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A review of AI for optimization of 3D printing of sustainable polymers and composites

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ABSTRACT

In recent years, 3D printing has experienced significant growth in the manufacturing sector due to its ability to produce intricate and customized components. The advent of Industry 4.0 further boosted this progress by seamlessly incorporating artificial intelligence (AI) in 3D printing processes. As a result, design precision and production efficiency have significantly improved. Although numerous studies have explored the integration of AI and 3D printing, the literature still lacks a comprehensive overview that emphasizes material selection and formulation, predictive modeling, design optimization, and quality control. To fully understand the impacts of these emerging technologies on advanced manufacturing, a thorough assessment is required. This review aims to examine the intersection of AI and 3D printing to create a technologically advanced and environment-friendly manufacturing environment. It examines factors such as material, process efficiency, and design enhancements to highlight the benefits of combining these technologies. By focusing on predictive modeling, material selection and quality control, this analysis aims to unlock the potential for a sustainable and efficient 3D printing process. This review provided a thorough analysis of the challenges and potential benefits, proving valuable for academics and practitioners alike. It presents solutions that may establish a foundation for sustained growth and outlines a strategy for leveraging 3D printing and AI capabilities in the manufacturing sector.

1. Introduction

The worldwide production of plastic exceeded 390 million tonnes in 2021, with the Asia-Pacific region contributing over 190 million metric tonnes and the packaging sector accounting for over 40 % of the total plastic utilization [1]. However, recycling remains challenging, with only about 9 % of all plastic waste ever produced being recycled globally [2]. In 2020, European Union plastic package recycling rates reached 46 %, with some variance at the regional level [3]. The widespread issue of plastic pollutants is evidenced by the annual inflow of about 14 million tonnes of plastic into the oceans, with an estimated 171 trillion pieces of plastic, weighing around 2.3 million tonnes, currently floating in the oceans [4,5]. To handle these environmental challenges, the adoption of sustainable polymers and composites is vital. The global marketplace for biodegradable plastics is projected to exceed USD 20.9 billion by 2028, at a compound annual growth rate of 21.3 % from USD 7.9 billion in 2023, reflecting an evolving emphasis on environmentally friendly alternatives [6]. Sustainable polymers and composites play a pivotal role in addressing environmental issues [7]. These materials are derived from renewable sources, recycled materials, and waste carbon assets, supplying an eco-friendlier alternative [8,9]. Importantly, on completion of their lifecycle, these materials can be recycled, biodegraded, or composted, offering a sustainable and circular approach to plastic usage [10,11]. As the world combats the consequences of plastic pollution, the adoption of these materials is important in paving the way towards a more sustainable and environmentally friendly future.

Two disruptive technologies—3D printing and artificial intelligence (AI) hold immense potential for reforming future technology. AI denotes computer capabilities that imitate specific cognitive functions of humans: perception, reasoning, learning, and problem-solving [12,13]. Its integration into various fields like manufacturing and healthcare promises to streamline tasks, boost decision-making, and ramp up efficiency [14–16]. In parallel, 3D printing is a revolutionary manufacturing technique that allows for the direct layer-by-layer production of complex parts from digital models [17,18]. It yields a competitive advantage over traditional methods by offering cost-effective production pathways to create low-volume and customized products with intricate geometries and unique material properties [19,20]. Projections indicate that by 2025, this technology could

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List of abbreviations

Abbreviation	*Definition*
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BR	Bayesian Regularization
Bi-LSTM	Bidirectional Long Short-Term Memory
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
DL	Deep Learning
EJ	Exajoules
FDM	Fused Deposition Modeling
FEA	Finite Element Analysis
GA	Genetic Algorithm
GAN	Generative Adversarial Network
KNN	k-Nearest Neighbor
LAAM	Laser-Aided Additive Manufacturing
LDPE	Low-Density Polyethylene
LM	Levenberg Marquardt
LOF	Local Outlier Factor
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
Mt	Megatons
PA	Polyamide
PBS	Poly(butylene succinate)
PC	Polycarbonate
PE	Polyethylene
PEF	Poly(ethylene furanoate)
PET	Poly(ethylene terephthalate)
PGA	Polyglycolide
PHA	Polyhydroxyalkanoate
PID	Proportional-Integral-Derivative
PLA	Polylactic acid
PP	Polypropylene
PSO	Particle Swarm Optimization
PU	Polyurethane
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Square Error
ROS	Robot Operating System
RSM	Response Surface Methodology
RVE	Representative Volume Element
SCG	Scaled Conjugate Gradient
SVM	Support Vector Machine
SVR	Support Vector Regression
TO	Topology Optimization
TPMS	Triply Periodic Minimal Surface
VAE	Variational Autoencoder
WOA	Whale Optimization Algorithm

potentially generate savings ranging from $170 to $593 billion; moreover, it might decrease primary energy supply between 2.54 EJ (exajoules) and 9.30 EJ, along with reducing CO2 emissions between 130.5 Mt (megatons) and 525.5 Mt [21]. An estimated global market size of $55.8 billion by 2027 [22] predicts the dominance of 3D printing in sectors such as aerospace, healthcare and automotive. Similarly, AI is expected to reach the US$2.5 trillion market by 2032 and will be used in manufacturing, finance, healthcare and retail [23]. As these technologies progress, their synergy not only revolutionizes manufacturing processes but also refines designs – they become integral to achieving sustainability goals on a worldwide scale.

3D printing encompasses various technologies such as material extrusion, binder jetting, vat photopolymerization, powder bed fusion, material jetting and direct energy deposition [24,25]. Using these techniques, functional components can be created from filaments, pellets, liquids, or powders [26–29]. Despite its capacity, 3D printing faces challenges, consisting of the formation of voids attributable to suboptimal print settings [30,31], that could impact the inter-layer properties [32,33], and the inhomogeneity of printed materials [34,35]. Additionally, problems like residual stress deformation can arise because of rapid cooling [36]. Addressing these challenges is essential to fully unlock the transformative potential of combining 3D printing with AI. The complex interplay between 3D printing processes and their constraints highlights an opportunity for integrating AI, which plays a pivotal role in addressing the challenges of 3D printing and expanding the limits of what is achievable in advanced manufacturing.

The integration of 3D printing and AI has resulted in transformative changes in various industries. The use of 3D printing opens up new possibilities for adaptability and customization in industries such as health care, consumer goods, automotive and aerospace. This review investigates the relationship between 3D printing and AI, focusing on their collective impact on advanced manufacturing, especially for sustainable polymers and composite materials. It analyzes the function of AI in optimizing numerous facets of the 3D printing technique, including predictive modelling, design and geometry optimization and quality control. Its objective is to analyze how AI can address the inherent, significant challenges associated with 3D printing. A particular emphasis is placed on environmental effect assessment, proceeding to offer a comprehensive know-how of the potential synergy among 3D printing and AI in addressing sustainability issues. This review examines how 3D printing and AI can work together, aiming to change manufacturing methods so that they do more than just meet industry needs — they exceed them.

2. Scope of the review

This review explores the integration of 3D printing and AI in the sustainable materials domain. It provides a detailed analysis of the ways in which 3D printing contributes to the use of environmentally friendly materials. In addition, this study highlights the advances made by AI to enhance the overall 3D printing process. The particular emphasis lies in exploring how AI can enhance different aspects of the 3D printing processes, such as material selection and formulation, predictive modeling, design optimization, and quality control. Furthermore, this review thoroughly analyzes the environmental consequences of this integration, aiming to offer valuable insights into the potential fusion of 3D printing, AI, and sustainability. By examining the challenges and future prospects, this review seeks to gain a thorough understanding of how the combined power of 3D printing and AI can transform advanced manufacturing practices toward a more sustainable and environmentally conscious future.

3. 3D printing of sustainable polymers and composites

The 3D printing industry has grown significantly, with uses ranging from prototyping to the production of end-use components. There is a noticeable trend toward sustainability in this dynamic terrain, with a particular focus on the usage of sustainable polymers and composites. Sustainable polymers can be defined in several ways: (a) polymers produced from eco-friendly, safe-to-use and renewable feedstocks that also offer recyclability or disposal methods compatible with environmental preservation [8,37]; (b) polymers derived out of renewable materials showcasing closed-loop life cycles [38,39]; and (c) polymers that meet consumer demands while aligning corporate requisites without causing any health hazards, environmental destruction or economic strain [40]. The term "sustainable composite" refers to a material containing a polymer matrix with reinforcing fibers or particles [41]. It is specifically intended to minimize its effect on the environment and promote long-term ecological balance [7]. Factors such as employing environmentally benign raw materials, reducing energy consumption during manufacturing processes and guaranteeing recyclability or repurposability at its lifespan's end contribute directly to a composite's sustainability [42–45]. Additionally, sustainable composites can have properties such as durability, minimal toxicity, and adherence to circular economy principles; thus, they foster responsible utilization of resources while mitigating ecological impact [46,47].

Sustainable polymers can be categorized into two main groups: natural polymers and synthetic bio-based polymers [48,49]. Natural polymers include cellulose, hemicellulose, lignin, protein, starch and modified biopolymers [50–52]. Synthetic biobased polymers can be derived from fatty acids, plant oils, terpenes, furans, amino acids and rosin acids [53–55]. Moreover, sustainable polymers encompass those biologically or chemically synthesized from renewable monomer sources, such as polylactic acid (PLA) and polyhydroxyalkanoate (PHA) [56,57]. Polyglycolide (PGA), poly(butylene succinate) (PBS), polyethylene (PE), polypropylene (PP), poly(ethylene furanoate) (PEF), poly(ethylene terephthalate) (PET), polyamide (PA), polycarbonate (PC), and polyurethane (PU) can also be partially or even wholly synthesized from renewable feedstocks like biomass and carbon dioxide [58–60]. Some sustainable polymers, such as PLA and PBS, are biodegradable [61], while others, such as polyolefins, PET, PEF, and PA, are resistant to degradation [62,63]. To lessen the negative effects of the latter, it is important to put in place appropriate end-of-life strategies, such as recycling [64].

In sustainable composites, natural fiber composites incorporate materials like hemp, flax, bamboo, biocarbon from different biomasses, etc. into polymers [65,66]. Hemp-plastic composites leverage the strength and lightweight properties of hemp fibers, thus contributing to eco-friendly alternatives for various applications [67]. Biocomposites represent an innovative category that combines natural fibers or particles with biobased polymers [68–70]. Wood-plastic composites, which integrate wood fibers with polymers, exemplify this category, offering a sustainable solution with reduced reliance on synthetic materials [71,72].

3D printing of sustainable polymers and composites represents a technologically advanced approach to environmentally friendly production. Fig. 1 illustrates how 3D printing promotes sustainability and a circular economy. Through the selection of biodegradable polymers derived from renewable sources and recycled polymers, the resultant 3D-printed objects demonstrate a commitment to reducing their ecological impact by naturally decomposing over time and reducing landfill [73,74]. Concurrently, the incorporation of recycled polymers or composites into the 3D printing process establishes a closed-loop system, mitigating the demand for virgin materials and effectively managing plastic waste [75,76]. This approach not only promotes the use of environmentally friendly materials but also contributes to the overall sustainability of the product throughout its life cycle. The customizable nature of 3D printing ensures design optimization precision and minimal material usage while maintaining structural integrity [77]. The combination of 3D printing with sustainable polymers and composites is a technological step forward, creating a harmonious balance between innovation and environmental responsibility in advanced manufacturing.

4. AI in 3D printing: an overview

The term "artificial intelligence (AI)" was first used by John McCarthy in 1956 during the Dartmouth Workshop, a significant event that marked the beginning of AI as a separate area of research [78]. AI refers to the emulation of human intelligence processes by machines, particularly computer systems [79,80]. These processes encompass learning, reasoning and self-correction [81,82]. AI systems can be broadly

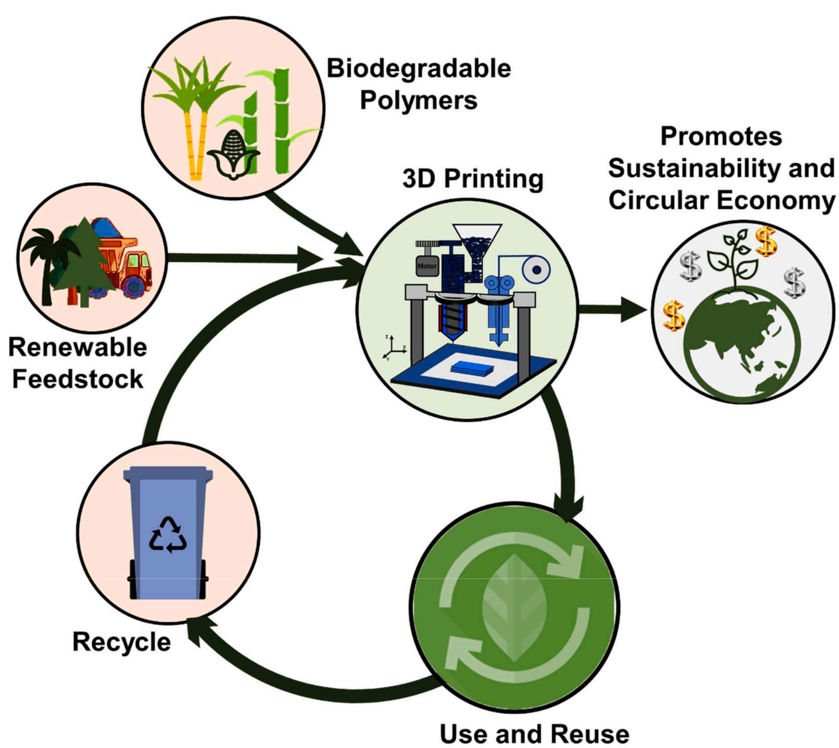

Fig. 1. 3D Printing for sustainability through the use of biodegradable and recycled polymers.

classified into two main types: narrow AI (weak AI) and general AI (strong AI) [83,84]. Narrow AI is developed and trained to execute specific tasks with remarkable proficiency, occasionally surpassing the capabilities of human beings. However, its ability to adapt its expertise to multiple tasks or domains is limited [85]. General AI, on the other hand, refers to machines having human-like intelligence capable of comprehending, learning, and applying information across a wide range of tasks [86]. Despite its potential, developing this level of AI remains largely theoretical [87]. The trajectory of AI's advancement can be categorized into several distinct waves as shown in Fig. 2 [88,89]: Symbolic AI (1950s–1980s), focused on logical rules and expert systems; Connectionist AI (1980s–1990s), which explored neural networks and parallel processing; Statistical AI (2000s–2010s), characterized by the prominence of machine learning (ML) and statistical techniques; and Modern AI (2010s-Present), marked by breakthroughs in deep learning (DL), reinforcement learning (RL), and large-scale data processing. The rapid advancement of AI is evident in various subfields, as can be seen in Fig. 3, such as ML, where algorithms evolve and improve through experience; neural networks, which mimic the human brain's structure and enhance pattern recognition; and DL, scaling neural networks to excel at processing vast amounts of data for complex tasks.

ML uses learning algorithms that train models to recognize patterns and utilize task-specific data to solve problems [90]. The process of creating ML systems involves three key steps: obtaining relevant datasets (training data), selecting an appropriate ML model, and training it for the specific task [91,92]. ML can be categorized into three primary learning paradigms: supervised, unsupervised, and RL [93,94]. Supervised learning trains an ML algorithm using data that includes both inputs and corresponding labels. The model learns to predict labels based on the provided input features. After training, the model can predict labels for new input features without labels [95,96]. This paradigm is valuable for tasks like image, voice, and object recognition, especially when large labeled datasets are available. Unsupervised learning, on the other hand, trains an ML model using only input features without corresponding labels [97]. It aims to achieve various goals, such as reducing feature dimensionality, clustering similar data points, replicating the training dataset, or identifying anomalies [98]. Unsupervised learning models can discover hidden patterns in data without human intervention during training [99]. RL, unlike the other paradigms doesn't rely on pre-existing training data. Instead, an RL agent interacts with an environment, generating training data that includes observations, actions taken, and rewards [100]. The environment represents the software that encapsulates the problem to be solved. Over time, the agent learns to maximize rewards and finds the best path to its goal [101]. Unlike supervised learning, RL doesn't require correct answers for each of its actions; it instead receives sparse feedback in the form of scalar rewards. RL finds significant utility in applications related to robotics and optimization [102,103].

