2 values between 0.97 and 0.99, substantially surpassing polynomial regression models, which typically plateau at $R^2 \approx 0.85$ when modelling frequency-dependent absorption, impedance spectra, or transmission loss [112]. As microstructural complexity increases, particularly in architected, porous, or anisotropic acoustic systems, the performance gap between these approaches becomes more pronounced.

Deep architectures for feature Deep learning models incorporating convolutional layers, residual blocks, or attention mechanisms extract high-dimensional nonlinear features that represent both local (pore geometry, cell size, fibre orientation) and global (macro-porosity gradients, multi-layer interactions) acoustic behaviors. This advanced feature extraction supports accurate prediction across diverse material classes, including microcellular foams, porous metamaterials, multi-layer absorbers, fibrous composites, and 3D-printed acoustic architectures.

- Role of Advanced Activation Functions:

Nonlinear activation functions, including Rectified Linear Unit (ReLU), Gaussian Error Linear Unit (GELU), and Exponential Linear Unit (ELU), enhance model stability during training, mitigate vanishing gradient issues, and improve convergence. Their use significantly increases predictive accuracy for large multi-frequency datasets, complex geometric descriptors, and heterogeneous acoustic materials [113].

8.2 A Benchmarking Framework for Artificial Intelligence Models in Acoustic Materials Prediction

Contemporary artificial intelligence (AI) techniques differ significantly in computational cost, predictive performance, data requirements, and suitability for various classes of composite and porous acoustic materials. Despite notable progress in AI-assisted acoustic modelling, the literature still lacks a unified benchmarking framework for comparing these algorithms across material systems and computational tasks. Recent reviews highlight substantial variations in accuracy and generalization behaviors among ANNs, CNNs, DNNs, PINNs, ensemble learning models, and hybrid machine learning–finite element method (ML–FEM) frameworks [25], [114].

Table 5 provides a structured comparison of these AI paradigms across key performance indicators, including accuracy, dataset size requirements, computational efficiency, strengths, weaknesses, and material applicability. Such benchmarking frameworks have been recommended in recent materials-informatics literature to guide model selection, enhance reproducibility, and improve cross-study comparability [26], [73]. The benchmarking methodology involves evaluating these models against predefined criteria such as predictive accuracy, dataset volume, computational resources, and ability to incorporate physical constraints.

Table 5. Benchmarking comparison of AI techniques for acoustic material prediction

AI Method	Accuracy	Data Requirement	Computation Time	Strengths	Weaknesses	Suitable Applications	Ref.
ANN	R^2 = 0.95–0.99; MAE ≈ 0.02–0.06	Low–Moderate (50–500 samples)	Very fast (ms–s)	Excellent for tabular acoustic data, low computational cost, robust for small datasets	Poor at high-dimensional inputs; cannot process microstructure images	Porous foams, natural-fibre composites, impedance-tube SAC prediction	[116], [117]
CNN	R^2 > 0.97; error < 3%	High (hundreds–thousands of images)	Moderate (s–min)	Extracts microstructural features, captures tortuosity and anisotropy, excellent for image-based prediction	High dataset requirement; expensive training	Meta-porous materials, 3D-printed lattices, micro-perforated panels	[118], [119]
DNN	R^2 = 0.97–0.995; MSE < 0.002	Moderate–High	Moderate	Learns highly nonlinear behavior; predicts multi-resonance phenomena	Overfitting risk; architecture tuning required	Helmholtz resonators, multilayer composites, resonant metamaterials	[120]
PINN	R^2 = 0.98–0.995	Low–Moderate	Slow–Moderate (min–hr)	Integrates governing acoustic PDEs, excellent extrapolation, robust for limited/noisy data	High training time; implementation complexity	Poroelastic materials, frequency-dependent wave propagation, coupled thermo-viscous effects	[25]
Ensemble Models	R^2 = 0.90–0.98	Low	Very fast	Strong feature ranking, robust to noise, good for heterogeneous tabular inputs	Cannot process image data; limited frequency-domain prediction	Natural-fibre composites, acoustic emission diagnostics	[10], [121], [122]
Hybrid ML–FEM	Error < 2 dB vs FEM; R^2 > 0.995	Low–Moderate	Very fast inference; slow initial training	Replaces slow FEM simulations; ideal for optimization and parametric sweeps	Requires FEM expertise; significant setup time	Metamaterials, lattice structures, aerospace/automotive acoustic panels	[73], [123]

Note: The reported performance ranges are compiled from multiple independent studies with varying datasets, material systems, and validation protocols. These values represent indicative ranges rather than directly comparable benchmarks.

An example application scenario illustrates its practical relevance: a researcher working on the acoustic properties of novel porous composites may consult the benchmarking framework to identify the most appropriate AI model for predictive modelling. If the researcher possesses limited experimental data but requires high accuracy and strong extrapolation capability, a physics-informed neural network would be suitable due to its integration of governing physical laws, such as the Helmholtz and poro-elastic wave equations [25,26]. Conversely, when working with large micro-CT or SEM datasets, CNN-based architectures offer superior performance because of their ability to extract morphological features such as pore connectivity, tortuosity, and anisotropy directly from imaging data [115]. ANN and DNN performance typically range between $R^2 \approx 0.90$–0.99, depending on dataset size, feature representation, and validation protocol. Higher values (>0.97) are generally observed under controlled or interpolative conditions, while lower values are reported in cross-material or extrapolative scenarios. This framework, therefore, provides evidence-based guidance for selecting the most appropriate AI model for diverse acoustic engineering applications in automotive, aerospace, architectural, and materials-science domains. Table 5 summarizes the author-derived comparative synthesis of AI model performance across reviewed studies.

8.3. Cross-Dataset Generalization and Limitations

AI methods have shown significant promise in modelling sound absorption, acoustic impedance, transmission loss, damping behavior, and broadband noise reduction, offering prediction accuracies comparable to experimental measurements and numerical simulations. Traditional ML methods such as support vector machines (SVMs), k-nearest neighbors (k-NN), decision trees, random forests, and ANNs have demonstrated the ability to learn nonlinear, multidimensional acoustic relationships from limited datasets without requiring explicit prior assumptions. However, these methods also present limitations, particularly in handling complex, high-dimensional acoustic data and microstructural interactions. Table 6 presents the strengths and limitations of commonly employed traditional machine learning methods for predicting material properties. Understanding these factors helps select appropriate shallow learning techniques to predict the acoustic properties of composite materials.

Although traditional ML methods can identify correlations between material microstructure and acoustic performance, their effectiveness is limited by several factors. Manual feature extraction is required, which depends on expert knowledge to select parameters such as porosity, tortuosity, airflow resistivity, and pore-size distribution. This approach is time-intensive and may miss subtle microstructural features that significantly affect thermo-viscous dissipation and resonance behavior. Additionally, the shallow architectures of traditional ML models restrict their ability to capture the complex, nonlinear, and multi-physics interactions present in acoustic materials, where performance is influenced by geometry, viscosity, thermal boundary layers, and microstructural heterogeneity. Furthermore, separating feature engineering from prediction can reduce computational efficiency and limit the models' ability to identify deep, high-order correlations that govern acoustic phenomena.

Deep learning (DL) methods facilitate automated feature extraction from raw acoustic signals, high-dimensional simulation data, and microstructural images. Techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), autoencoders (AEs), deep belief networks (DBNs), and generative adversarial networks (GANs) address the limitations of traditional ML and have been utilized to predict absorption curves, optimize metamaterial topologies, and extract microstructural descriptors from two- and three-dimensional images. However, DL approaches require larger datasets, longer training times, and significant computational resources. Additionally, their 'black-box' nature presents interpretability challenges, which restrict adoption in safety-critical acoustic engineering domains such as aerospace. Table 7 presents the strengths and limitations of deep learning methods for predicting acoustic properties. Awareness of these factors facilitates the selection of suitable deep learning approaches for composite material analysis.

Table 6. Strengths and weaknesses of common shallow learning methods applied in acoustic property prediction

Traditional ML Methods	Strengths	Weaknesses
Support Vector Machine (SVM)	• High prediction accuracy for small acoustic datasets • Performs well in high-dimensional feature spaces (e.g., porosity, tortuosity, resistivity) • Robust to overfitting with proper kernel selection	• Not suitable for very large acoustic datasets • Sensitive to noise in measurement data • Requires careful kernel tuning for broadband acoustic predictions
k-Nearest Neighbor (k-NN)	• Simple and easy to implement • Naturally handles non-linear acoustic relationships • Performs well when data distribution is smooth	• Computationally expensive for large datasets • Performance degrades in high-dimensional acoustic feature spaces • Strongly influenced by the choice of *k* and feature scaling
Decision Tree	• Easy to interpret and visualize • Able to handle mixed acoustic features (categorical + continuous) • Fast training	• Prone to overfitting, especially for spectral acoustic data • Requires pruning and domain knowledge • May produce unstable results with small datasets
Random Forest	• Reduces overfitting compared to single trees • Works well with multi-dimensional acoustic measurements • Handles noisy experimental data better	• Computationally more expensive • Still lacks intrinsic interpretability for frequency-dependent phenomena
Artificial Neural Network (ANN)	• Capable of modelling highly nonlinear acoustic responses • High prediction accuracy for absorption and impedance • Effective at mapping complex microstructure–acoustic relationships	• Requires large datasets to avoid overfitting • Training is computationally expensive • Limited interpretability ("black box" behavior)

In summary, AI algorithms are instrumental in advancing research on acoustic materials. Traditional ML methods are appropriate for scenarios with limited data and yield more interpretable models, whereas DL methods excel at capturing complex, nonlinear acoustic interactions and microstructure-dependent effects. A comparative summary, as presented in Table 8, is essential for helping researchers select suitable AI techniques for specific acoustic applications. Despite these advances, several challenges persist. A primary limitation is the scarcity of large, high-quality acoustic datasets. Acquiring acoustic data through impedance tube measurements, reverberation chamber tests, micro-CT imaging, finite element method (FEM) or boundary element method (BEM) simulations, and Kundt's tube measurements is time-consuming, costly, and requires specialized equipment. Limited datasets impede the training, validation, and generalizability of AI models. Furthermore, inconsistent measurement techniques and the absence of standardized acoustic databases introduce noise and bias, hindering reproducibility and complicating cross-study benchmarking.

The design of deep learning model architectures remains challenging due to the numerous hyperparameters that must be optimized to achieve stable learning and accurate predictions across various frequency ranges and material structures. In the absence of standardized protocols for acoustic model tuning, performance can vary considerably between studies. Moreover, deep learning methods frequently lack interpretability, providing accurate predictions without elucidating how microstructure, frequency-dependent thermo-viscous effects, or material defects influence attenuation or resonance. This lack of transparency limits the trust and acceptance of AI models in applications requiring certification and traceability, particularly in aerospace cabin acoustics, structural noise control, and automotive noise, vibration, and harshness (NVH) systems.