In the era of the 4th industrial revolution, also known as "Industry 4.0," various manufacturing industries, including the 3D printing sector, generate massive amounts of data. 3D printing is experiencing a substantial surge in data generation, closely tied to the role of ML. In 3D printing, ML algorithms can take center stage, allowing users to fine-tune printing parameters, resulting in improved print quality and operational efficiency. Moreover, ML can facilitate informed decisions regarding sustainable material choices and composite formulation design, revolutionizing these critical aspects of 3D printing. It can play a pivotal role in developing sophisticated models that delve deeper into the behavior of polymers and composites during the printing process. These predictive models will enable real-time adjustments, guided by ML, to yield desired printing outcomes, a feat otherwise challenging to attain. Quality control and defect detection receive significant attention within the purview of ML. AI-based methods, underpinned by ML techniques, become instrumental in ensuring consistency and reliability in the quality of 3D printed components. In sectors with stringent standards like aerospace, ML stands as a critical tool for defect detection and quality assurance. Moreover, generative design and simulations, enriched by ML, reshape the landscape of structural optimization. ML algorithms facilitate the generation of intricate and high-performance part geometries, while enhancing simulations such as finite element analysis (FEA) and computational fluid dynamics (CFD). These insights highlight the transformative and empowering role of ML in the field of 3D printing within the framework of Industry 4.0. Fig. 4 shows the types of ML and their applications in different areas of 3D printing technology. Although integrating ML into 3D printing has potential benefits like optimizing printing parameters and reducing waste, it also comes with various challenges. These challenges include data availability, real-time feedback, hardware compatibility, overfitting, interpretability, cost of computational resources, privacy, ethics, user expertise, and regulation.

5. AI-driven 3D printing process optimization

Achieving efficient, high-quality, and cost-effective results requires optimizing the 3D printing process. The fine-tuning of parameters is critical for decreasing material waste and manufacturing costs [104–106]. By optimizing the printing speed, time efficiency can be increased, which is especially advantageous in industries where rapid turnover is important [107]. In addition, the careful adjustment of printing settings improves the overall quality of printed products, addressing problems related to surface finish, dimensional accuracy, and

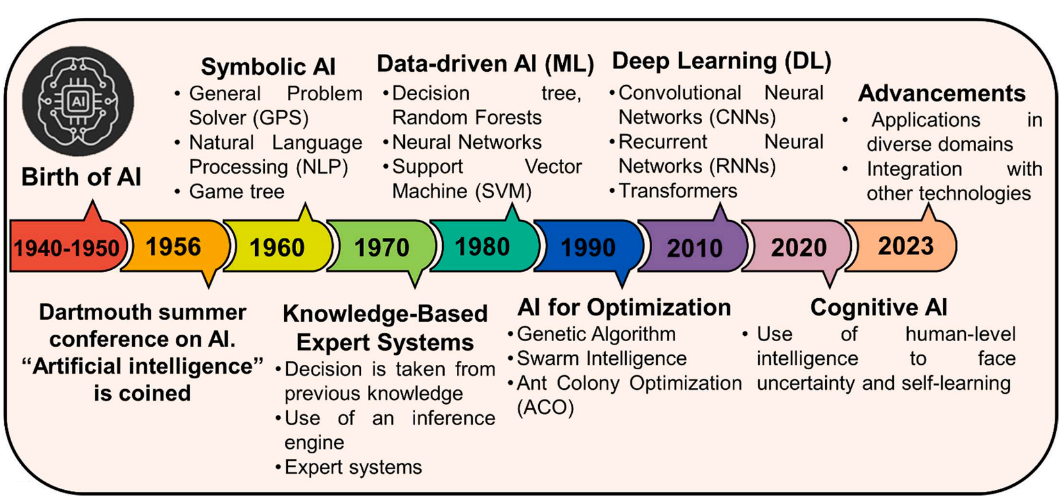

Fig. 2. History of AI from its inception to 2023.

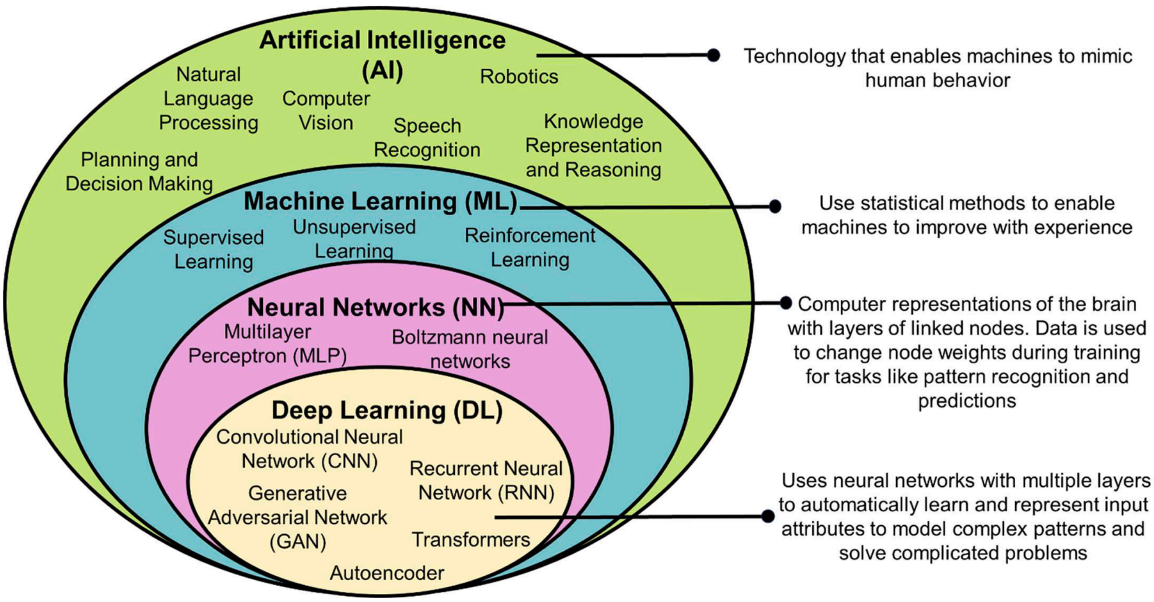

Fig. 3. AI advancements including machine learning, neural networks, and deep learning.

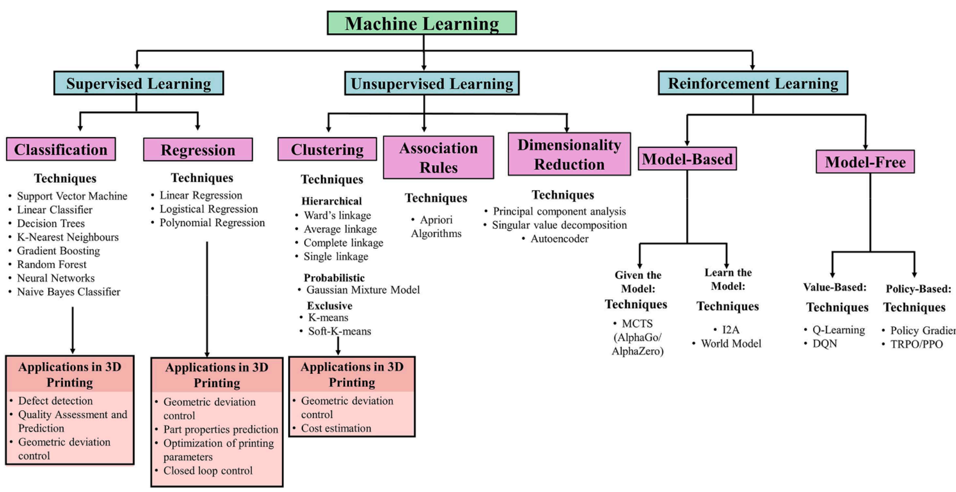

Fig. 4. ML types and their applications to different areas of 3D Printing.

layer adhesion [108,109]. Process optimization facilitates the customization of parameters for specific requirements, enabling the printing of complex geometries and intricate designs with precision [110]. This adaptability is especially valuable in industries like healthcare, aerospace, and automotive [111–114]. Additionally, optimization ensures compatibility with different materials, preventing issues like warping as well as enhancing material utilization [115]. Energy efficiency, increased machine utilization, and the establishment of consistent and reliable printing processes contribute to the wider adoption of 3D printing technology across diverse applications.

The rapid expansion of 3D printing has heightened the need for accurate parameter identification, especially given the growing variety of materials and their distinct characteristics that add complexity to determining the optimal combination of parameters. To address this, Oberloier et al. [116] introduced the "PSO Experimenter," an open-source platform using particle swarm optimization (PSO) algorithms to simplify computational intelligence applications. The study optimized the 3D printing of recycled Low-Density Polyethylene (LDPE) with five particles, programmed for explorative behavior to avoid premature convergence on local minima. Fitness functions were integrated into a spreadsheet, linking fitness to input values. The optimization had three phases: refining extrusion lines, enhancing single-layer planes, and further refining solid cubes. Significant improvements were observed, reducing stool production costs from $24.62 to $3.22 (87 % reduction) and achieving a remarkable 97 % reduction in research time for parameter optimization. Similarly, an autonomous calibration system for low-cost fused deposition modeling (FDM) 3D printers was developed by Ganitano et al. [117], showcasing the optimization of process parameters for complex model printing. This system employed metaheuristics and an efficient optimization method to fine-tune printing parameters. Various camera systems were used to detect issues such as nozzle clogging, incomplete printing, layer shifting, and infill deviation. Convolutional Neural Networks (CNNs) were employed for real-time defect detection during printing. The system, employing a sequential pipeline and a calibration object, evaluated the quality of 3D printer process parameters. Simulated annealing efficiently explored the parameter space, minimizing the computer vision evaluation. The modified Stanford bunny model was used for calibration, yielding sub-millimeter dimensional accuracy. Despite initial defects, the Creality Ender-3D printer achieved high-quality prints with a 0.047 mm average deviation from the CAD model, using PLA, PLA Pro, and PVB thermoplastic materials in experimental evaluations.

Various other strategies were implemented in addition to simulated annealing to enhance the 3D printing process and optimize parameters for improved output quality and efficiency. The Expert-Guided Optimization (EGO) strategy for optimizing 3D printing parameters by Abdollahi et al. [118] involved expert-defined parameter space selection, hill-climbing optimization guided by real-time feedback, and expert reassessment if results were unsatisfactory. The iterative hill-climbing algorithm optimized parameters based on expert-defined factors, showing transferability across materials and geometries. In a study by Rojek et al. [119], artificial neural networks (ANNs) were used to predict relationships between input and output variables. The two ANNs were constructed: one for predicting electricity consumption and another for forecasting air pollution levels. The selected ANN models demonstrated promising results in predicting energy consumption and air pollution, achieving the lowest Root Mean Square Error (RMSE) values. Kumar et al. [120] introduced an ANN with WOA optimization approach aimed at minimizing critical factors affecting 3D printed part quality, such as surface roughness, volume percentage error, and production time. Their self-learning model, optimized through a multi-layered feed-forward perceptron technique, yielded optimal results by minimizing Mean Squared Error (MSE) and achieving a large regression value (R_L). The investigation focused on key parameters including nozzle temperature, layer thickness, printing speed, and raster width, identifying optimal conditions for minimal surface roughness. Phogat et al. [121] employed genetic algorithm (GA) with ANN to predict and optimize wear rates. The cylindrical specimens were produced using a Geeetech A30 3D printer, following a central composite design by design experts. The ANN model was trained with data from 38 parameter sets, and the optimization process yielded the optimal parameter values that minimized wear. PLA demonstrated a wear rate of 0.155,371 mm^3/m, with specific parameter settings such as infill density of 95.207 %, raster angle of 89.258°, nozzle temperature of 220.009 °C, wall thickness of 1.198 mm and printing speed of 40.043 mm/s.

In an exploration of image-based quality inspection techniques for 3D-printed parts, a combination of transfer and ensemble learning was employed by Yang et al. [122] to enhance defect detection and classification accuracy. Various pretrained CNNs, including VGG16, VGG19, InceptionV3, ResNet50, EfficientNetB0, and EfficientNetV2L, were used for feature extraction from the image dataset. To train defect-detection models, ensemble learning methods like bagging and boosting were used. The dataset comprised 3D-printed objects with different filament colors (blue, green, and gray). Results indicated that combining specific pretrained models, such as VGG16 and VGG19, with ensemble learning methods yielded the highest accuracy for defect detection.

Albahkali et al. [123] and Fouly et al. [124] both employed a similar approach to enhance the mechanical and tribological characteristics of PLA composites for biomedical applications. In the former study, the focus was on improving PLA for artificial knee joints by incorporating date pit powder to mitigate brittleness issues in ceramic knee joint materials. Through heat treatment and the application of an Adaptive Neuro-Fuzzy Inference System (ANFIS), the study demonstrated that higher concentrations of date pit powder, along with heat treatment, resulted in increased hardness, improved compressive properties, and enhanced wear resistance of PLA composites. The ANFIS model exhibited precise predictions, with an average percentage error of less than 0.00931 %, thereby contributing to the optimization of PLA for biomedical applications. Similarly, in the latter study, ANFIS models were developed to predict the mechanical behavior of PLA green composites for biomedical applications, considering variations in production parameters such as the weight fraction of date pit particles and annealing time. The incorporation of date pit particles, combined with a 5-hour heat treatment, resulted in enhanced load-carrying capacity and improved mechanical characteristics. The ANFIS model accurately predicted the hardness, modulus of elasticity, and strength of PLA-date pit composites, aligning well with experimental results and demonstrating the significant impact of date pit concentration and annealing duration on mechanical properties.

These studies highlight the importance of optimization techniques for navigating the complexities of 3D printing, especially with the growing variety of materials and challenges in identifying the right parameters. A range of methods were discussed, including PSO, autonomous calibration, expert-guided strategies, and ANNs, with notable successes like reducing costs and time, defect detection, and optimizing quality metrics. The incorporation of transfer learning and ensemble learning in spotting defects through images demonstrates the collaborative potential of ML and 3D printing. However, it's essential to note that while these studies provide valuable insights and practical applications, they often lack in-depth discussions about the limitations and scalability of their methods across different materials, printers, and real-world situations. Future research should prioritize addressing these challenges to make these techniques more widely applicable in various 3D printing scenarios.

6. Material selection for 3D printing using AI

The incorporation of AI has substantially improved material selection for 3D printing. AI is critical in keeping large databases with up-to-date information on various 3D printing materials, including their qualities and compatibility with different printing processes [125]. ML algorithms predict material performance under specific printing conditions, anticipating mechanical behavior [126–128]. By taking into account variables such as nozzle temperature, raster angle, and layer thickness, simulations and models powered by AI are able to optimize the 3D printing process [129,130]. Additionally, AI evaluates cost parameters, improving material selection to reduce manufacturing costs and environmental effect [131]. Furthermore, through the incorporation of data derived from the real-world performance of printed objects, the technology creates a feedback loop that iteratively enhances material selection models [132–134]. Customization and personalization of material choices based on specific requirements can be facilitated by AI, contributing to the evolution of 3D Printing. Xue et al. [135] focused on elastic moduli control using ML techniques to automatically select design parameters without human interference. They employed variational autoencoders (VAEs) and generative adversarial networks (GANs) as generative models in the optimization framework. VAEs were used to compress Representative Volume Element (RVE) images to a reduced latent space, and Bayesian Optimization was applied to find an optimal RVE configuration meeting the prescribed design goal as shown in Fig. 5. Computational homogenization for linear elasticity provided averaged macroscopic mechanical properties from a composite solid with multiple materials. The VAE model was implemented in PyTorch, and 200 samples were drawn from low dimensional space. These samples, along with obtained decoded RVE images, underwent computational homogenization. Principal component analysis compressed the latent space into a 2D representation. Experimental validation involved 3D printing multi-material structures using UV-assisted replica molding. The consistently higher Young's modulus values than predicted indicate a manufacturing process consistently favoring PU over soft silicone, resulting in a high macroscopic Young's modulus. Rojek et al. [114] developed 3D-printed hand exoskeleton components using FDM and optimized the process through ANNs supported by GA. The essential physical properties for exoskeleton parts, encompassing durability, elasticity, hardness, compressibility, resilience, and temperature, were evaluated through 50 printed samples, revealing that PLA+ surpasses PLA in elasticity, and the optimized components achieve a balance between tensile force and low weight.

7. Predictive modeling using AI for enhanced 3D printing

Understanding the optimal parameters for 3D printing is essential for improving printed part performance. Teharia et al. [136] address this need by utilizing an ANN approach to assess the impact of various

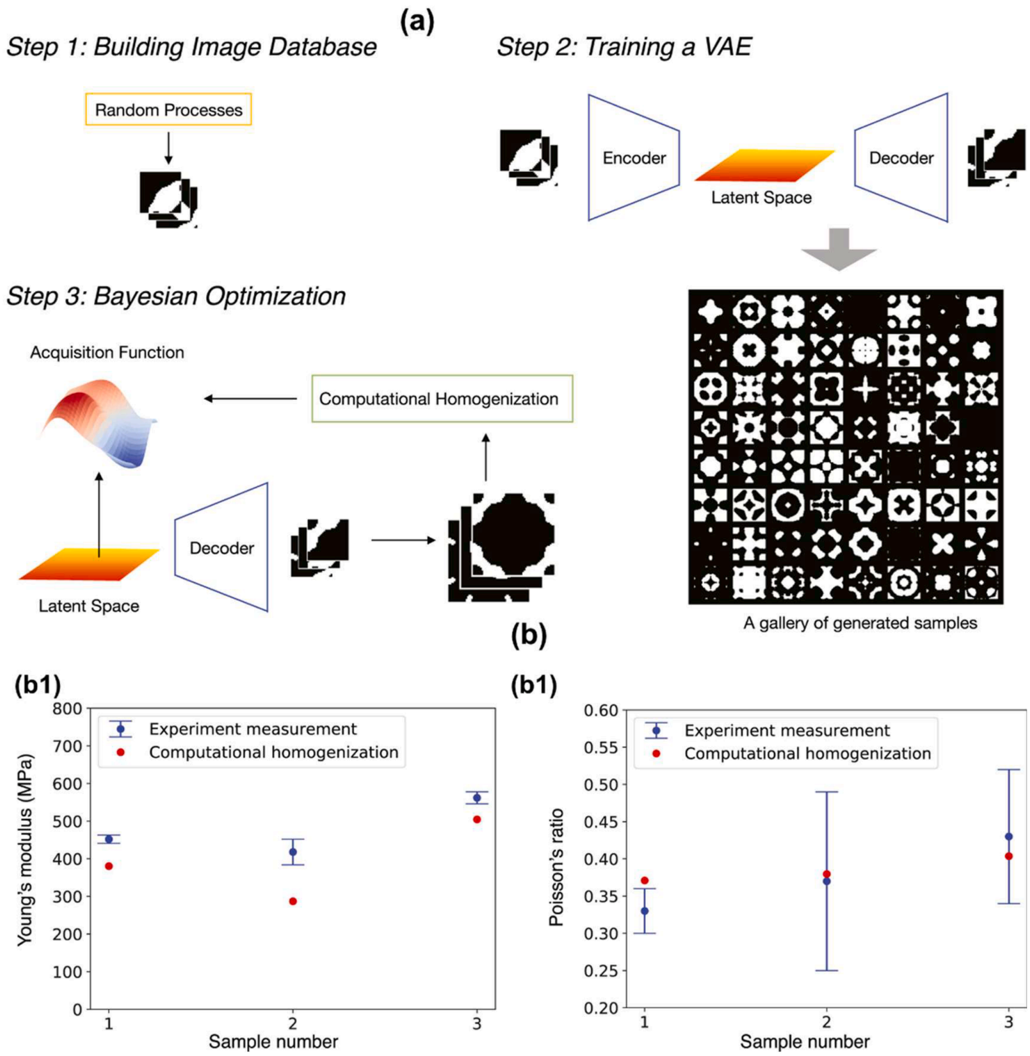

Fig. 5. (a) Illustration of the Bayesian optimization framework, where (a) outlines the steps: generating an artificial RVE image database (Step 1), training a VAE for realistic 56 × 56 images (Step 2), and utilizing Bayesian Optimization (BayesOpt) for achieving optimal RVE design for specified elastic moduli (Step 3); The experimental validation section, (b), includes (b1) a comparative analysis of macroscopic Young's modulus for three RVEs, contrasting experimental results with computational homogenization, and (b2) a similar examination of macroscopic Poisson's ratio for the same RVEs, comparing experimental findings with computational homogenization. Adapted with permission from [135], Copyright 2020 by the Elsevier.

printing parameters on printed specimen performance, aiming to optimize process parameters for optimal tensile strength. Examined factors included infill pattern, nozzle temperature, layer thickness, printing speed, and raster angle. Using an L27 orthogonal array for experimental design, specimens were printed and tested. Taguchi analysis revealed that tensile strength is influenced by factors such as printing speed and layer thickness. The architecture of the ANN included 10 neurons in layer 1 and 3 neurons in layer 2. A crucial aspect for error minimization was ensuring that the overall R values of the training, testing, and validation plots closely approached 1. The ANN model identified optimal parameters for desired tensile strength as follows: layer thickness of 200 μm, speed/feed rate of 50 mm/min, grid infill pattern, raster orientation of 0°, resulting in a tensile strength of 52.688 MPa. In a related study by Ali et al. [137], the Taguchi method and ANN were employed to predict the tensile strength of parts made from PLA using FDM. The ANN model was trained using different optimizers i.e., scaled conjugate gradient (SCG), Bayesian regularization (BR), and Levenberg Marquardt (LM). Among these, LM and BR were recommended for nonlinear systems, both in simulated and real-world data, owing to their capacity to minimize squared errors and weights. The ANN underwent training using 25 sets of input process parameters and tensile strength as output response. The optimal parameters for maximizing tensile strength were determined to be a layer thickness of 0.22 mm, printing speed of 45 mm/s, nozzle temperature of 205 °C, raster angle of 70°, and 4 perimeter numbers. To extend the exploration, Deb et al. [138] utilized ANNs to predict the impact of various process parameters on part attributes in PLA printing. Five key parameters were considered: raster angle, layer thickness, nozzle temperature, build orientation, and printing speed. The study explored infill angles using a zigzag structure at 50 % relative density and raster angles of 0°, 30°, and 45° around the Z-axis. The Taguchi Orthogonal Array method was applied to identify a specific combination of process parameters. Three individual ANN models were developed to predict part characteristics (tensile strength, surface roughness, dimensional accuracy), while a combined ANN model was created to establish relationships between process parameters and part attributes. The ANN models underwent training through a Rule of Thumb approach, achieving optimal performance by employing a single hidden layer comprising six neurons and utilizing a tangent sigmoid transfer function. Training involved various optimizers such as LM, BR, one-step secant, and gradient descent. The evaluation of model performance was conducted based on ANN predictions, utilizing metrics such as RMSE and correlation coefficient. The combined output model exhibited exceptional performance, achieving a minimal mean square error of 0.143289. However, the individual model for dimensional accuracy outperformed the combined model, reaching its lowest gradient at epoch 4. Regarding tensile strength predictions, the individual model outperformed the combined model, demonstrating a very low RMSE. Optimal parameters for surface finish were determined, including a 0.1 mm layer thickness, 40 mm/s printing speed, 220 °C extruder temperature, 0° deposition direction, and 0° build orientation. Improved mechanical properties were achieved with a 0.1 mm layer thickness, 80 mm/s printing speed, 210 °C extruder temperature, 45° deposition direction, and 90° build orientation.

Understanding the mechanical behavior of 3D printed materials is important for optimizing printing processes and achieving desired material properties. To address this, Grozav et al. [139] developed a predictive model using ANNs to create an orthotropic material profile, aiming to simulate the mechanical behavior of PLA printed through FDM. The neural network comprised three fully connected hidden layers, each containing eight nodes. It featured two potential configurations for inputs and outputs: one for horizontal orientation tensile strength values and another for vertical orientation. Adamax was employed as the optimizer for the neural network, with the Mean Absolute Percentage Error serving as the loss function. Activation functions for the hidden and output layers were selected through performance evaluation and consideration of input/output data ranges. The tensile test data were split, allocating 80 % for training and 20 % for validation. The model accurately predicted a tensile strength of 50.12 MPa with prediction accuracy of 93 %, showcasing its potential for predicting tensile strength in future parameter combinations. Similarly, Jatti et al. [140] optimized the printing process parameters i.e., layer height, infill percentage, nozzle temperature and printing speed with the aim of improving the tensile, impact, and flexural strength of PLA parts. Higher infill percentages and nozzle temperatures led to an increase in tensile strength. Flexural strength showed improvement with higher layer height, infill percentage, and nozzle temperature, while it slightly decreased with high print speeds. Impact strength demonstrated sensitivity to all parameters, rising with layer height, infill percentage, and printing speed but decreasing significantly with higher nozzle temperature. A mathematical model was developed using nonlinear regression for predicting flexural strength, tensile strength, and impact strength of a 3D-printed part. The optimized parameters for impact strength included infill of 70 %, layer height of 0.08 mm, printing speed of 20 mm/s, and nozzle temperature of 201 °C. For flexural strength, the optimum values were 100 % infill, 52 mm/s printing speed, 0.24 mm layer height, and 203 °C nozzle temperature. To attain the highest tensile strength, the recommended parameters were infill of 100 %, layer height of 0.0962 mm, printing speed of 20 mm/s, and nozzle temperature of 230 °C.

Moradi et al. [141] aimed to optimize PLA printed part production by studying thickness deviation, production cost and toughness of tensile specimens. They employed ANN and ANN-GA techniques, confirming the feasibility of enhancing toughness for end-use applications. Optimal settings were identified as 0.28 mm layer thickness, 34 %, infill percentage, and 222 °C nozzle temperature, with build time significantly impacting production cost. The interaction between layer thickness and infill percentage was highlighted important for part thickness. Enhanced toughness primarily resulted from increased ductility. The hybrid ANN-GA method demonstrated better accuracy in predicting output values compared to a single ANN model. Moreover, Moradi et al. [141] utilized RSM to determine the ideal window of operability. Utilizing contour maps derived from multiple responses, RSM facilitated the creation of optimal printed samples. Singh et al. [142] used an ANN model with a tansig activation function to predict FDM process responses. The study investigates the impact of six process parameters on the FDM response, encompassing build orientation, nozzle diameter, layer height, infill density, raster pattern and printing speed. The model utilized two hidden layers, each with 10 neurons, and one output layer with four responses: build time, tensile strength, surface roughness, and material consumption. The effectiveness of the developed neural network model was evaluated through correlation analysis. The obtained correlation value was 0.99483, indicating a strong correlation between experimental values and predicted model values. The predicted results of the ANN model for the testing dataset demonstrated a close alignment with the actual experimental data. Comparative results and error values lead to the conclusion that a well-trained neural network model exhibits a higher level of accuracy in predicting output responses of the FDM process. Rojel et al. [114] utilized an ANN in conjunction with GA to optimize the 3D printing process, aiming to achieve maximum tensile force. A feed-forward neural network with a back-propagation algorithm was utilized for training and parameter optimization. The GA reduced input variables in constructing the ANN model. The 3D printer ANN used normalized and scaled input variables for consistent interpretation. GA, a heuristic search technique, automatically optimized the ANN structure using an original fitness function. MSE calculated the neural network model's accuracy after a specific number of training epochs. A three-layer feed-forward neural network with back-propagation optimized connection weights. The models underwent testing for learning speed and generalization, with processes averaging 10,000 iterations and 500 to 1000 learning epochs. The proposed method, which utilizes a multi-layer perceptron (MLP) architecture, contributes towards standardization, with better results observed for PLA+ compared to PLA, attributed to its greater elasticity. In another study, Rojel et al. [143] conducted a comparison of the optimization of 3D printing process for achieving the maximum tensile force using two distinct approaches: a DL approach centered on CNNs and traditional ANNs. The findings indicate that as the complexity of printed objects increases, DL approaches are expected to emerge as the preferred method for 3D printing optimization. Compared to traditional ANN methods, DL-based optimization offers increased quality, decreased MSE, and faster calculation speeds.

Jayasudha et al. [144] evaluated the performance of five supervised ML models in predicting mechanical properties. These models included Linear Regression, Gradient Boosting Regression, AdaBoost Regression, XGBoost Regression, and Random Forest (RF) Regression. The study comprised two case studies. In the first case study, the investigation focused on the tensile strength of printed part, with a specific emphasis on three process parameters: nozzle temperature, shell thickness and layer height. A full factorial design was employed to assess the impact of these parameters. The correlation between tensile strength and process parameters was evaluated through a Pearson correlation heatmap, as depicted in Fig. 6 (a). Fig. 6 (b) reveals significant deviations between actual tensile strength and linear regression predicted values, particularly in overprediction at lower tensile strength values and underprediction at higher values, even within the training set. Fig. 6 (c) shows that RF regression performs slightly better than linear regression on training data but exhibits poor performance on testing data. AdaBoost regression (Fig. 6 (d)) demonstrates improved fitting characteristics on training data compared to RF regression and linear regression, although testing data performance remains subpar. Gradient boost regression (Fig. 6 (e)) and XGBoost regression (Fig. 6 (f)) exhibit ideal fitting on training data, with XGBoost showing slightly better performance on testing data. Both algorithms demonstrate an equal likelihood of overprediction or underprediction on testing data, suggesting unbiased models. The results demonstrated that different ML algorithms exhibited varying performance, with XGBoost demonstrating the best performance in terms of RMSE, median absolute error and Mean Absolute Error (MAE). In the second case study, the researchers aimed to predict tensile strength, taking into consideration factors such as layer thickness and angles. Here, the models once again showcased differing performance, with XGBoost outperforming other algorithms in terms of prediction accuracy.

Tura et al. [145] introduced ANN and Fuzzy Logic modeling to predict 3D printing outcomes. The ANN accurately forecasted results

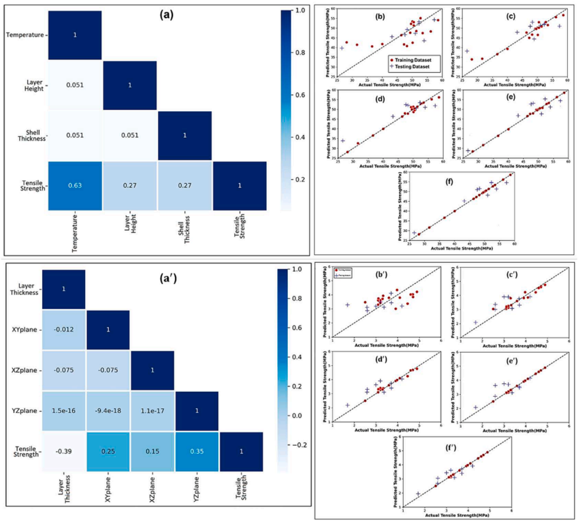

Fig. 6. (a) Pearson Correlation Heatmap illustrating the relationship between process parameters and tensile strength and comparison of Actual versus Predicted Tensile Strength using Various ML Algorithms: (b) Linear Regression, (c) RF Regression, (d) AdaBoost Regression, (e) Gradient Boost Regression, and (f) XG Boost Regression. Adapted from [144], MDPI open access Creative Common CC BY licence.

based on experimental data, while the fuzzy logic model employed triangle membership functions for output prediction. An analysis of variance assessing the impact of process parameters on tensile strength identified infill density as pivotal, with nozzle temperature and printing speed playing lesser roles. The ANN model exhibited an error of 0.40 % from experimental data, although one sample notably over-predicted. In contrast, the fuzzy logic model demonstrated an average percentage error of 1.84 %, underscoring the superior accuracy of the ANN in the comparative evaluation of predictive models.

The study by Charalampous et al. [146] focuses on the impact of different printing conditions on the tensile strength of the printed parts. The study encompassed five different levels of printing conditions, including factors such as nozzle temperature, printing speed, and layer height. Treating the prediction of tensile strength as a regression problem, ML based regression algorithms namely RF, k-Nearest Neighbors (KNN) and support vector regression (SVR) were applied. The KNN model demonstrated the best performance with test set absolute errors being less than 2.50 %. This outcome suggests that the established regression model is adept at effectively predicting the tensile strength of products produced through FDM.

Cai et al. [147] developed sustainable 3D-printed continuous ramie fiber reinforced polypropylene composites using in-situ impregnation 3D printing. The Box-Behnken design was employed to study the effect of printing parameters, specifically focusing on nozzle temperature, extrusion rate, layer thickness and printing speed. Three-point bending tests assessed interlayer and intralayer adhesion properties, with prediction models employing response surface methodology (RSM), ANN and RF. The ANN model achieved high R2 scores (Inter-Strength: 0.9682, Intra-Strength: 0.9677) with no overfitting. Results showed increased strength with higher extrusion rate and nozzle temperature. Parameter optimization decreased strength by 4 % and 12 % at an 80 % threshold but improved forming efficiency, highlighting broader 3D printing applications.