Table 7. Strengths and weaknesses of common deep learning methods applied in acoustic property prediction

Deep Learning Methods	Strengths	Weaknesses
Convolutional Neural Network (CNN)	• Well-suited for microstructure image data (e.g., micro-CT scans) • Excellent at extracting pore morphology, tortuosity, and topology features • Strong performance in mapping structure to frequency-dependent absorption	• Requires large labelled datasets • Long training times • Prone to overfitting, especially with narrow frequency bands
Recurrent Neural Network (RNN)	• Ideal for sequential acoustic signals (time-domain and frequency-domain data) • Can model temporal and harmonic patterns in acoustic responses	• Difficult to train due to vanishing/exploding gradients • Requires large sequences for robust learning • Complex implementation
Autoencoder (AE)	• Useful for feature extraction and dimensionality reduction • Efficient for compressing broadband acoustic spectra • Reduces noise in measured acoustic data	• Requires large training data • Sensitive to noise in initial layers • Performance degrades if latent features fail to capture multiscale acoustic effects
Deep Belief Network (DBN)	• Extracts high-level acoustic features automatically • Performs well for moderate-sized datasets • Pre-training reduces the need for labelled data	• Slow training due to complex layer initialization • Inference through stochastic hidden layers is difficult • Limited suitability for high-resolution acoustic spectra
Generative Adversarial Network (GAN)	• Effective for generating synthetic acoustic data • Can augment limited datasets (e.g., rare frequency bands) • Useful for generating new metamaterial and porous architectures	• Difficult training and optimization • Sensitive to dataset imbalance • Performance decreases when training data are extremely limited

Another complication is the limited generalizability of AI models across different composite materials, fabrication methods, and frequency regimes. Models trained on specific natural fibers, three-dimensional printed architectures, or porosity gradients frequently underperform when applied to novel materials or altered boundary conditions. While transfer learning and domain adaptation present promising solutions, these approaches remain underexplored in the context of acoustic materials. Experimental validation of AI predictions is also essential, which increases both time and cost. A notable research gap is that most studies concentrate on predicting a single acoustic property, typically sound absorption, rather than employing multi-target AI models capable of predicting comprehensive acoustic spectra including absorption, impedance, damping, and transmission loss for multifunctional materials.

To advance the field, several targeted research directions are recommended. Data augmentation strategies, including synthetic data generation, physics-based simulations, and generative models such as GANs and variational autoencoders (VAEs), can mitigate data limitations. Hybrid modeling approaches that integrate AI with physics-based frameworks, such as the Helmholtz equation, Johnson–Champoux–Allard theory, and viscoelastic constitutive models, can enhance interpretability and physical consistency. Multi-scale modeling, which combines microstructural imaging, mesoscale architecture, and macro-acoustic behavior through FEM/BEM–AI coupling, enables the characterization of acoustic responses across multiple length scales.

Enhancing interpretability should also be prioritized. Techniques such as SHapley Additive exPlanations (SHAP), Gradient-weighted Class Activation Mapping (Grad-CAM), and attention mechanisms can elucidate how microstructural features influence frequency-dependent behavior. Collaboration between AI researchers and acoustic experimentalists is essential for validating and refining predictive models. Additionally, the development of domain-specific AI architectures for porous absorbers, micro-perforated panels, metamaterial resonators, and layered acoustic barriers is crucial for producing high-fidelity, application-ready design tools.

Table 8. Strengths and weaknesses of ML and DL methods for acoustic property prediction

AI Methods	Strengths	Weaknesses
Traditional Machine Learning	• Performs well on small acoustic datasets • Faster training and lower computational cost • Easier to interpret than deep models • Useful when microstructural features are known beforehand	• Less accurate for complex, multi-physics acoustic interactions • Requires manual feature engineering • Struggles with nonlinear broadband behavior • Sensitive to data preprocessing
Deep Learning	• High accuracy with large, high-dimensional datasets • Automatically extracts features from microstructure images and spectra • Captures nonlinear, multiscale acoustic behavior • Effective for acoustic metamaterials and topological design	• Requires large datasets and GPU resources • Black-box nature reduces trust and interpretability • Risk of overfitting for narrow-band acoustic data • Hyperparameter tuning is complex and non-standard

9. Conclusion

This review provides a comprehensive evaluation of artificial intelligence applications in predicting and optimizing the acoustic properties of composite materials. By combining physics-based acoustic modelling principles with quantitative machine-learning performance assessment, the study establishes a reproducible benchmarking framework for evaluating AI models used in acoustic material design. AI-based models have demonstrated prediction accuracies approaching those of experimental measurements and numerical simulations in several controlled studies; however, their performance remains dependent on dataset quality, model design, and validation strategy.

Hybrid modelling strategies that integrate machine learning with established acoustic theories, such as the Helmholtz equation, Johnson–Champoux–Allard model, and Biot poroelastic theory, show particular promise in improving physical consistency and predictive robustness. However, several challenges remain, including limited dataset availability, inconsistent benchmarking practices, model interpretability issues, and reduced generalizability across material systems and operating conditions.

Current research also reveals several technical bottlenecks. At the algorithmic level, deep neural networks often require long training convergence times and large datasets, which limits their practical deployment in acoustic engineering workflows. Future research should therefore focus on three key areas: the development of hybrid neural network architectures that incorporate physical constraints, the exploration of adaptive training strategies within meta-learning frameworks, and the construction of robust structure–acoustic coupling models for multi-physics prediction.

From a technological perspective, acoustic neural networks are expected to evolve toward multimodal learning frameworks that integrate microstructural imaging, experimental acoustic measurements, and numerical simulations. Furthermore, the establishment of standardized benchmark datasets containing acoustic responses under diverse operating conditions is urgently needed. The development of unified evaluation metrics and reporting protocols will also be critical for enabling consistent cross-study comparisons.