The studies described in this section highlight the importance of optimizing 3D printing processes through the integration of AI. These investigations cover diverse aspects, including printing parameter optimization, material profile creation for numerical simulations, strength enhancement through parameter adjustments, and the exploration of different ML models for predicting mechanical properties. Researchers have employed a combination of experimental design, Taguchi analysis, and ANNs to identify optimal parameters for maximizing tensile strength, emphasizing factors like layer thickness, infill patterns and printing speed. Many studies have focused on the choice of optimization- and architecture-related hyperparameters or compared different machine learning methods. The exploration extends to considering various process parameters, including infill and raster angles, demonstrating the power of ANN in predicting attributes like surface roughness, tensile strength, and dimensional accuracy. Additionally, studies have delved into creating orthotropic material profiles, simulating the anisotropic nature of 3D-printed materials. The integration of ANNs with GAs showcases the potential for comprehensive optimization strategies, addressing multiple material properties such as toughness, thickness, and production cost. The comparison of different ML models highlights the importance of selecting appropriate algorithms for specific applications. Factors such as nozzle temperature, layer thickness, printing speed, infill pattern and raster orientation have been found to influence the tensile strength of printed parts. Exploration of the hybrid ANN-GA method confirmed its superiority in predicting thickness deviation, toughness and production cost, highlighting the interaction between infill percentage and layer thickness. Introduction of ANN and Fuzzy Logic modeling underscored the importance of infill density in predicting tensile strength. The application of ML-based regression algorithms to predict tensile strength under varied printing conditions, with the model exhibiting optimal performance, further enriches the understanding of 3D printing optimization. Lastly, a focus on sustainable 3D printing, using ANN and ML algorithms, provides valuable insights into optimizing parameters for enhanced mechanical properties while maintaining sustainability. Table 1 provides an overview of recent research efforts focusing on predictive modeling to improve mechanical properties in 3D printing using AI techniques.

8. AI-based design and geometry optimization for 3D printing

AI-driven design and geometry optimization are revolutionary developments in several sectors as by harnessing the capabilities of AI, engineers can explore unprecedented levels of creativity and efficiency. AI-driven generative design facilitates the rapid generation of a wide range of design possibilities while taking into account complex parameters and constraints [148]. This iterative technique, often used in topology optimization, improves geometries to attain optimum performance, including structural integrity and weight reduction [149]. Recent reports reveal a substantial reduction in design iteration time by 30–50 % when utilizing AI-based generative design compared to traditional methods. Additionally, it showcases a remarkable 10–50 % reduction in part weight and 6–20 % decrease in manufacturing costs, highlighting the economic benefits of AI-driven geometry optimization [150,151]. Moreover, AI facilitates automated simulations and testing, reducing reliance on physical prototypes [152].

Sangeun et al. [153] explored the application of AI, specifically generative models like VAEs and GANs, in optimizing engineering design. Their study introduced a framework considering both engineering performance and aesthetics, using Boundary Equilibrium GANs (BEGANs) for robust visual quality. Global convergence was assessed by determining the reconstruction that minimized the absolute value of the proportional control algorithm error as image diversity increased. The study utilized an autoencoder to assess design novelty and proposed a regression model for data-insufficient cases, focusing on a 2D design space with pixel-wise images to develop a recommendation system for suitable designs. Yao et al. [154] introduced a hybrid ML algorithm for recommending design features for the 3D printing of conceptual designs. The approach involves encoding 3D printing design features and target components, conducting hierarchical clustering, establishing a support vector machine (SVM) classifier, and implementing an SVM-based progressive dendrogram cutting algorithm. The study applied this methodology to four components: the suspension arm, bumper, driveshaft

Table 1
Overview of recent work focusing on predictive modeling to enhance mechanical properties in 3D printing through the application of AI; LT: Layer Thickness, LH: Layer Height NT: Nozzle Temperature, BT: Bed Temperature, PS: Printing Speed, RA: Raster Angle, IP: Infill Pattern, BO: build orientation, ID: Infill Density, ND: Nozzle Diameter, ST: Shell Thickness.

Study	Objective	Methodology	Model architecture	Parameters examined	Optimal parameters	Key findings
[136]	Tensile strength optimization	ANN	2 hidden layers (10 neurons in layer 1, 3 neurons in layer 2)	LT, NT, PS, RA and IP	LT: 0.2 mm, NT: 210 °C, PS: 50 mm/min, Grid IP and RA as 0°	• RA impact: Strength decreases with angle increase; higher strength with aligned fibers • IP influence: Grid > rectilinear > full honeycomb in tensile strength • PS effects: High PS reduces strength, compromises surface finish, and bonding • LT variation: Strength increases with thicker layers • NT dependency: <200 °C hampers bonding; >200 °C boosts tensile strength
[137]	Tensile strength prediction	LM, SCG and BR	1 hidden layer	LT, PS, NT, RA and number of perimeters	LT: 0.22 mm, PS: 45 mm/s, NT: 205 °C, RA: 70°, and perimeter numbers: 4	• Tensile strength varied between 37.34 MPa to 54.74 MPa • ANN predictions exhibited a maximum error of 8.91 %, surpassing the 19.96 % error of the mathematical model
[138]	Prediction of dimensional accuracy, surface roughness, and tensile strength	ANN	1 hidden layer (6 neurons, tangent sigmoid transfer function)	LT, NT, PS, BO and RA	**Surface roughness:** 0.1 mm LT, 220 °C NT, 40 mm/s PS, 0° BO, and 0° RA; **Tensile Strength:** 0.1 mm LT, 210 °C NT,80 mm/s PS, 90° BO, and 45° RA; **Dimensional Accuracy:** 210 °C NT and 45° RA	• Combined ANN model, which simultaneously analyzes the relationship between five process parameters and three part attributes, exhibited exceptional performance, surpassing individual models in accuracy and predictive capability.
[139]	Prediction of material model to simulate mechanical behavior of 3D printed PLA	ANN with Adamax optimizer	Three hidden layers (8 nodes each), two configurations for horizontal and vertical orientation tensile strength	PS, NT and BO	NT: 195 °C, PS 45 mm/s and horizontal orientation	• Achieved 93 % accuracy in predicting mechanical characteristics • Demonstrated the effectiveness of ANN in accurately predicting and simulating mechanical behavior in 3D printing processes.
[141]	Optimize PLA printed part production for toughness, thickness, and cost	ANN and ANN-GA techniques	1 hidden layer with 6 nodes	LT, ID and NT	LT: 0.28 mm, ID: 34 %, and NT: 222 °C	• Hybrid ANN-GA method out-performed single ANN model for all three outputs. • Enhanced toughness in optimized specimen was due to increased ductility, not strength. • LT and ID interaction identified as key parameter influencing printed part thickness.
[142]	Prediction of tensile strength, material consumption, build time and surface roughness	ANN with feedforward backpropagation (FFBP) algorithm	2 hidden layers with 10 neurons each	ND, BO, ID, RA and LH	–	• FFBP with sigmoid transfer function showed outstanding performance with R2 values for testing (0.99343), training (0.99366), and validation (0.99372) • Highest tensile strength recorded at 57.633 MPa • Lowest surface roughness measured was 1.71 μm • Minimal build time achieved was 0.35 h • Least material consumption observed was 7.8 g
[143]	Optimization for maximum tensile force	ANN and CNN	1 hidden layer for ANN with 20 neurons 2 hidden layers with 20 neurons each for CNN	LH, ST, top and bottom thickness, ID, PS, BT and NT	LH: 0.2 mm, ST: 1.2 mm, top and bottom thickness: 2 mm, ID: 40 %, PS: 70 mm/s, BT: 215 °C and NT 220 °C	DL-based optimization surpassed traditional ANN methods: • 1.5 times faster • Higher quality: learning accuracy of 0.9577, testing accuracy of 0.9721 • Reduced MSE to 0.001
[144]	Prediction of tensile strength	Linear Regression, RF, AdaBoost,	–	NT, LH, ST, BO and LT	–	• Superiority ranking of ML algorithms: XGBoost > gradient

(continued on next page)

Table 1 (*continued*)

Study	Objective	Methodology	Model architecture	Parameters examined	Optimal parameters	Key findings
		Gradient Boosting, XGBoost				boost > AdaBoost > RF > linear regression
[145]	Prediction of tensile strength	ANN and Fuzzy Logic	1 hidden layer with 10 neurons	ID, NT, and PS	ID: 100 %, NT: 200 °C, and PS: 100 mm/s	• Fuzzy Logic and ANN models accurately predicted tensile strength with errors of 3.29 % and 2.21 %, respectively • ID had the most significant impact on tensile strength, while NT and PS had minimal effects
[146]	Prediction of tensile strength	RF, SVR and KNN	–	NT, PS and LH	NT: 210 °C, PS: 70 mm/s and LH: 100μm	• KNN demonstrated best performance with absolute errors on the test set less than 2.50 %.
[147]	Optimized printing parameters to enhance production efficiency and ensure desired interfacial performance	RF and ANN	**RF:** Maximum tree depth of 4, a minimum leaf node sample requirement of 1, a minimum internal node split requirement of 2, and it consisted of 50 trees in the forest **ANN:** 2 hidden layers with 3 neurons each	Extrusion flow rate, NT, LT and PS	Extrusion flow rate: 90 %, NT: 215 °C, LT: 0.35 mm and PS: 450 mm/min	• ANN demonstrated high prediction accuracy. • Extrusion flow rate emerged as the most influential parameter on both Inter-Strength and Intra-Strength. • PS had a relatively small effect compared to the extrusion flow rate.

and wheel, showcasing its efficacy in suggesting 3D printing design features for racing car components and reducing labor and time consumption for designers. In another study, Yao et al. [155] aimed to minimize cost increments resulting from adjustments in 3D printing process settings while maximizing flexibility in manipulating the printing process. They employed a multi-objective GA to address the optimization problem and developed a knowledge-based expert system to establish relationships between design constraints and printing parameters. The expert system utilized a Mamdani-type fuzzy inference system with aim to identify the optimal combination of platform modules and unique modules for maximizing customer-perceived utility. The proposed design methodology demonstrated improvements in both performance and cost savings, making it applicable to various 3D printing techniques.

Kumar et al. [156] optimize custom splint topology using 3D scanning-assisted parametric modeling, presenting it to AI in the ANSYS Workbench for design optimization. The thermal and mechanical properties of the desired project material were defined using the static structural module. The mesh generation process involved domain discretization, load and support assignment, and a load cell sensor. Structural responses, including induced stresses and deflection under applied load, were evaluated. The potential for design optimization was evaluated using the Topology Optimization (TO) module, which aimed to minimize compliance and maximize stiffness by removing excess material from the domain. Results were then validated in a standalone static structural module under defined supports and loads. The thermal simulation of topologically optimized orthosis replaced force with heat, stiffness with thermal conductivity, and displacement with temperature. The optimized splint topology allowed for 149.19 % more heat dissipation, aiding patient recovery and improving ventilation ease. The customized orthotic appliances, printed using FDM 3D printing, resulted in a 42.6 % lighter splint compared to the unoptimized version. Rade et al. [157] introduced a DL-based topology optimization method that significantly reduces computational time. The methodology involved training CNNs on low-resolution 3D geometries and transferring the learned weights to higher-resolution geometries using a Pyramid U-Net architecture. To handle memory-intensive high-resolution optimization, they integrated a data-parallel distributed training scheme on a GPU high-performance computing (HPC) cluster. Their approach applied multigrid techniques from solving partial differential equations (PDEs) to CNNs, smoothing errors on coarse meshes and gradually interpolating to finer ones. Their hybrid architecture, Multigrid Pyramid U-Net, included multiple U-Net modules with different pooling strides for improved feature learning. Data-parallel training divided data among devices and processed local mini-batches asynchronously, updating model parameters with a global gradient. The study employed a voxel printing approach to create print instructions. The multigrid framework converted predicted density values into binary occupancy values. They generated a 3D dataset with 31,093 nodes and 154,677 elements, originating from various cube topologies. The study assessed manufacturability, successfully printing models with minimal artifacts, although some challenges arose, such as limited manufacturing constraints specific to FDM 3D printing and nozzle diameter dictating voxel size. Rasulzade et al. [158] presents a CNN-based topology optimization method for 3D printing structures, aiming to reduce material usage while maintaining stiffness. The method uses the Messerschmitt-Bölkow-Blohm (MBB) beam as an example, and ML methods to accelerate TO and reduce computational time. The proposed U-net model, which includes convolution, pooling, dropout, and up-sampling, was tested on synthetic data. The model achieved a maximum accuracy of 99 % for material distribution, with depths of 3 being better for faster results.

Saleh et al. [159] focus on enhancing the performance of 3D printed Triply Periodic Minimal Surface (TPMS) structures. They used two materials, PLA and carbon fiber-reinforced PLA (CFRPLA), to fabricate TPMS structures with different cell topologies (Diamond, Gyroid and Primitive) as well as sizes. Researchers considered factors like relative density (RD), cell size, and material composition to optimize mechanical properties. An ANFIS model was employed to predict TPMS structure performance in terms of energy absorption, peak load, and specific energy absorption (SEA), enhancing prediction accuracy. The Diamond-based TPMS structure showed the highest compressive modulus, while Gyroid structures exhibited lower peaks. ANFIS models exhibited superior performance over mathematical models in predicting mechanical characteristics with reduced deviation. Desirability analysis helped identify optimal settings for cell size, topology, and carbon fiber incorporation to maximize TPMS lattice structure performance.

To illustrate the application of generative optimized design techniques, Pollák and Török [160] selected a plastic backrest from an office chair. Before scanning, a non-transparent coating was applied to the component, and chalk spray facilitated the recognition of the projected laser pattern. In Creo Parametric, the shape was converted into a parametric volumetric model. Utilizing the Multibody Design function, a single body could be divided into multiple parts in one session, with the ability to assign distinct parameters to each part. After configuring the necessary parameters, the simulation revealed the consumption of 284 m of 1.75 mm diameter material, equivalent to 19 h of the 3D printing process. An ANN-based predictive model was developed to forecast the mechanical characteristics of 3D-printed PLA by Grozav et al. [139]. The neural network was trained on data from 48 test samples produced through FDM with different parameter combinations. The predicted mechanical properties were then employed to establish an orthotropic material profile for finite element analysis. The study's results demonstrated a strong correlation between process parameters and tensile strength, with the trained neural network achieving a prediction accuracy of 93 %. Finite element analysis further confirmed the orthotropic behavior of the material and validated the predicted mechanical characteristics. Fouly et al. [124] explore the potential of using 3D-printed PLA-DP (Polylactic Acid - Date Pit) composites for orthotic applications. The study aimed to determine the maximum load-carrying capacity of both treated and untreated PLA-DP composites through FEA and ANN. The model utilized for training was ANFIS comprising five layers: fuzzification, product, normalization, and output layers. Results indicated that the incorporation of date pit particles in PLA filament reduced flexibility, enhancing mechanical properties. After 5 h of heat treatment, the modulus of elasticity and strength of PLA-DP composites increased by 2.7 % and 25.7 %, respectively. The ANFIS model accurately predicted the mechanical properties of PLA-DP composites, with negligible average percentage errors of $9.88x10^{-3}$ % for hardness, 0.18 % for modulus of elasticity, and 0.08 % for strength.

The use of AI in design and geometry optimization has been highly effective across various industries, providing engineers with enhanced creativity and productivity. In particular, AI has significantly improved generative design, especially in topology optimization, leading to a substantial reduction in design iteration time by 30–50 %. This has demonstrated economic advantages, including a 10–50 % reduction in part weight and a 6–20 % decrease in manufacturing costs when compared to conventional methods. Furthermore, AI facilitates automated simulation and testing, reducing reliance on physical models. These studies have explored the use of various AI techniques, such as variational autoencoders, GANs, and ML algorithms, in optimizing engineering designs, offering frameworks that consider both engineering performance and aesthetics. Hybrid ML algorithms have been proposed for 3D printing design feature recommendations, and multi-objective GAs have been employed for 3D printing process optimization. The optimization of custom splints using AI has demonstrated significant improvements in heat dissipation, patient recovery, and a 42.6 % reduction in splint weight through FDM 3D printing. DL-based topology optimization methods have been introduced to reduce computational time in 3D printing structures, employing CNNs and multigrid techniques. Additionally, studies focus on enhancing the performance of 3D printed structures, such as TPMS structures, using ANFIS for predicting mechanical properties. The application of generative design techniques has been demonstrated in the design of a plastic backrest for an office chair. Furthermore, predictive models based on ANNs have been developed to forecast the mechanical characteristics of 3D-printed materials, showcasing strong correlations between process parameters and tensile strength. The inclusion of date pit particles in PLA filament for orthotic applications has been explored, with the ANFIS model accurately predicting mechanical properties, indicating improvements in flexibility and strength with heat treatment. Table 2 offers a succinct summary of various studies focusing on AI-based design and geometry optimization for 3D printing, outlining the methodology, algorithms employed, and the corresponding performance metrics assessed in each study. These studies demonstrate the significant impact of AI-driven design and optimization techniques on a wide range of engineering applications, including product design, manufacturing, healthcare, and orthotics.