With continued advances in algorithm development, physics-informed modelling, and hardware acceleration, artificial intelligence is likely to play a transformative role in acoustic materials engineering. These developments will accelerate the design of next-generation noise-control materials and enable disruptive applications in aerospace noise mitigation, structural acoustics, and advanced acoustic metamaterial design.

Acknowledgements

This work was founded by the Tshwane University of Technology, Pretoria, South Africa.

References

[1] de Kluizenaar Y, et al. Urban road traffic noise and annoyance: The effect of a quiet façade. J Acoust Soc Am. 2011;130(4):1936-1942. https://doi.org/10.1121/1.3621180
[2] Münzel T, Schmidt FP, Steven S, Herzog J, Daiber A, Sørensen M. Environmental noise and the cardiovascular system. J Am Coll Cardiol. 2018;71(6):688-697. https://doi.org/10.1016/j.jacc.2017.12.015
[3] Basner M, et al. Auditory and non-auditory effects of noise on health. Lancet. 2014;383(9925):1325-1332. https://doi.org/10.1016/S0140-6736(13)61613-X
[4] Mehrotra A, Shukla SP, Shukla AK, Manar MK, Singh SK, Mehrotra M. A comprehensive review of auditory and non-auditory effects of noise on human health. Noise Health. 2024;26(121):59-69. https://doi.org/10.4103/nah.nah_124_23
[5] Themann CL, Masterson EA. Occupational noise exposure: A review of its effects, epidemiology, and impact with recommendations for reducing its burden. J Acoust Soc Am. 2019;146(5):3879-3905. https://doi.org/10.1121/1.5134465
[6] Evandt J, Oftedal B, Krog NH, Nafstad P, Schwarze PE, Aasvang GM. A population-based study on nighttime road traffic noise and insomnia. Sleep. 2017;40(2):zsw055. https://doi.org/10.1093/sleep/zsw055
[7] Stansfeld S, Clark C. Health effects of noise exposure in children. Curr Environ Health Rep. 2015;2(2):171-178. https://doi.org/10.1007/s40572-015-0044-1
[8] Themann CL, Masterson EA, Peterson JS, Murphy WJ. Preventing Occupational Hearing Loss: 50 Years of Research and Recommendations from the National Institute for Occupational Safety and Health. In: Seminars in hearing. Thieme Medical Publishers, Inc.; 2023. p. 351-393. https://doi.org/10.1055/s-0043-1769499
[9] Ciaburro G, Iannace G. Machine-learning-based methods for acoustic emission testing: A review. Appl Sci. 2022;12(20):10476. https://doi.org/10.3390/app122010476
[10] Chen J, et al. Application of machine learning on the design of acoustic metamaterials and phonon crystals: A review. Smart Mater Struct. 2024;33(7):73001. https://doi.org/10.1088/1361-665X/ad51bc
[11] Korjakins A, Sahmenko G, Lapkovskis V. A Short Review of Recent Innovations in Acoustic Materials and Panel Design: Emphasizing Wood Composites for Enhanced Performance and Sustainability. Appl Sci. 2025;15(9):4644. https://doi.org/10.3390/app15094644
[12] Pasqual AM, Lara LT. Time-domain simulation of acoustic impedance tubes. J Brazilian Soc Mech Sci Eng. 2017;39(1):67-79. https://doi.org/10.1007/s40430-016-0515-9
[13] Kek T, et al. Characterization of biocomposites and glass fiber epoxy composites based on acoustic emission signals, deep feature extraction, and machine learning. Sensors. 2022;22(18):6886. https://doi.org/10.3390/s22186886
[14] Chen S, et al. A review of tunable acoustic metamaterials. Appl Sci. 2018;8(9):1480. https://doi.org/10.3390/app8091480
[15] Bravo-Moncayo L, Puyana-Romero V, Argotti-Gómez M, Ciaburro G. Enhanced environmental sustainability for the acoustic absorption properties of cabuya fiber in building construction using machine learning predictive model. Sustainability. 2024;16(14):6204. https://doi.org/10.3390/su16146204
[16] Mago J, Sunali, Negi A, Bolton JS, Fatima S. Sound insulation: key concepts and technologies. Handb Vibroacoustics, Noise Harshness. 2024:1-44. https://doi.org/10.1007/978-981-99-4638-9_27-1