Table 2
Summary of studies focusing on AI-based design and geometry optimization for 3D printing, outlining the methodology, algorithms employed, and performance metrics.

Study	Focus area	Methodology	Performance metrics/ key findings
Sangeun et al. [153]	Design optimization	Developed a framework integrating generative models (variational autoencoders, GANs - BEGANs) considering both engineering performance and aesthetics.	• Global convergence measured via the closest reconstruction with minimum absolute value of proportional control algorithm error as image diversity increased • Design novelty evaluated using an autoencoder
Yao et al. [154]	Design feature recommendation	Utilized a hybrid ML algorithm for recommending design features in 3D printing. The process involved coding AM design features, hierarchical clustering, SVM classifier, and an SVM-based progressive dendrogram cutting algorithm	
Yao et al. [155]	Platform design methodology	Utilized GA to optimize 3D printing process settings. Developed a knowledge-based expert system to map relationships between 3D printing process settings and product platform design constraints, incorporating a Mamdani-type fuzzy inference system.	• Minimized cost increments caused by 3D printing process setting adjustments • Maximized freedom in manipulating the printing process • Formulated a platform variant design optimization problem • Achieved performance improvements and cost savings
Kumar et al. [156]	Topology optimization	Used 3D scanning-assisted parametric modeling and ANSYS Workbench for custom splint topology optimization. Integrated static structural and thermal modules for comprehensive analysis.	• Achieved topology optimization of custom splints • Enhanced heat dissipation capabilities • Reduction in weight
Rade et al. [157]	Topology optimization	Introduced a topology optimization method utilizing CNN with a Pyramid U-Net architecture. Integrated multigrid techniques for enhanced efficiency.	• Successfully predicted final shapes compared to the SIMP method.

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Table 2 (*continued*)

Study	Focus area	Methodology	Performance metrics/ key findings
Rasulzade et al. [158]		Implemented a CNN based topology optimization approach for 3D printing structures, with the Messerschmitt-Bölkow-Blohm (MBB) beam as a demonstration.	• Aimed to reduce material usage while maintaining stiffness in 3D printing structures • Achieved a maximum accuracy of 99 % for material distribution
Saleh et al. [159]	Optimization of 3D printed TPMS structures	Focused on improving the performance of 3D printed TPMS structures using PLA and CFRPLA, utilizing an ANFIS model for performance prediction	• Enhanced TPMS structure performance through material and design optimization • Used ANFIS for accurate prediction of mechanical characteristics.
Pollák et al. [160]	Generative optimized design	Applied generative optimized design techniques to a plastic backrest for an office chair, leveraging 3D scanning, VXelements 6, and Creo Parametric 7.0 for modeling and simulation, and developed an ANN based predictive model for material consumption.	• Demonstrated the application of generative optimized design techniques to reduce material consumption in 3D printing.
Fouly et al. [124]	PLA-DP composites for orthotic applications using FEA and ANN	Explored 3D-printed PLA-DP composites for orthotic applications, assessing mechanical properties using FEA and ANN, and incorporated an ANFIS model combining ANN with fuzzy logic.	• Reduced flexibility of PLA chains in PLA-DP composites, improving mechanical properties. • Accurately predicted mechanical properties using the ANFIS model.

9. Quality control and defect detection in 3D printing using AI

Quality control and defect detection in 3D printing have witnessed significant advancements with the incorporation of AI. AI-driven algorithms enhance the accuracy of defect detection in 3D-printed objects, achieving a detection rate of over 80 % [161]. AI systems, particularly ML models, are trained on extensive datasets of 3D-printed objects to identify deviations from design specifications and recognize common printing defects such as layer misalignments, voids, or irregularities [162,163]. The real-time monitoring capabilities of AI in 3D printing ensures that defects are identified during the printing process, minimizing material waste and saving time [164,165]. This is important, especially in industries such as aerospace and healthcare, where precision is paramount. The integration of AI into 3D printing quality control not only enhances the overall efficiency of the 3D printing process but also contributes to the production of high-quality, defect-free components. As the 3D printing industry continues to expand, AI's role in ensuring the reliability and quality of printed objects is becoming increasingly indispensable.

Paraskevoudis [166] presented a methodology for identifying defects in 3D printing using AI-based Computer Vision. This technique offers the capability to halt the printing process or adjust parameters to address identified defects. The study involved gathering images of defective 3D printed objects and employing various data augmentation methods. A final dataset comprising 2500 images was prepared. Annotation of these images was performed using LabelImg annotation tools, resulting in XML files following the Pascal Visual Object Classes (PASCAL VOC) format for each training image. The Single Shot Detector was selected due to its ability to detect single shots at high frame rates while maintaining low input resolution. The model consisted of two phases: a feed-forward CNN and a fully connected layer. The VGG16 CNN served as the base network, boasting a 92.7 % test accuracy in ImageNet. Training of the Processes Deep Neural Network utilized the TensorFlow API, with computational power provided by a NVIDIA Tesla K80 GPU featuring 2496 CUDA cores and 12GB of GDDR5 VRAM. Evaluation of detection results employed the Intersection over Union (IoU) metric, quantifying the overlap between bounding boxes and facilitating the calculation of True Positives, False Positives, or False Negatives from a test set. At an IoU of 0.4, the trained model achieved a Precision of 0.44 and Recall of 0.69, while at an IoU of 0.5, Precision was 0.41 and Recall was 0.63. For an IoU of 0.6, Precision stood at 0.4 with Recall at 0.62. The F1-Score for an IoU threshold of 0.4 was 0.55. Subsequently, the model was deployed in a live 3D printing environment, with a Raspberry Pi 4 microprocessor situated in front of the printing bed, supported by a wrapper algorithm to interpret predictions and probability scores.

To investigate how printing parameters affect dimensional accuracy across various geometries like cylindrical shafts, holes, and rectangular slots, Sharma et al. [167] employed the decision tree (DT) to predict dimensional variations, achieving an R2 score of 0.67, indicating its efficacy. Using the RSM on Design Expert Software, they designed the sample space, generating runs with different print parameter combinations for both ABS and PLA materials. The model's evaluation with training set proportions of 50 % and 80 % resulted in R2 scores of 0.64 and 0.67, respectively, demonstrating its ability to capture 67 % of independent variable variation and their impact on dependent variables. Notably, the model exhibited satisfactory accuracy across both test-train split configurations. Analysis of data revealed that while the outer diameter of shafts displayed minimal deviation, the inner diameter showed the highest deviation, possibly due to slower cooling rates inside the shafts, leading to increased material flowability. Additionally, significant dimensional variations were observed in holes and rectangular slots.

Westphal et al. [168] explored the utilization of advanced ML algorithms for categorizing environmental sensor data in FDM processes. They identified the XceptionTime architecture as the most effective model, achieving a minimum accuracy of 95 %. The study involved analyzing various sensor parameters like temperature, humidity, air pressure, and gas particle resistance during 3D printing. Fig. 7 (a) illustrates the procedural flow from sensor data input to classification results. Supervised learning utilized two datasets: balanced and unbalanced. The research covered data preprocessing, hyperparameter tuning, and model evaluation. Fig. 7 (b) showcased results for one component under different 3D printing conditions, comparing quality with optical 3D scans for three components in each class. The XceptionTime model emerged as the top performer, offering potential for real-time evaluation in FDM manufacturing for quality assurance and process monitoring, with future prospects for automation and self-optimization. Kadam et al. [169] introduced a computer vision system, driven by ML, to monitor and improve 3D printing process quality. Utilizing layer-wise image capture, the system detects defects and predicts potential failures early in the process. The methodology focused on monitoring each layer of printed components, primarily using PLA as the printing material. Feature extraction and anomaly detection were performed using MATLAB, incorporating advanced algorithms like KNN, SVM, Naive Bayes, DT, and RF for classification. Ensemble learning techniques were applied to improve model efficiency

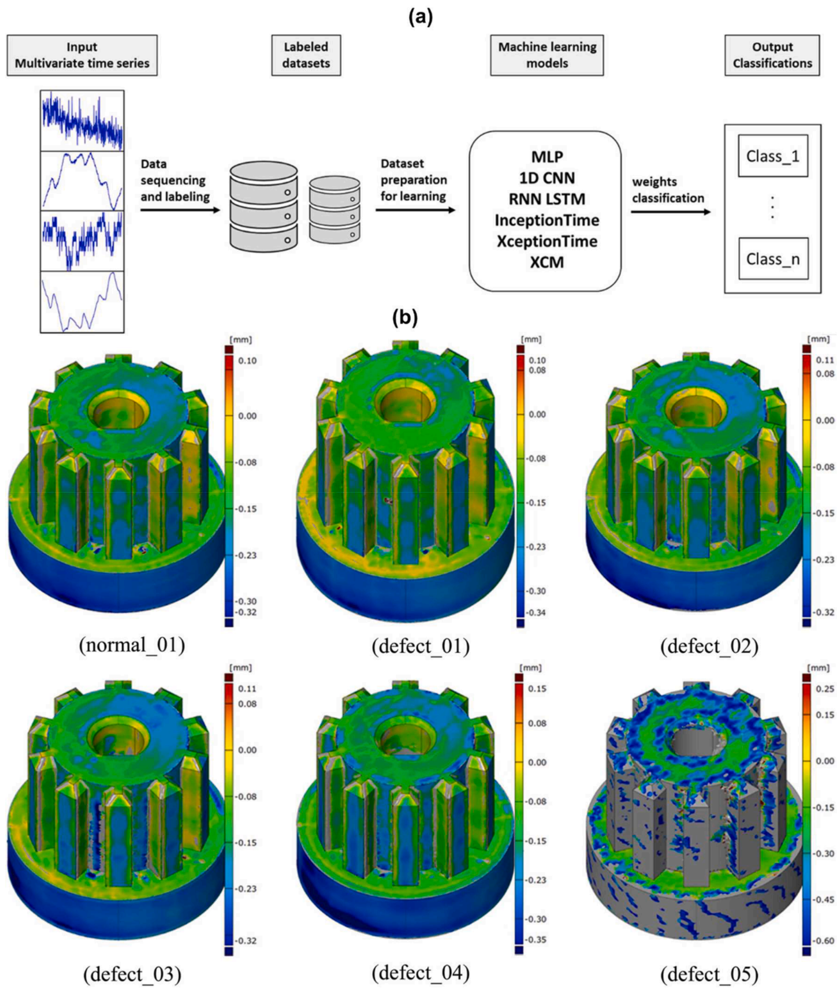

Fig. 7. (a) Basic process flow of ML analyses with FDM environmental sensor data, (b) Quality comparison of 3D printed parts using an optical 3D light scanner. Color-coded dimensional deviations, associated with numerical values, highlight differences between specified CAD reference data and generated part geometries. Notably, 'defect_05' exhibits significant deviations and incomplete 3D scan coverage, distinguishing it from other printing conditions. Color Code: Yellow and green signify minimal deviations, blue indicates larger negative differences, and red represents maximum positive area differences. Adapted with permission from [168], Copyright 2021 Elsevier.

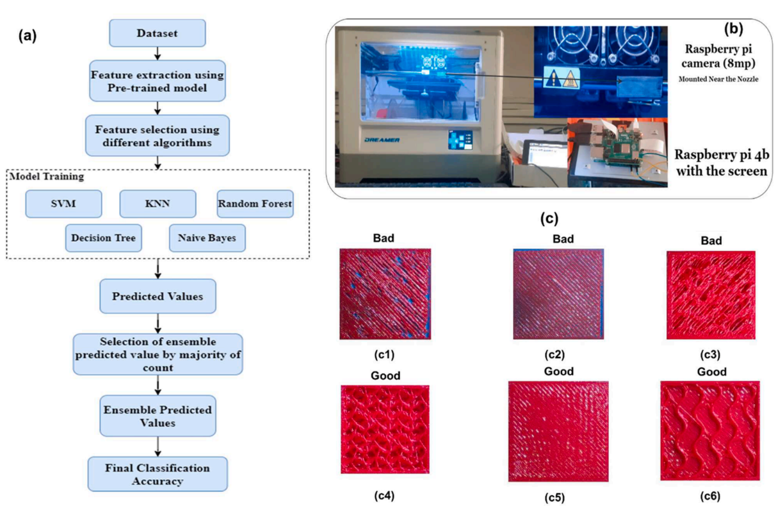

Fig. 8. (a) Ensemble learning approach; (b) Experimental setup; and (c) Real-time detection results: (c1-c3) Output for input images identified as bad layers; (c4-c6) Output for input images identified as good layers. Adapted from [169], MDPI open access Creative Common CC BY licence.

and accuracy, as depicted in the flowchart in Fig. 8 (a). The evaluation process involved manual image capture and labeling to create datasets comprising defective and non-defective layers in the printing process. The experimental setup utilized an 8MP Raspberry Pi camera, layer-wise image capture, and a dataset consisting of 1700 images with varying process parameters (Fig. 8 (b)). The results indicated that the combination of AlexNet and the SVM algorithm achieved the highest accuracy with minimal computational time. The pre-trained model algorithm accurately distinguished between defective and non-defective layers, classifying them as "bad" and "good," respectively. Fig. 8 (c) illustrates the model's response to the input layer image, where images (c1–c3) represent a positive response for the non-defective layer, while images (c4–c6) depict a response indicative of a defective layer, labeled as "bad".

Scheffel et al. [170] emphasized the importance of environmental sensor parameters, such as temperature, humidity, air pressure, and gas particle resistance, in the monitoring and classification process. They employed an ensemble of ML algorithms, including KNN, SVM, Naive Bayes, DT, and RF, to analyze sensor data and classify printing conditions. Notably, the study compared various ML architectures, highlighting InceptionTime, XceptionTime, and XCM as state-of-the-art DL models well-suited for this task due to their resilience against overfitting. The study revealed that air pressure played a significant role in ML analyses, followed by humidity, temperature, and gas particles. Despite the challenges of overfitting, particularly in the absence of air pressure data, the ML algorithms performed well. In this context, the XceptionTime model emerged as a dependable choice for real-time evaluation of FDM manufacturing data. Delli et al. [171] developed Python code to detect both completion failure defects and geometrical or structural defects in 3D printed material. The experimental setup involved a 3D printer, a camera, and a code to automate real-time monitoring of the printing process. Image processing was performed by dividing each image into 16 identical sections in a 4×4 matrix, and the average RGB values of all pixels were calculated for each section. If the experimental error value of at least four sections is > 10 %, an alert is generated to detect potential errors or defects. Empirical testing using a 3D model of DNA revealed that this method successfully detected both completion failure defects and structural or geometrical defects during the printing process, with an accuracy rate of 93 %. Straub [172] introduced a system that employs visible light imaging to identify incorrect material usage in 3D printers, with a specific focus on its applicability in large-scale manufacturing facilities. The study presented experimental findings involving various filament types and examined the incorporation of material discrimination identification into quality assurance procedures. It underscored the significance of digital inspection and highlighted security implications, particularly in the context of large-scale manufacturing where cyber-attacks or physical filament substitution are potential concerns.

Nascimento et al. [173] introduced a novel methodology for quality assessment of material extrusion parts using AI-based Computer Vision, primarily focusing on parts produced through FDM. The proposed automatic inspection system comprises four main stages: pre-processing, color analysis (utilizing the Otsu method for color thresholding), shape analysis (employing Hu moments for defect identification), and defect location (via morphological operations and blob detection). The system was designed for post-print analysis, making it cost-effective for mass-production setups with multiple 3D printers. Testing on 52 surfaces yielded promising results with an accuracy of 82.1 % and the potential for material recycling for rejected parts, enhancing both quality assurance and sustainability in 3D printing processes. Lyu and Manoochehri [174] presented an online laser-based process monitoring and closed-loop control system aimed at ensuring the geometric accuracy and in-plane surface quality of 3D printed parts in real-time. The system utilized point clouds for monitoring and adjusted extruder temperature and feed rate based on CNN classification results of the upper surface. The concept of online quality control was introduced as vital for maintaining the quality of 3D printed parts. The system employed a 3D laser scanner to monitor geometric accuracy and in-plane surface quality, pre-processing techniques to clean and prepare raw data, and a PID-based closed-loop control method to rectify deviations during the FFF process. In-plane surface anomalies were effectively identified and addressed through transfer learning and the VGG16 CNN architecture. The system's effectiveness was demonstrated through experiments on a Creality Ender 5 FFF machine, showcasing its potential applicability in other AM systems and quality assurance scenarios, including bioprinting. The proposed system's accuracy and ability to reduce process variability highlighted its significance in advancing AM quality control. Chen et al. [175] introduced a novel in-situ point cloud processing method designed for Directed Energy Deposition (DED) in 3D printing. The method was developed to enable automatic surface monitoring without sensor intermittence, achieving a high surface defect identification accuracy of 93.15 %. Based on the Laser-Aided Additive Manufacturing (LAAM) system, which utilized a high-power laser to melt metallic powders as they were deposited, the LAAM system comprised various components, including a robot, laser head, laser source, powder feeder, and laser profiler. The sensor was mounted on the robot's axis and communicated with the controller to calculate the distance between the sensor and the target surface. The captured 2D profile data was transformed into 3D point clouds. Controlled by a central computer running Linux OS, the system used robot operating system (ROS) for communication between different nodes, including the robot driver, sensor capturing, point cloud transformation, point cloud processing, and visualization nodes. The point cloud processing node employed a subprocess strategy to enable parallel programs for in-situ point cloud processing without sensor interruptions, applying various filtering and segmentation techniques to isolate the targeted surface and performed surface defect identification using machine learning. The study focused on identifying surface defects in additively manufactured parts using unsupervised and supervised machine learning techniques. Four classes of surface defects were considered: no defect, bulge defect, dent defect, and wavy defect. The DBSCAN clustering algorithm was used to find clusters of points representing defective or defect-free regions. Eight different classification algorithms were trained and compared for their accuracy in surface defect identification. The chosen classifier was used for defect identification in real-time, ensuring continuous surface monitoring without sensor interruptions. Sarabi et al. [176] explored the use of microneedles (MNs) as a novel injection alternative to conventional needles. They created a comprehensive data library consisting of ten different MN designs, each subjected to various etching exposure doses. ML models were trained using this dataset to extract similarity metrics, enabling the prediction of new fabrication outcomes for MNAs (Microneedle Arrays). The MNAs were fabricated using FDM with PLA and subsequently etched with potassium hydroxide (KOH) solution to improve their geometrical features. Image-based classification and defect detection were performed using DL models, which demonstrated high accuracy. ML was employed to extract similarity indices between the designed MNAs and the fabricated ones. Furthermore, a graphical user interface (GUI) was developed to predict MNAs' quality based on geometric and etching features, streamlining the quality control process. The study also assessed the MNAs' skin penetration capability and their potential for drug delivery using porcine skin as an ex vivo model. Charalampous et al. [177] presented a vision-based real-time monitoring system for 3D printing, aiming to detect dimensional errors during printing. By comparing high-resolution point cloud data of the printed part with the digital 3D model, computer vision algorithms are employed to ensure the quality of the printed part. The system utilizes a high-resolution structural light 3D scanner, a commercial FDM 3D printer, and a Raspberry Pi for real-time monitoring. It involves the development of software tools for point cloud processing, background noise filtering, and build plate segmentation. The system's effectiveness was validated using a functional engineering part, demonstrating its capability to detect and quantify dimensional deviations in the printed object, with MAE of 0.223 and RMSE of 0.331. This approach offers a promising solution for automated and in-situ quality assurance in 3D printing processes.

Kumar et al. [178] introduced a layer-wise approach for fault detection in 3D printing. To address the diversity in characteristics and structures of printed objects, SVM classifiers capable of handling both linear and non-linear functions were employed. The methodology involved capturing layer-wise photographs of the printing component and processing them using MATLAB for feature extraction and anomaly detection. The printing ink was made from PLA. Ensemble learning was utilized to enhance model consistency and predictive abilities. Images of both faulty and non-defective layers were collected for dataset creation, and variables like temperature, printing speed, and density were adjusted during printing. The study achieved an overall accuracy of over 96 % using various pre-trained models and techniques, with a hybrid of Alexnet and SVM chosen for real-time monitoring. Rachmawati et al. [179] developed a digital twin (DT) for Industry 4.0, enabling real-time workspace monitoring with FDM 3D printer sensor data. They created a lightweight CNN for fault classification in FDM 3D printers, satisfying edge device criteria. Their system involved data collection, preprocessing, and DL model development. The DL model had three Conv1D layers, MaxPooling, merging, and two dense layers, accepting three inputs with six features and producing one output. The DT replicated physical objects, improving AM operations by monitoring and providing feedback on faults, reducing filament waste. The system architecture included 3D printers, edge nodes, DT servers, and DT platforms. They collected and labeled sensor data from 3D printers and assessed performance using TensorFlow and Unity Engine, evaluating classification accuracy, classification loss, F1-Score, model complexity, training time, memory usage, latency, and system overhead. Simulation results showed CNN and Bi-LSTM (Bidirectional Long Short Term Memory) achieved high accuracy, followed by CNN, CLSTM (CNN-LSTM), Concatenate CNN-LSTM, and LSTM. CNN had the lowest loss. CNN also had the lowest model complexity, FLOPs, algorithm file size, latency, and system overhead, making it suitable for real-time workplace monitoring and control. Kumar et al. [180] introduced four ML algorithms to identify anomalies in a 3D printer and assessed their performance. They applied One-Class SVM for novelty detection, adjusting parameters nu and gamma through trial and error for optimal results. The Local Outlier Factor (LOF) algorithm determined outliers by assessing local density deviation, achieving an accuracy of 54.79 % on pre-processed accelerometer data. Similarly, the SVM algorithm underwent training, testing, and validation, yielding accuracies of 89.27 %, 97.60 %, and 97.21 % respectively. For time-series anomaly detection, the Long Short-Term Memory (LSTM) algorithm was utilized. The supervised LSTM model demonstrated an overall accuracy of 97.17 %, surpassing other supervised and unsupervised methods, suggesting its potential for ensuring error-free 3D printing.

The combination of AI-driven methodologies and 3D printing processes shows great potential for improving quality control and identifying defects in printed products. From computer vision systems to machine learning algorithms, these approaches showcase impressive accuracy rates and effectiveness in various aspects of quality assessment. Various studies demonstrate effective detection of defects, accurate prediction of dimensional variations, and continuous monitoring of environmental sensor data in FDM processes. Furthermore, the importance of continuous quality assurance in 3D printing is underscored by the development of real-time monitoring systems. These advancements can greatly improve efficiency, sustainability, and scalability in 3D printing industries, while also streamlining manufacturing processes. Due to the continuous progress in AI technologies and their smooth integration with 3D printing workflows, more enhancements and automation in quality control processes can be expected. This will improve the acceptance and practicality of 3D printing methods across various industries. Table 3 offers a comprehensive summary of the methodology, algorithms, evaluation metrics, and deployment strategies used in different studies that concentrate on quality control and defect detection in 3D printing with AI technologies.

10. Environmental impact assessment

The manufacturing sector plays an important role in global economic development, but it is also confronted with negative environmental impacts. In order to address these challenges, manufacturers are adopting energy-efficient technologies to reduce their carbon footprint and improve energy efficiency. ML can contribute to improving energy efficiency and provide decision support for sustainable manufacturing. Characterization of manufacturing stages is useful for understanding energy consumption, which can help practitioners improve energy and time inefficiencies. Industry 4.0 technologies such as low-cost IoT sensors, AI, data analytics, information and communication technology and cloud services have enabled affordable and effective energy monitoring systems. Data analytics is enabled using ML models that use data and algorithms to reveal untapped insights and provide decision support for better production, environmental performance, significant savings, and operational opportunities. Kumar et al. [181] proposed an algorithm that identifies value-added energy (printing stage), non-value-added energy (standby stage), and non-value-added but necessary energy (pre-heating stage) in the FDM process and provides users with data to take corrective measures. The experimental setup includes a 3D printer integrated with Octoprint, an open-source 3D printer controller application, and a Beckhoff system module. To obtain the required training data, nine sets of experiments were performed for each filament material. The developed ML model contains a layer of 100 nodes, a dense output layer of three nodes, an optimizer, and a loss function that is trained using experimental data. The LSTM model was fitted with the training dataset and trained for 30 epochs, resulting in a validation accuracy of 98.2 %. The model correctly classified 2561 points out of 2639 points for PLA, 5959 points out of 6301 points for ABS, and 99.76 % for PETG. Estimation of energy consumption using Simpson's rule yielded valuable insights into patterns of energy usage during the printing process. For example, the energy consumption prediction error for PLA material ranged from 5.51 % to 11.31 %, whereas for ABS material, it varied from 8.11 % to 18.88 %. The PETG material had a notably higher prediction error in the preheating stage (9.37 %), which may be due to data point misclassification in the preheating and printing stages. This improvement in energy monitoring and characterization has significant potential for sustainable manufacturing practices, which contributes to reducing the environmental impact and increasing the efficiency of manufacturing. El idrissi et al. [182] aimed to predict energy consumption and FDM printing time using a neural network. The study utilized the r3DiM dataset collected using standard hardware components and sensors. Various machine learning algorithms, including MLP, EXtreme Gradient Boosting (XGBoost), RF, and SVM, were employed and statistically compared to determine the best-performing model. The MLP-based model demonstrated superior performance, outperforming other models. A total of 156 neural networks were developed using the Keras library with twelve inputs and two outputs. Different activation functions were explored to optimize model performance, with the sigmoid function yielding the best results. Successful training was achieved with minimal MSE at epoch 1523. The results indicated the effectiveness of the proposed model in predicting energy consumption and printing time, optimizing costs.

Rojel et al. [183] focused on designing a lightweight and ergonomic 3D printed elbow exoskeleton using PLA filament. They employed ANN to explore and predict relationships between datasets, particularly non-linear relationships that were difficult to capture using traditional analysis methods. A network with 438 neurons was used to optimize printing parameters. The study utilized external and internal concepts to achieve maximum flexion of the elbow. The external concept focused on the elbow movement, while the internal concept considered the movement of the wrist as well. The models were simplified and met specific

Table 3
Overview of the methodology, algorithms, evaluation metrics, and deployment strategies pertaining to quality control and defect detection in 3D printing utilizing AI.

Study	Methodology	Model/algorithm	Evaluation metrics	Deployment	Results
[166]	Used Single Shot Detector with VGG16 CNN. Evaluated using Intersection over Union (IoU).	Single Shot Detector with VGG16 CNN	Precision, Recall, F1-Score, IoU	Deployed on a live 3D printing environment with Raspberry Pi 4 microprocessor	• Precision (0.44), Recall (0.69) at IoU 0.4, Precision (0.41), Recall (0.63) at IoU 0.5 • Precision (0.4), Recall (0.62) at IoU 0.6, F1-Score (0.55) at IoU 0.4
[167]	Used DT to study effect of printing parameters on dimensional accuracy	DT	R2 Scores	The model was implemented on a webpage hosted on a local computer using Flask	• Model evaluation at different training set proportions (50 % and 80 %) yielded R2 scores of 0.64 and 0.67, respectively • Model's capable to comprehend 67 % of the variation in independent variables
[168]	Employed XceptionTime in ML based approach for effective quality assurance using environmental sensor data	MLP, 1D CNN, RNN LSTM, Inception time, Xception time and XCM	Accuracy, Macro Average Precision, Macro Average Recall and Macro F1-Score	In the deployment phase, environmental sensor data, including air pressure, temperature, gas particles and humidity was collected during printing. A novel data preparation method was introduced, and various ML algorithms, with a focus on XceptionTime, were employed for analysis and modeling.	• XceptionTime architecture outperformed other ML algorithms • Achieved over 95 % accuracy for both small and large databases • Maintained Macro F1-Scores above 89 %, indicating robust classification across 3D printing conditions
[169]	Proposed a computer vision system for monitoring and enhancing 3D printed part quality. Used layer-wise image capture, ML algorithms, and ensemble learning. Evaluated with accuracy.	SVM, KNN, RF, DT and Naive Bayes	Accuracy	Real-time monitoring deployed AlexNet and SVM for efficient defect detection during printing. Capturing layer-wise images, the model responds with "good" or "bad," allowing continuous improvement for enhanced performance.	• AlexNet + SVM: 99.70 % accuracy, AlexNet + K-NN: 99.40 % • In ensemble learning, AlexNet outperformed EfficientNet by achieving an accuracy of 100 %, whereas EfficientNet-B0 achieved a slightly lower accuracy of 99.10 %. • ResNet50 excelled in parameter-wise density classification, achieving a flawless accuracy of 100 %
[170]	IoT technologies are employed to acquire, verify, and securely store real-time data. CNN classifier was developed for online monitoring and fault detection.	CNN	Accuracy, recall, and precision	Trained CNN analyzed frame data to detect defects in printed pieces by identifying patterns associated with previous defects	• CNN-based fault detection system achieves high accuracy and minimizes false positives/negatives • Interrupts the printing process upon defect detection, reducing total printing time for defective pieces by around 50 %
[171]	Combines a camera, image processing, and SVM for real-time quality assessment of 3D printed parts. Images at critical stages are classified as 'good' or 'defective,' preventing material and time wastage	SVM	Experimental error	A 3D DNA model, printed with ABS material, underwent quality checks at five checkpoints. Using scikit-learn, an SVM model predicted the part quality ('good' or 'defective') based on images captured during printing, enhancing fault detection in real-time.	• Detected both completion failure and structural/geometrical defects with high accuracy.
[173]	Introduced a methodology for quality assessment of material extrusion parts using AI-based Computer Vision. Used four main stages: pre-processing, color analysis, shape analysis, and defect location.	AI-based Computer Vision	Sensitivity, precision, accuracy, and percentage of wrong classifications	Surface defects identified by filtering the gray image with a median filter, subtracting from the original, inverting, and binarizing. A mask applied for precise defect localization	• Method achieved 78.6 % sensitivity and 84.6 % accuracy in classifying defect-free surfaces • Across 28 surfaces, attained 82.1 % accuracy • Demonstrated orientation independence and suitability for various geometries but had a 17.9 % PWC, mainly due to reflections • Suggested improvements include adjusting lighting conditions and dissimilarity values for different geometries • Overall system evaluation resulted in an 86.5 % accuracy and 13.4 % PWC, with misclassifications in shape analysis attributed to lighting-induced reflections on surfaces
[174]	Presented an online laser-based process monitoring and closed-loop control system for 3D printed parts. Utilized point clouds for monitoring and adjusted parameters based on CNN classification results.	CNN	Accuracy	3D laser scanner captured point cloud data for part height and surface depth. CNN, based on VGG16, classified in-plane anomalies. Two PID-based closed-loop control systems reduced height deviation errors and corrected surface anomalies	• Model achieves 90.08 % overall anomaly classification accuracy • Two PID-based closed-loop control systems implemented: (a) Maintain 0.1 % height deviation (b) Automatically correct anomalies by adjusting process parameters

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Table 3 (*continued*)

Study	Methodology	Model/algorithm	Evaluation metrics	Deployment	Results
[177]	Presented a vision-based real-time monitoring system for 3D printing. Utilized computer vision algorithms for dimensional error detection. Validated effectiveness with a functional engineering part.	Computer vision algorithms	Mean Absolute Error and Root Mean Square Error	The proposed vision-based method was validated on a complex 3D model, specifically a centrifugal impeller with varying sections	• Monitoring revealed decreased dimensional accuracy with increased geometric complexity • MAE and RMSE metrics, measuring deviations, are 40 % higher compared to a simpler case (spur gear)
[178]	Introduced a layer-wise approach for fault detection in 3D printing. Used SVM classifiers for diverse structures of printed objects. Employed ensemble learning for model consistency.	SVM classifiers with ensemble learning	Accuracy	Utilized Raspberry Pi camera for image capture and Raspberry Pi 4B for processing (2.5 cm, 30 cm, 5 mm). Over 1850 picture datasets created, noise removed. Parameter variations produced 32 unique 3D profiles.	• AlexNet and EfficientNetB0 model with SVM achieve highest accuracy at 99.34 %, followed by ResNet50 and SVM with 99.84 % • SVM consistently outperforms other methods across different pre-trained models, maintaining accuracy above 96 % for all models • Among individual models, AlexNet achieves perfect accuracy, and EfficientNet B0 follows closely at 99.62 % • Ensemble learning with GoogleNet shows the lowest accuracy at 97.62 %
[179]	Developed a digital twin for real-time workspace monitoring with FDM 3D printer sensor data. Created a Lightweight CNN for fault classification.	Lightweight CNN	Classification accuracy and loss, F1-score, model complexity, memory usage, and latency and system overhead (SO)	Post-printing, data labeled by final product outcome (fault or normal). Dataset: 15,432 points from 11 objects (5 fault, 6 normal). Split: 80 % training, 20 % testing. Feature engineering handles irrelevant data normalized using StandardScaler(). Labels categorically encoded (0 for normal, 1 for error).	• CNN outperforms with an F1-Score of 0.9981 and reduces trainable parameters by 18.40 % • The proposed CNN demonstrates a 45 % memory reduction for 3D printer fault detection based on FLOPs • Latency and system overhead (SO) in the DT environment show a total latency of 995.4253 ms and SO of 808.3983 ms
[180]	Proposed four ML algorithms for anomaly detection in a 3D printer	One-class SVM, LOF, SVM and LSTM	Accuracy, recall, and precision	Experimental setup includes an MPU-6050 vibration sensor attached to the top beam of a 3D printer for fault detection. The sensor interfaces with a Raspberry Pi 4 via I2C, transmitting real-time raw vibration data for monitoring at a 5 Hz sampling rate.	• Supervised LSTM achieved 97.17 % accuracy, surpassing SVM, One-Class SVM, and LOF • Unsupervised methods exhibited quicker anomaly detection during 3D printing

criteria for simulating upper limb movements and manufacturing exoskeletons. The prototype of the exoskeleton differed from the concept version, with the large "wings" replaced by holders for mounting straps. The optimized ANN achieved better results and reduced waste in the printing process. The ANN, named MLP-142-102-8 using sigmoid neurons, achieved the best results after 1000 epochs. The model before optimization weighed 0.07474 kg, and after optimization, it weighed 0.07268 kg. The waste weight decreased by 30.9531 times, allowing for one free print after every 6.67 prints.