[17] Kaselouris E, Dimitriou V. A Review of Finite Element Studies on Laser-Based Acoustic Applications in Solid Media. Modelling. 2025;6(2):26. https://doi.org/10.3390/modelling6020026
[18] Yu L, et al. Deep Learning Approach-based Prediction of Transfer Functions in Structure-Acoustic Coupling Models. Results Eng. 2025:108054. https://doi.org/10.1016/j.rineng.2025.108054
[19] Zhang H, Wang Y, Lu K, Zhao H, Yu D, Wen J. SAP-Net: Deep learning to predict sound absorption performance of metaporous materials. Mater Des. 2021;212:110156. https://doi.org/10.1016/j.matdes.2021.110156
[20] Tezsezen E, Yigci D, Ahmadpour A, Tasoglu S. AI-based metamaterial design. ACS Appl Mater Interfaces. 2024;16(23):29547-29569. https://doi.org/10.1021/acsami.4c04486
[21] Sadiq MA, Kovács G. Optimization of composite sandwich structures: A review. Machines. 2025;13(7):536. https://doi.org/10.3390/machines13070536
[22] Cerniauskas G, Sadia H, Alam P. Machine intelligence in metamaterials design: a review. Oxford Open Mater Sci. 2024;4(1):itae001. https://doi.org/10.1093/oxfmat/itae001
[23] Esan TM, Kupolati WK, Ackerman C. Advances in Additive Manufacturing for Architectural Acoustics: Design, Materials, Validation, and Implementation Challenges in Building Construction. Addit Manuf Lett. 2026:100368. https://doi.org/10.1016/j.addlet.2026.100368
[24] Allard J, Atalla N. Propagation of sound in porous media: modelling sound absorbing materials 2e. John Wiley & Sons; 2009. https://doi.org/10.1002/9780470747339
[25] Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys. 2019;378:686-707. https://doi.org/10.1016/j.jcp.2018.10.045
[26] Karniadakis GE, Kevrekidis IG, Lu L, Perdikaris P, Wang S, Yang L. Physics-informed machine learning. Nat Rev Phys. 2021;3(6):422-440. https://doi.org/10.1038/s42254-021-00314-5
[27] Kasani HA, Selvadurai APS. A review of techniques for measuring the Biot coefficient and other effective stress parameters for fluid-saturated rocks. Appl Mech Rev. 2023;75(2):20801. https://doi.org/10.1115/1.4055888
[28] Yan C. A review on spectral data preprocessing techniques for machine learning and quantitative analysis. IScience. 2025;28(7). https://doi.org/10.1016/j.isci.2025.112759
[29] McCarthy RA, Zhang Y, Verburg SA, Jenkins WF, Gerstoft P. Machine learning in acoustics: A review and open-source repository. npj Acoust. 2025;1(1):18. https://doi.org/10.1038/s44384-025-00021-w
[30] Bianco MJ, et al. Machine learning in acoustics: a review. arXiv Prepr arXiv190504418. 2019.
[31] Kuttruff H, Vorländer M. Room acoustics. CRC Press; 2024. https://doi.org/10.1201/9781003389873
[32] Grimm S. Directivity Based Multichannel Audio Signal Processing For Microphones in Noisy Acoustic Environments. Springer; 2019. https://doi.org/10.1007/978-3-658-25152-9
[33] Falcón Pérez R. Domain-aware deep learning for room acoustics: Parameter estimation, localization, and source separation. 2026.
[34] Chen X, Chang L, Yu X, Huang Y, Tu X. A Survey on World Models Grounded in Acoustic Physical Information. arXiv Prepr arXiv250613833. 2025.
[35] Li W, et al. FE-based machine learning model for predictive damage assessment in bonded composite joints via acoustic emission. Compos Part A Appl Sci Manuf. 2024;187:108494. https://doi.org/10.1016/j.compositesa.2024.108494
[36] Miele SA. Vibro-Acoustic Testing and Machine Learning for Concrete Structures Damage Diagnosis. 2022.
[37] Morales EF, Escalante HJ. A brief introduction to supervised, unsupervised, and reinforcement learning. In: Biosignal processing and classification using computational learning and intelligence. Elsevier; 2022. p. 111-129. https://doi.org/10.1016/B978-0-12-820125-1.00017-8
[38] Sarker IH. Machine learning: Algorithms, real-world applications and research directions. SN Comput Sci. 2021;2(3):160. https://doi.org/10.1007/s42979-021-00592-x
[39] Wang Y, et al. Machine learning for predictive design and optimization of high-performance thermoelectric materials: a review. J Mater Informatics. 2025;5(3):N-A. https://doi.org/10.20517/jmi.2025.18
[40] Huang G, Guo Y, Chen Y, Nie Z. Application of machine learning in material synthesis and property prediction. Materials (Basel). 2023;16(17):5977. https://doi.org/10.3390/ma16175977
[41] Alpaydin E. Introduction to machine learning. MIT press; 2020.
[42] Yang X, Song Z, King I, Xu Z. A survey on deep semi-supervised learning. IEEE Trans Knowl Data Eng. 2022;35(9):8934-8954. https://doi.org/10.1109/TKDE.2022.3220219
[43] Sivamayil K, Rajasekar E, Aljafari B, Nikolovski S, Vairavasundaram S, Vairavasundaram I. A systematic study on reinforcement learning based applications. Energies. 2023;16(3):1512. https://doi.org/10.3390/en16031512
[44] Sattari K, Xie Y, Lin J. Data-driven algorithms for inverse design of polymers. Soft Matter. 2021;17(33):7607-7622. https://doi.org/10.1039/D1SM00725D

[45] Xie T, France-Lanord A, Wang Y, Shao-Horn Y, Grossman JC. Graph dynamical networks for unsupervised learning of atomic scale dynamics in materials. Nat Commun. 2019;10(1):2667. https://doi.org/10.1038/s41467-019-10663-6
[46] Papadopoulos VD, Beligiannis GN, Hela DG. Combining experimental design and artificial neural networks for the determination of chlorinated compounds in fish using matrix solid-phase dispersion. Appl Soft Comput. 2011;11(8):5155-5164. https://doi.org/10.1016/j.asoc.2011.05.044
[47] Qamar R, Zardari BA. Artificial neural networks: An overview. Mesopotamian J Comput Sci. 2023;2023:124-133. https://doi.org/10.58496/MJCSC/2023/015
[48] Liu L, et al. Application of artificial neural networks to acoustic composites: A review. Mater Today Commun. 2025;45:112342. https://doi.org/10.1016/j.mtcomm.2025.112342
[49] Nwankpa CE. Advances in optimisation algorithms and techniques for deep learning. Adv Sci Technol Eng Syst J. 2020;5(5):563-577. https://doi.org/10.25046/aj050570
[50] Alqushaibi A, Abdulkadir SJ, Rais HM, Al-Tashi Q. A review of weight optimization techniques in recurrent neural networks. In: 2020 international conference on computational intelligence (ICCI). IEEE; 2020. p. 196-201. https://doi.org/10.1109/ICCI51257.2020.9247757
[51] Movassagh AA, et al. Artificial neural networks training algorithm integrating invasive weed optimization with differential evolutionary model. J Ambient Intell Humaniz Comput. 2023;14(5):6017-6025. https://doi.org/10.1007/s12652-020-02623-6
[52] Liao G, Luan C, Wang Z, Liu J, Yao X, Fu F. Acoustic metamaterials: A review of theories, structures, fabrication approaches, and applications. Adv Mater Technol. 2021;6(5):2000787. https://doi.org/10.1002/admt.202000787
[53] Bhuvaneswari V, et al. A critical review on hygrothermal and sound absorption behavior of natural-fiber-reinforced polymer composites. Polymers (Basel). 2022;14(21):4727. https://doi.org/10.3390/polym14214727
[54] Goodfellow I, Bengio Y, Courville A, Bengio Y. Deep learning, vol. 1, no. 2. MIT press Cambridge; 2016.
[55] Shukla V, Choudhary S. Deep learning in neural networks: an overview. Deep Learn Vis Comput signal Process. 2022:29-53. https://doi.org/10.1201/9781003277224-2
[56] Abiodun OI, et al. Comprehensive review of artificial neural network applications to pattern recognition. IEEE Access. 2019;7:158820-158846. https://doi.org/10.1109/ACCESS.2019.2945545
[57] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-444. https://doi.org/10.1038/nature14539
[58] Mahesh K, Kumar Ranjith S, Mini RS. Inverse design of a Helmholtz resonator based low-frequency acoustic absorber using deep neural network. J Appl Phys. 2021;129(17). https://doi.org/10.1063/5.0046582
[59] Yang H, Zhang H, Wang Y, Zhao H, Yu D, Wen J. Prediction of sound absorption coefficient for metaporous materials with convolutional neural networks. Appl Acoust. 2022;200:109052. https://doi.org/10.1016/j.apacoust.2022.109052
[60] Wang H, Zhao H, Lian Z, Tan B, Zheng Y, E E. An optimized neural network acoustic model for porous hemp plastic composite sound-absorbing board. Symmetry (Basel). 2022;14(5):863. https://doi.org/10.3390/sym14050863
[61] Zulfiqar A, et al. Artificial-neural-network-based predicted model for seam strength of five-pocket denim jeans: a review. Textiles. 2024;4(2):183-217. https://doi.org/10.3390/textiles4020012
[62] Bejani MM, Ghatee M. A systematic review on overfitting control in shallow and deep neural networks. Artif Intell Rev. 2021;54(8):6391-6438. https://doi.org/10.1007/s10462-021-09975-1
[63] Gómez JT, et al. Communicating smartly in molecular communication environments: Neural networks in the internet of bio-nano things. arXiv Prepr arXiv250620589. 2025.
[64] Li J, Wang H. Gaussian Process Regression for Uncertainty Quantification: An Introductory Tutorial. arXiv Prepr arXiv250203090. 2025.
[65] Manfredi P, Trinchero R. A probabilistic machine learning approach for the uncertainty quantification of electronic circuits based on Gaussian process regression. IEEE Trans Comput Des Integr Circuits Syst. 2021;41(8):2638-2651. https://doi.org/10.1109/TCAD.2021.3112138
[66] Klapa Antonion XW, Raissi M, Joshie L. Machine learning through physics-informed neural networks: Progress and challenges. Acad J Sci Technol. 2024;9(1):2024. https://doi.org/10.54097/b1d21816
[67] Luo K, et al. Physics-informed neural networks for PDE problems: A comprehensive review. Artif Intell Rev. 2025;58(10):323. https://doi.org/10.1007/s10462-025-11322-7
[68] Hu Z, Zayed T, Cheng L. A critical review of acoustic modeling and research on building façade. Build Acoust. 2022;29(1):107-134. https://doi.org/10.1177/1351010X211022736
[69] Yang M, PF L. Sound absorption structures: From porous media to acoustic metamaterials. Annu Rev Mater Res. 2017;47(1):83-114. https://doi.org/10.1146/annurev-matsci-070616-124032