The world is confronted with significant challenges such as climate change, biodiversity loss and resource scarcity, which can be addressed through sustainable practices. Live life cycle assessment (LCA) is a standardized methodology for identifying, assessing, and evaluating the potential environmental impacts of a product or process during its life cycle phases. The manufacturing sector accounts for a significant share of greenhouse gas emissions and there is an urgent need to develop more sustainable practices, methods and tools for the production of products with minimal impact on these issues. Kumar et al. [184] proposed a framework for the live life cycle assessment of 3D printed products using cyber-physical production systems. Live LCA was implemented using the CPPS approach to intertwine the physical and cyber worlds to provide real-time monitoring of environmental impacts. This system has been used to obtain legacy data for the Taguchi method analysis, which provides an optimal process setting to minimize environmental impacts. The GWP per unit print volume was obtained for nine trials using the Taguchi L-9 orthogonal array based on different combinations of printing parameters. The optimum setting of the printing parameters corresponds to Infill-10 %, layer height-0.2 mm, and scale 100 %, which significantly reduces the environmental impact. Rojek et al. [119] constructed two ANNs to assess electricity consumption and air pollution. The results of the ANN1 model were linked to 3D printing technology, allowing the evaluation and prediction of energy consumption for different types of 3D printers and related processes within Industry 4.0. The ANN2 model was used to predict air pollution for different types of 3D printers and associated processes within Industry 4.0. The results confirm that CI-based solutions are useful for 3D printing sustainability, safety improvement, and environmental impact reduction.

The combination of ML and Industry 4.0 technologies into manufacturing processes signifies a significant change towards sustainable practices and improved energy efficiency. Manufacturers now use ML algorithms to improve energy efficiency, improve production efficiency, and reduce environmental impact. Through energy consumption analytics and real-time monitoring systems, practitioners can identify inefficiencies and take corrective actions to reduce waste and increase productivity. Research by Kumar et al. [178], El idrissi et al. [179], and Rojel et al. [116] demonstrate the effectiveness of ML models in accurately predicting energy consumption, optimizing printing designs, and reducing waste in a 3D printing process. Furthermore, the use of life cycle analysis (LCA) methods can lead to enhanced environmental monitoring and bolster sustainability throughout the product life cycle. By integrating the physical and digital realms in cybernetic physical manufacturing processes, manufacturers can achieve continuous environmental monitoring and optimization. This enables the adoption of sustainable manufacturing practices and reduces environmental impact. The combination of ML and Industry 4.0 technologies has tremendous potential to advance sustainability efforts, reduce greenhouse gas emissions, and can force an efficient and environment friendly production worldwide.

11. Challenges and future prospects

The rapidly evolving field of AI-integrated 3D printing is experiencing enormous shifts, and there are new challenges and possibilities that will shape its future direction. One of the main challenges is to ensure that AI algorithms are sufficiently resilient and flexible to work with a variety of 3D printing materials and techniques. In order to solve this problem, real-time learning and adaptive algorithms must be developed. Ethical factors, such as data protection and responsible use of AI, are further obstacles that require the adoption of standards and ethical frameworks across industries. Global cooperation and sharing of information will help to overcome limited datasets and complicated material interactions. However, the cost-effective and widespread availability of AI-integrated 3D printing technology needs thoughtful planning.

On the other hand, the future presents exciting opportunities. Advanced generative design algorithms driven by AI offer the potential to create intricate and optimised structures, revolutionizing product design for enhanced efficiency and functionality. The ability of AI to analyze extensive datasets swiftly opens doors for the customization and personalization of 3D-printed products, leading to a new era of tailored solutions that meet individual consumer needs. Leveraging AI for environmental sustainability in 3D printing provides opportunities to optimize processes, reduce waste, and select eco-friendly materials, significantly contributing to minimizing the ecological footprint of 3D printing. The integration of artificial intelligence-driven 3D printing with Industry 4.0 principles offers opportunities for smart manufacturing, with real-time monitoring and data-driven decision-making enhancing overall efficiency and productivity. In order for the field to deal with these future challenges and take advantage of these opportunities, cooperation, innovation and a proactive approach to ethical considerations will be crucial. Embracing these challenges as an opportunity for growth will lead to the continued evolution of this exciting integration of artificial intelligence and 3D printing, paving the way for significant advances in the field of 3D printing. Fig. 9 depicts some of the challenges and hotspots for future research.

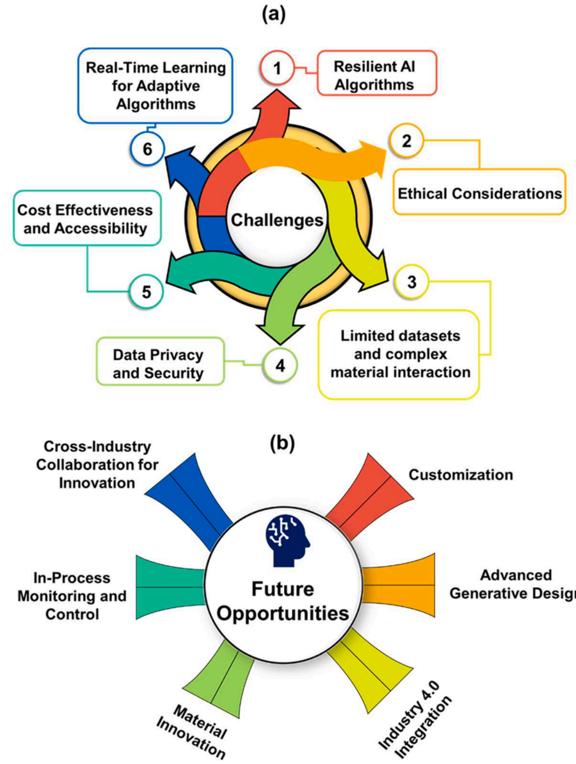

Fig. 9. Current challenges and future prospects of AI-integrated 3D printing.

12. Conclusion

This review provides insights into AI's role in advancing 3D printing technology. This highlights the critical importance of optimizing process parameters such as layer thickness, infill density, and printing speed. Focusing on these optimizations can lead to an improvement in quality while delivering cost-effective results. This will not only help to reduce waste and production costs, but also improve efficiency in time. This optimization approach can greatly benefit industries with paced production requirements. In addition, ML techniques such as ANN, PSO, and autonomous calibration systems have shown substantial success in optimizing the 3D printing parameters. These methods contribute to a significant reduction in production costs, printing time and quality. The combination of transfer learning and ensemble learning was found to be effective in defect detection, highlighting the collaborative potential of AI and 3D printing. The use of AI in design and geometry optimization represents a significant step forward, particularly in generative design and topology optimization. AI has led to an unprecedented level of creativity and efficiency, significantly reducing design iteration times and manufacturing costs. DL-based topology optimization methods demonstrate adaptability to complex optimization tasks. Automated simulations and testing facilitated by AI minimize the reliance on physical prototypes, streamlining the design workflow across various sectors These studies also emphasize the efficacy of AI, especially ANNs and ANFIS, in predicting mechanical properties and enhancing the performance of 3D-printed structures.

Quality control and defect detection have undergone substantial advancements through the incorporation of AI-driven methodologies. ML algorithms, particularly those based on CNNs, contribute to the accuracy of defect detection in 3D-printed objects, minimizing material waste and time in precision-critical industries such as aerospace and healthcare. The review also highlights the importance of AI in sustainability efforts within the manufacturing sector. Energy-efficient technologies and ML play pivotal roles in enhancing energy efficiency and support eco-friendly manufacturing practices. Neural network models, such as LSTM and MLP, aid in predicting energy consumption, optimizing printing parameters, and fostering sustainable practices.

Overall, the integration of optimization strategies, ML, and AI will have a transformative impact on 3D printing technology, contributing to enhanced efficiency, reduced costs, improved product quality, and sustainable production. These advancements will collectively propel the field forward by addressing critical challenges and expanding our understanding of the intricate interplay between printing parameters and material properties.

CRediT authorship contribution statement

Malik Hassan: Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Manjusri Misra:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Validation. **Graham W. Taylor:** Investigation, Methodology, Supervision, Validation, Writing – review & editing. **Amar K. Mohanty:** Investigation, Methodology, Resources, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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References

[1] Plastics Europe. Plastics the fact 2022. 2021.
[2] R. Geyer, J.R. Jambeck, KL. Law, Production, use, and fate of all plastics ever made, Sci. Adv. 3 (2017) 25–29, https://doi.org/10.1126/sciadv.1700782.
[3] G. Bishop, D. Styles, PNL. Lens, Recycling of European plastic is a pathway for plastic debris in the ocean, Environ. Int. 142 (2020) 105893, https://doi.org/10.1016/j.envint.2020.105893.
[4] International Union for Conservation of Nature 2021:376–376. https://doi.org/10.18356/9789210056755c213.
[5] M. Eriksen, W. Cowger, L.M. Erdle, S. Coffin, P. Villarrubia-Gómez, C.J. Moore, et al., A growing plastic smog, now estimated to be over 170 trillion plastic particles afloat in the world's oceans—urgent solutions required, PLoS. One 18 (2023) 1–12, https://doi.org/10.1371/journal.pone.0281596.
[6] Biodegradable plastics market forecast report 2023-2028: changing consumer preference toward eco friendly plastic products and increasing use of packaging and compostable bags n.d. https://finance.yahoo.com/news/biodegradable-plastics-market-forecast-report-010000739.html (accessed November 23, 2023).
[7] A.K. Mohanty, S. Vivekanandhan, J.M. Pin, M. Misra, Composites from renewable and sustainable resources: challenges and innovations, Science (80-) 362 (2018) 536–542, https://doi.org/10.1126/science.aat9072.
[8] A.K. Mohanty, F. Wu, R. Mincheva, M. Hakkarainen, J.M. Raquez, D. F. Mielewski, et al., Sustainable polymers, Nat. Rev. Methods Prim. 2 (2022), https://doi.org/10.1038/s43586-022-00124-8.
[9] B.A. Makinde-Isola, A.S. Taiwo, I.O. Oladele, A.D. Akinwekomi, S.O. Adelani, LN. Onuh, Development of sustainable and biodegradable materials: a review on banana and sisal fibre based polymer composites, J. Thermoplast. Compos. Mater. 0 (2023) 1–21, https://doi.org/10.1177/08927057231186324.
[10] I.R. Campbell, M.Y. Lin, H. Iyer, M. Parker, J.L. Fredricks, K. Liao, et al., Progress in sustainable polymers from biological matter, Annu Rev. Mater. Res. 53 (2023) 81–104, https://doi.org/10.1146/annurev-matsci-080921-083655.
[11] T.D. Moshood, G. Nawanir, F. Mahmud, F. Mohamad, M.H. Ahmad, A. AbdulGhani, Sustainability of biodegradable plastics: new problem or solution to solve the global plastic pollution? Curr. Res. Green Sustain. Chem. 5 (2022) https://doi.org/10.1016/j.crgsc.2022.100273.
[12] J.F. Arinez, Q. Chang, R.X. Gao, C. Xu, J. Zhang, Artificial intelligence in advanced manufacturing: current status and future outlook, J. Manuf. Sci. Eng. Trans. ASME 142 (2020) 1–16, https://doi.org/10.1115/1.4047855.
[13] Y.K. Dwivedi, L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, et al., Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, Int. J. Inf. Manage 57 (2021) 101994, https://doi.org/10.1016/j.ijinfomgt.2019.08.002.
[14] S.W. Kim, J.H. Kong, S.W. Lee, S. Lee, Recent advances of artificial intelligence in manufacturing industrial sectors: a review, Int. J. Precis. Eng. Manuf. 23 (2022) 111–129, https://doi.org/10.1007/s12541-021-00600-3.
[15] Z. Jan, F. Ahamed, W. Mayer, N. Patel, G. Grossmann, M. Stumptner, et al., Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities, Expert. Syst. Appl. 216 (2023) 119456, https://doi.org/10.1016/j.eswa.2022.119456.
[16] P. Kumar, S. Chauhan, LK. Awasthi, Artificial intelligence in healthcare: review, ethics, trust challenges & future research directions, Eng. Appl. Artif. Intell. 120 (2023) 105894, https://doi.org/10.1016/j.engappai.2023.105894.
[17] C.M.S. Vicente, M. Sardinha, L. Reis, A. Ribeiro, M. Leite, Large-format additive manufacturing of polymer extrusion-based deposition systems: review and applications, Prog. Addit. Manuf. (2023), https://doi.org/10.1007/s40964-023-00397-9.
[18] G. Prashar, H. Vasudev, D. Bhuddhi, Additive manufacturing: expanding 3D printing horizon in industry 4.0, Int. J. Interact. Des. Manuf. 17 (2023) 2221–2235, https://doi.org/10.1007/s12008-022-00956-4.
[19] S. Singh, R.P. Mohanty, S.K. Mangla, V. Agrawal, Critical success factors of additive manufacturing for higher sustainable competitive advantage in supply chains, J. Clean. Prod. 425 (2023) 138908, https://doi.org/10.1016/j.jclepro.2023.138908.
[20] I. Fidan, O. Huseynov, M.A. Ali, S. Alkunte, M. Rajeshirke, A. Gupta, et al., Recent inventions in additive manufacturing: holistic review, Inventions 8 (2023), https://doi.org/10.3390/inventions8040103.
[21] M. Gebler, A.J.M. Schoot Uiterkamp, C. Visser, A global sustainability perspective on 3D printing technologies, Energy Policy 74 (2014) 158–167, https://doi.org/10.1016/j.enpol.2014.08.033.
[22] Reasons Why 3D Printing is Reaching Mainstream | Smithers n.d. https://www.smithers.com/resources/2017/jul/reasons-why-3d-printing-is-reaching-the-mainstream (accessed November 23, 2023).
[23] Artificial intelligence (AI) market size, growth, report by 2032 n.d. https://www.precedenceresearch.com/artificial-intelligence-market (accessed November 23, 2023).
[24] Q. Liu, R. Ge, C. Li, Q. Li, Y. Gan, Digital design and additive manufacturing of structural materials in electrochemical and thermal energy storage systems: a review, Virtual. Phys. Prototyp. 18 (2023), https://doi.org/10.1080/17452759.2023.2273949.
[25] L.J. Tan, W. Zhu, K. Zhou, Recent progress on polymer materials for additive manufacturing, Adv. Funct. Mater. 30 (2020) 1–54, https://doi.org/10.1002/adfm.202003062.
[26] P. Parandoush, D. Lin, A review on additive manufacturing of polymer-fiber composites, Compos. Struct. 182 (2017) 36–53, https://doi.org/10.1016/j.compstruct.2017.08.088.
[27] V. Mishra, S. Negi, S. Kar, FDM-based additive manufacturing of recycled thermoplastics and associated composites, J. Mater. Cycles. Waste Manage. 25 (2023) 758–784, https://doi.org/10.1007/s10163-022-01588-2.
[28] S.Y. Chin, V. Dikshit, B.M. Priyadarshini, Y. Zhang, Powder-based 3D printing for the fabrication of device with micro and mesoscale features, Micromachines (Basel) 11 (2020) 29–40, https://doi.org/10.3390/MI11070658.
[29] F. Lupone, E. Padovano, O. Ostrovskaya, A. Russo, C. Badini, Innovative approach to the development of conductive hybrid composites for selective laser sintering, Compos. Part a Appl. Sci. Manuf. 147 (2021) 106429, https://doi.org/10.1016/j.compositesa.2021.106429.
[30] X. Sun, M. Mazur, CT. Cheng, A review of void reduction strategies in material extrusion-based additive manufacturing, Addit. Manuf. 67 (2023) 103463, https://doi.org/10.1016/j.addma.2023.103463.
[31] P. Ferretti, C. Leon-Cardenas, G.M. Santi, M. Sali, E. Ciotti, L. Frizziero, et al., Relationship between fdm 3d printing parameters study: Parameter optimization for lower defects, Polymers. (Basel) 13 (2021), https://doi.org/10.3390/polym13132190.
[32] S. Wickramasinghe, T. Do, P. Tran, FDM-Based 3D printing of polymer and associated composite: a review on mechanical properties, defects and treatments, Polymers. (Basel) 12 (2020) 1–42, https://doi.org/10.3390/polym12071529.
[33] C.Y. Liaw, J.W. Tolbert, L.W. Chow, M. Guvendiren, Interlayer bonding strength of 3D printed PEEK specimens, Soft. Matter. 17 (2021) 4775–4789, https://doi.org/10.1039/d1sm00417d.
[34] V. Shanmugam, M.V. Pavan, K. Babu, B. Karnan, Fused deposition modeling based polymeric materials and their performance: a review, Polym. Compos. 42 (2021) 5656–5677, https://doi.org/10.1002/pc.26275.
[35] M. Naftaly, G. Savvides, F. Alshareef, P. Flanigan, G. Lui, M. Florescu, et al., Non-destructive porosity measurements of 3D printed polymer by terahertz time-domain spectroscopy, Appl. Sci. 12 (2022), https://doi.org/10.3390/app12020927.
[36] D. Xie, F. Lv, Y. Yang, L. Shen, Z. Tian, C. Shuai, et al., A review on distortion and residual stress in additive manufacturing, Chinese J. Mech. Eng. Addit. Manuf. Front. 1 (2022) 100039, https://doi.org/10.1016/j.cjmeam.2022.100039.
[37] N.A. Tarazona, R. Machatschek, J. Balcucho, J.L. Castro-Mayorga, J. F. Saldarriaga, A. Lendlein, Opportunities and challenges for integrating the development of sustainable polymer materials within an international circular (bio)economy concept, MRS Energy Sustain. 9 (2022) 28–34, https://doi.org/10.1557/s43581-021-00015-7.
[38] X. Zhang, M. Fevre, G.O. Jones, RM. Waymouth, Catalysis as an enabling science for sustainable polymers, Chem. Rev. 118 (2018) 839–885, https://doi.org/10.1021/acs.chemrev.7b00329.
[39] Y. Zhu, C. Romain, CK. Williams, Sustainable polymers from renewable resources, Nature 540 (2016) 354–362, https://doi.org/10.1038/nature21001.
[40] H. Mutlu, L. Barner, Getting the terms right: green, sustainable, or circular chemistry? Macromol. Chem. Phys. 223 (2022) 1–7, https://doi.org/10.1002/macp.202200111.
[41] S. Maiti, M.R. Islam, M.A. Uddin, S. Afroj, S.J. Eichhorn, N. Karim, Sustainable fiber-reinforced composites: a review, Adv. Sustain. Syst. 6 (2022), https://doi.org/10.1002/adsu.202200258.
[42] F. Vilaplana, E. Strömberg, S. Karlsson, Environmental and resource aspects of sustainable biocomposites, Polym. Degrad. Stab. 95 (2010) 2147–2161, https://doi.org/10.1016/j.polymdegradstab.2010.07.016.
[43] J. Bachmann, C. Hidalgo, S. Bricout, Environmental analysis of innovative sustainable composites with potential use in aviation sector—a life cycle assessment review, Sci. China Technol. Sci. 60 (2017) 1301–1317, https://doi.org/10.1007/s11431-016-9094-y.
[44] M.M.A. Nassar, K.I. Alzebdeh, T. Pervez, N. Al-Hinai, A. Munam, Progress and challenges in sustainability, compatibility, and production of eco-composites: a state-of-art review, J. Appl. Polym. Sci. 138 (2021), https://doi.org/10.1002/app.51284.
[45] V. Lunetto, M. Galati, L. Settineri, L. Iuliano, Sustainability in the manufacturing of composite materials: a literature review and directions for future research, J. Manuf. Process. 85 (2023) 858–874, https://doi.org/10.1016/j.jmapro.2022.12.020.