[70] Feng D, Wang X, Wang X, Ding S, Zhang H. Deep convolutional denoising autoencoders with network structure optimization for the high-fidelity attenuation of random GPR noise. Remote Sens. 2021;13(9):1761. https://doi.org/10.3390/rs13091761
[71] Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In: International Conference on Medical image computing and computer-assisted intervention. Springer; 2015. p. 234-241. https://doi.org/10.1007/978-3-319-24574-4_28
[72] Williams CL. Understanding Microstructure-ultrasound Relationships in Additively Manufactured Materials: Experiments and Numerical Simulations. The Pennsylvania State University; 2025.
[73] Zheng X, Zhang X, Chen T, Watanabe I. Deep learning in mechanical metamaterials: from prediction and generation to inverse design. Adv Mater. 2023;35(45):2302530. https://doi.org/10.1002/adma.202302530
[74] Keen SC, Odom KJ, Webster MS, Kohn GM, Wright TF, Araya-Salas M. A machine learning approach for classifying and quantifying acoustic diversity. Methods Ecol Evol. 2021;12(7):1213-1225. https://doi.org/10.1111/2041-210X.13599
[75] Sun B, Xue M, Su M. Physics-informed neural network enhanced acoustic source identification via cross-spectral correlation of microphone array signals. Mech Syst Signal Process. 2025;236:113027. https://doi.org/10.1016/j.ymssp.2025.113027
[76] Olivieri M, Karakonstantis X, Pezzoli M, Antonacci F, Sarti A, Fernandez-Grande E. Physics-informed neural network for volumetric sound field reconstruction of speech signals. EURASIP J Audio Speech Music Process. 2024;2024(1):42. https://doi.org/10.1186/s13636-024-00366-2
[77] Wu RT, Jokar M, Jahanshahi MR, Semperlotti F. A physics-constrained deep learning based approach for acoustic inverse scattering problems. Mech Syst Signal Process. 2022;164:108190. https://doi.org/10.1016/j.ymssp.2021.108190
[78] Zargar SA, Yuan FG. Physics-informed deep learning for scattered full wavefield reconstruction from a sparse set of sensor data for impact diagnosis in structural health monitoring. Struct Health Monit. 2024;23(5):2963-2979. https://doi.org/10.1177/14759217231202547
[79] Wang J. An intuitive tutorial to Gaussian process regression. Comput Sci Eng. 2023;25(4):4-11. https://doi.org/10.1109/MCSE.2023.3342149
[80] Dudek A, Baranowski J. Gaussian processes for signal processing and representation in control engineering. Appl Sci. 2022;12(10):4946. https://doi.org/10.3390/app12104946
[81] Aziz I, Soltanaghai E, Watts A, Alipour M. Bayesian inversion of GPR waveforms for sub-surface material characterization: An uncertainty-aware retrieval of soil moisture and overlaying biomass properties. Remote Sens Environ. 2024;313:114351. https://doi.org/10.1016/j.rse.2024.114351
[82] Ilemobayo JA, et al. Hyperparameter tuning in machine learning: A comprehensive review. J Eng Res Reports. 2024;26(6):388-395. https://doi.org/10.9734/jerr/2024/v26i61188
[83] Therrien JD, Nicolaï N, Vanrolleghem PA. A critical review of the data pipeline: how wastewater system operation flows from data to intelligence. Water Sci Technol. 2020;82(12):2613-2634. https://doi.org/10.2166/wst.2020.393
[84] Picetti F. How Deep Learning Can Help Solving Geophysical Inverse Problems. In: Special Topics in Information Technology. Springer; 2022. p. 141-152. https://doi.org/10.1007/978-3-031-15374-7_12
[85] Mao R, et al. Rapid CFD prediction based on machine learning surrogate model in built environment: A review. Fluids. 2025;10(8):193. https://doi.org/10.3390/fluids10080193
[86] Alizadeh R, Allen JK, Mistree F. Managing computational complexity using surrogate models: a critical review. Res Eng Des. 2020;31(3):275-298. https://doi.org/10.1007/s00163-020-00336-7
[87] Malashin I, Martysyuk D, Tynchenko V, Gantimurov A, Nelyub V, Borodulin A. Data-driven optimization of discontinuous and continuous fiber composite processes using machine learning: a review. Polymers (Basel). 2025;17(18):2557. https://doi.org/10.3390/polym17182557
[88] Prantikos K, Chatzidakis S, Tsoukalas LH, Heifetz A. Physics-informed neural network with transfer learning (TL-PINN) based on domain similarity measure for prediction of nuclear reactor transients. Sci Rep. 2023;13(1):16840. https://doi.org/10.1038/s41598-023-43325-1
[89] Chen S, Guo W. Auto-encoders in deep learning-a review with new perspectives. Mathematics. 2023;11(8):1777. https://doi.org/10.3390/math11081777
[90] Mienye ID, Swart TG. Deep Autoencoder Neural Networks: A Comprehensive Review and New Perspectives: ID Mienye, TG Swart. Arch Comput Methods Eng. 2025;32(7):3981-4000. https://doi.org/10.1007/s11831-025-10260-5
[91] Islam MM, Belal TMA, Anik MAH, Sharif A. Predicting Materials Using Variational Autoencoders: A Systematic Literature Review. Arch Comput Methods Eng. 2026:1-52. https://doi.org/10.1007/s11831-025-10485-4
[92] Attari V, Khatamsaz D, Allaire D, Arroyave R. Towards inverse microstructure-centered materials design using generative phase-field modeling and deep variational autoencoders. Acta Mater. 2023;259:119204. https://doi.org/10.1016/j.actamat.2023.119204

[93] Kingma DP, Welling M. An introduction to variational autoencoders. Found Trends® Mach Learn. 2019;12(4):307-392. https://doi.org/10.1561/2200000056
[94] Zhang Y, et al. On the properties of kullback-leibler divergence between multivariate gaussian distributions. Adv Neural Inf Process Syst. 2023;36:58152-58165. https://doi.org/10.52202/075280-2535
[95] Mirzaee H, Kamrava S, Tahmasebi P. Minireview on porous media and microstructure reconstruction using machine learning techniques: Recent advances and outlook. Energy Fuels. 2023;37(20):15348-15372. https://doi.org/10.1021/acs.energyfuels.3c02126
[96] Vinodkumar PK, Karabulut D, Avots E, Ozcinar C, Anbarjafari G. Deep learning for 3d reconstruction, augmentation, and registration: A review paper. Entropy. 2024;26(3):235. https://doi.org/10.3390/e26030235
[97] Alqahtani H, Kavakli-Thorne M, Kumar G. Applications of Generative Adversarial Networks (GANs): An Updated Review: H. Alqahtani et al. Arch Comput Methods Eng. 2021;28(2):525-552. https://doi.org/10.1007/s11831-019-09388-y
[98] Mosser L, Dubrule O, Blunt MJ. Reconstruction of three-dimensional porous media using generative adversarial neural networks. Phys Rev E. 2017;96(4):43309. https://doi.org/10.1103/PhysRevE.96.043309
[99] Alrfou K, Kordijazi A, Zhao T. Computer vision methods for the microstructural analysis of materials: the state-of-the-art and future perspectives. arXiv Prepr arXiv220804149. 2022.
[100] Sahib MM, Kovács G. Multi-objective optimization of composite sandwich structures using Artificial Neural Networks and Genetic Algorithm. Results Eng. 2024;21:101937. https://doi.org/10.1016/j.rineng.2024.101937
[101] Liu X, et al. Design optimization of laminated composite structures using artificial neural network and genetic algorithm. Compos Struct. 2023;305:116500. https://doi.org/10.1016/j.compstruct.2022.116500
[102] Kanchipuram C, Nadu T. Optimization Techniques and Genetic Algorithms in AI. Math Innov. 2025:82.
[103] Jin Y, et al. Intelligent on-demand design of phononic metamaterials. Nanophotonics. 2022;11(3):439-460. https://doi.org/10.1515/nanoph-2021-0639
[104] Chiappetta M, Carraturo M, Raßloff A, Kästner M, Auricchio F. An Efficient Bayesian Framework for Inverse Problems via Optimization and Inversion: Surrogate Modeling, Parameter Inference, and Uncertainty Quantification. arXiv Prepr arXiv260204537. 2026. https://doi.org/10.2139/ssrn.5584546
[105] Shahriari B, Swersky K, Wang Z, Adams RP, De Freitas N. Taking the human out of the loop: A review of Bayesian optimization. Proc IEEE. 2015;104(1):148-175. https://doi.org/10.1109/JPROC.2015.2494218
[106] Lu Q, Polyzos KD, Li B, Giannakis GB. Surrogate modeling for Bayesian optimization beyond a single Gaussian process. IEEE Trans Pattern Anal Mach Intell. 2023;45(9):11283-11296. https://doi.org/10.1109/TPAMI.2023.3264741
[107] De Ath G, Everson RM, Rahat AAM, Fieldsend JE. Greed is good: Exploration and exploitation trade-offs in Bayesian optimisation. ACM Trans Evol Learn Optim. 2021;1(1):1-22. https://doi.org/10.1145/3425501
[108] Li C. Bayesian methods in machine learning applications and challenges. Econ Manag Innov. 2025;2(2):15-28. https://doi.org/10.71222/j5gxe564
[109] Nickl R. Bayesian non-linear statistical inverse problems. EMS Press Berlin; 2023. https://doi.org/10.4171/zlam/30
[110] Shaikh M, Yadav D. A review of particle swarm optimization (PSO) algorithm. Technol. 2022;13(7):19-44.
[111] Deng W, et al. An enhanced fast non-dominated solution sorting genetic algorithm for multi-objective problems. Inf Sci (Ny). 2022;585:441-453. https://doi.org/10.1016/j.ins.2021.11.052
[112] Paknejad SH, Vadood M, Soltani P, Ghane M. Modeling the sound absorption behavior of carpets using artificial intelligence. J Text Inst. 2021;112(11):1763-1771. https://doi.org/10.1080/00405000.2020.1841954
[113] Niu H, Gong Z, Ozanich E, Gerstoft P, Wang H, Li Z. Deep-learning source localization using multi-frequency magnitude-only data. J Acoust Soc Am. 2019;146(1):211-222. https://doi.org/10.1121/1.5116016
[114] Wu J, Feng X, Cai X, Huang X, Zhou Q. A deep learning-based multi-fidelity optimization method for the design of acoustic metasurface. Eng Comput. 2023;39(5):3421-3439. https://doi.org/10.1007/s00366-022-01765-9
[115] Graczyk KM, Matyka M. Predicting porosity, permeability, and tortuosity of porous media from images by deep learning. Sci Rep. 2020;10(1):21488. https://doi.org/10.1038/s41598-020-78415-x
[116] Puyana-Romero V, Chuquín JSA, Chicaiza SIM, Ciaburro G. Characterization and Simulation of Acoustic Properties of Sugarcane Bagasse-Based Composite Using Artificial Neural Network Model. Fibers. 2023;11(2):18. https://doi.org/10.3390/fib11020018

[117] Caniato M, D'Amore GKO, Kaspar J, Gasparella A. Sound absorption performance of sustainable foam materials: Application of analytical and numerical tools for the optimization of forecasting models. Appl Acoust. 2020;161:107166. https://doi.org/10.1016/j.apacoust.2019.107166
[118] Yi W, Guo J, Zhou T, Jiang H, Fang Y. A machine learning approach for predicting the Johnson-Champoux-Allard parameters of a fibrous porous material. Appl Acoust. 2024;220:109966. https://doi.org/10.1016/j.apacoust.2024.109966
[119] Emmerich L, et al. A data-driven two-microphone method for in situ sound absorption measurements of porous materials. J Acoust Soc Am. 2025;158(3):1711-1722. https://doi.org/10.1121/10.0039101
[120] Muralidharan J, Abdullah D. AI-Driven Acoustic Metamaterial Optimization for Broadband Noise Control. Adv Comput Acoust Eng. 2023;1(1):25-32.
[121] Arenas JP, Li Z. Composites and biocomposites for noise and vibration control in automotive structures. In: Biocomcomposite and Synthetic composites for automotive applications. Elsevier; 2021. p. 305-345. https://doi.org/10.1016/B978-0-12-820559-4.00012-2
[122] He L, Li Y, Torrent D, Zhuang X, Rabczuk T, Jin Y. Machine learning assisted intelligent design of meta structures: a review. Microstructures. 2023;3(4):N-A. https://doi.org/10.20517/microstructures.2023.29
[123] Si L, Niu R, Dang C, Bao X, Zhuang Y, Zhu W. Advances in artificial intelligence for artificial metamaterials. APL Mater. 2024;12(12). https://doi.org/10.1063/5.0247369