[46] MA. Hubbe, Sustainable composites: a review with critical questions to guide future initiatives, Sustain 15 (2023), https://doi.org/10.3390/su151411088.
[47] B.P. Chang, A.K. Mohanty, M. Misra, Studies on durability of sustainable biobased composites: a review, RSC. Adv. 10 (2020) 17955–17999, https://doi.org/10.1039/c9ra09554c.
[48] Z. Wang, M.S. Ganewatta, C. Tang, Sustainable polymers from biomass: bridging chemistry with materials and processing, Prog. Polym. Sci. 101 (2020) 101197, https://doi.org/10.1016/j.progpolymsci.2019.101197.
[49] T.M. Joseph, A.B. Unni, K.S. Joshy, D. Kar Mahapatra, J. Haponiuk, S. Thomas, Emerging bio-based polymers from lab to market: current strategies, market dynamics and research trends, C-J. Carbon Res. 9 (2023), https://doi.org/10.3390/c9010030.
[50] A. Das, T. Ringu, S. Ghosh, N. Pramanik, A Comprehensive Review On Recent Advances in preparation, Physicochemical characterization, and Bioengineering Applications of Biopolymers, 80, Springer, Berlin Heidelberg, 2023, https://doi.org/10.1007/s00289-022-04443-4.
[51] R. Balart, D. Garcia-Garcia, V. Fombuena, L. Quiles-Carrillo, MP. Arrieta, Biopolymers from natural resources, Polymers. (Basel) 13 (2021) 1–9, https://doi.org/10.3390/polym13152532.
[52] A.C. Wibowo, M. Misra, H.M. Park, L.T. Drzal, R. Schalek, AK. Mohanty, Biodegradable nanocomposites from cellulose acetate: mechanical, morphological, and thermal properties, Compos. Part a Appl. Sci. Manuf. 37 (2006) 1428–1433, https://doi.org/10.1016/j.compositesa.2005.06.019.
[53] Z. Wang, L. Yuan, C. Tang, Sustainable elastomers from renewable biomass, Acc. Chem. Res. 50 (2017) 1762–1773, https://doi.org/10.1021/acs.accounts.7b00209.
[54] A. Gandini, T.M. Lacerda, A.J.F. Carvalho, E. Trovatti, Progress of polymers from renewable resources: furans, vegetable oils, and polysaccharides, Chem. Rev. 116 (2016) 1637–1669, https://doi.org/10.1021/acs.chemrev.5b00264.
[55] I. Delidovich, P.J.C. Hausoul, L. Deng, R. Pfützenreuter, M. Rose, R. Palkovits, Alternative monomers based on lignocellulose and their use for polymer production, Chem. Rev. 116 (2016) 1540–1599, https://doi.org/10.1021/acs.chemrev.5b00354.
[56] H. Nakajima, P. Dijkstra, K. Loos, The recent developments in biobased polymers toward general and engineering applications: polymers that are upgraded from biodegradable polymers, analogous to petroleum-derived polymers, and newly developed, Polymers. (Basel) 9 (2017) 1–26, https://doi.org/10.3390/polym9100523.
[57] A.Z. Naser, I. Deiab, BM. Darras, Poly(lactic acid) (PLA) and polyhydroxyalkanoates (PHAs), green alternatives to petroleum-based plastics: a review, RSC. Adv. 11 (2021) 17151–17196, https://doi.org/10.1039/d1ra02390j.
[58] G. Atiwesh, A. Mikhael, C.C. Parrish, J. Banoub, TAT. Le, Environmental impact of bioplastic use: a review, Heliyon. 7 (2021) e07918, https://doi.org/10.1016/j.heliyon.2021.e07918.
[59] S. Torres-Giner, K.J. Figueroa-Lopez, B. Melendez-Rodriguez, C. Prieto, M. Pardo-Figuerez, JM. Lagaron, Emerging trends in biopolymers for food packaging, Sustain. Food Packag Technol. (2021) 1–33, https://doi.org/10.1002/9783527820078.ch1.
[60] R. Muthuraj, M. Misra, AK. Mohanty, Injection molded sustainable biocomposites from poly(butylene succinate) bioplastic and perennial grass, ACS. Sustain. Chem. Eng. 3 (2015) 2767–2776, https://doi.org/10.1021/acssuschemeng.5b00646.
[61] J.H. Song, R.J. Murphy, R. Narayan, GBH. Davies, Biodegradable and compostable alternatives to conventional plastics, Philos. Trans. R Soc. B Biol. Sci. 364 (2009) 2127–2139, https://doi.org/10.1098/rstb.2008.0289.
[62] S.S. Ali, E.A. Abdelkarim, T. Elsamahy, R. Al-Tohamy, F. Li, M. Kornaros, et al., Bioplastic production in terms of life cycle assessment: a state-of-the-art review, Environ. Sci. Ecotechnology 15 (2023) 100254, https://doi.org/10.1016/j.ese.2023.100254.
[63] V. Siracusa, I. Blanco, Bio-polyethylene (Bio-PE), Bio-polypropylene (Bio-PP) and Bio-poly(ethylene terephthalate) (Bio-PET): Recent developments in bio-based polymers analogous to petroleum-derived ones for packaging and engineering applications, Polymers. (Basel) 12 (2020), https://doi.org/10.3390/APP10155029.
[64] J. Hopewell, R. Dvorak, E. Kosior, Plastics recycling: Challenges and opportunities, Philos. Trans. R Soc. B Biol. Sci. 364 (2009) 2115–2126, https://doi.org/10.1098/rstb.2008.0311.
[65] I. Elfaleh, F. Abbassi, M. Habibi, F. Ahmad, M. Guedri, M. Nasri, et al., A comprehensive review of natural fibers and their composites: An eco-friendly alternative to conventional materials, Results. Eng. 19 (2023) 101271, https://doi.org/10.1016/j.rineng.2023.101271.
[66] A.K. Mohanty, S. Vivekanandhan, O. Das, L.M. Romero Millán, N.B. Klinghoffer, A. Nzihou, et al., Biocarbon materials, Nat. Rev. Methods Prim. 4 (2024), https://doi.org/10.1038/s43586-024-00297-4.
[67] A. Ahmed, M.Z. Islam, M.S. Mahmud, M.E. Sarker, MR. Islam, Hemp as a potential raw material toward a sustainable world: a review, Heliyon. 8 (2022) e08753, https://doi.org/10.1016/j.heliyon.2022.e08753.
[68] O. Faruk, A.K. Bledzki, H.P. Fink, M. Sain, Biocomposites reinforced with natural fibers: 2000-2010, Prog. Polym. Sci. 37 (2012) 1552–1596, https://doi.org/10.1016/j.progpolymsci.2012.04.003.
[69] M. Akter, M.H. Uddin, IS. Tania, Biocomposites based on natural fibers and polymers: a review on properties and potential applications, J. Reinf. Plast. Compos. 41 (2022) 705–742, https://doi.org/10.1177/07316844211070609.
[70] V. Nagarajan, A.K. Mohanty, M. Misra, Biocomposites with Size-Fractionated Biocarbon: Influence of the Microstructure on Macroscopic Properties, ACS. Omega 1 (2016) 636–647, https://doi.org/10.1021/acsomega.6b00175.
[71] P.F. Sommerhuber, J.L. Wenker, S. Rüter, A. Krause, Life cycle assessment of wood-plastic composites: analysing alternative materials and identifying an environmental sound end-of-life option, Resour. Conserv. Recycl. 117 (2017) 235–248, https://doi.org/10.1016/j.resconrec.2016.10.012.
[72] M. Ramesh, L. Rajeshkumar, G. Sasikala, D. Balaji, A. Saravanakumar, V. Bhuvaneswari, et al., A critical review on wood-based polymer composites: processing, properties, and prospects, Polymers. (Basel) 14 (2022) 589.
[73] M. Bardot, MD. Schulz, Biodegradable poly(Lactic acid) nanocomposites for fused deposition modeling 3d printing, Nanomaterials 10 (2020) 1–20, https://doi.org/10.3390/nano10122567.
[74] M.N. Andanje, J.W. Mwangi, B.R. Mose, S. Carrara, Biocompatible and biodegradable 3D printing from bioplastics: a review, Polymers. (Basel) 15 (2023), https://doi.org/10.3390/polym15102355.
[75] M. Hassan, A.K. Mohanty, M. Misra, 3D printing in upcycling plastic and biomass waste to sustainable polymer blends and composites: a review, Mater. Des. 237 (2023) 112558, https://doi.org/10.1016/j.matdes.2023.112558.
[76] B. Maldonado-García, A.K. Pal, M. Misra, S. Gregori, AK. Mohanty, Sustainable 3D printed composites from recycled ocean plastics and pyrolyzed soy-hulls: optimization of printing parameters, performance studies and prototypes development, Compos. Part C Open Access 6 (2021) 100197, https://doi.org/10.1016/j.jcomc.2021.100197.
[77] T.D. Ngo, A. Kashani, G. Imbalzano, K.T.Q. Nguyen, D. Hui, Additive manufacturing (3D printing): a review of materials, methods, applications and challenges, Compos. Part B Eng. 143 (2018) 172–196, https://doi.org/10.1016/j.compositesb.2018.02.012.
[78] Y. Mintz, R. Brodie, Introduction to artificial intelligence in medicine, Minim. Invasive Ther. Allied. Technol. 28 (2019) 73–81, https://doi.org/10.1080/13645706.2019.1575882.
[79] MS. Alkatheiri, Artificial intelligence assisted improved human-computer interactions for computer systems, Comput. Electr. Eng. 101 (2022) 107950, https://doi.org/10.1016/j.compeleceng.2022.107950.
[80] A. Goel, A.K. Goel, A. Kumar, The role of artificial neural network and machine learning in utilizing spatial information, Spat. Inf. Res. 31 (2023) 275–285, https://doi.org/10.1007/s41324-022-00494-x.
[81] J. Mata, I. de Miguel, R.J. Durán, N. Merayo, S.K. Singh, A. Jukan, et al., Artificial intelligence (AI) methods in optical networks: a comprehensive survey, Opt. Switch Netw. 28 (2018) 43–57, https://doi.org/10.1016/j.osn.2017.12.006.
[82] F. Kibrete, T. Trzepieciński, H.S. Gebremedhen, DE. Woldemichael, Artificial intelligence in predicting mechanical properties of composite materials, J. Compos. Sci. 7 (2023), https://doi.org/10.3390/jcs7090364.
[83] M. Cui, DY. Zhang, Artificial intelligence and computational pathology, Lab Investig. 101 (2021) 412–422, https://doi.org/10.1038/s41374-020-00514-0.
[84] L. Ma, S. Yu, X. Xu, S. Moses Amadi, J. Zhang, Z. Wang, Application of artificial intelligence in 3D printing physical organ models, Mater. Today Bio 23 (2023) 100792, https://doi.org/10.1016/j.mtbio.2023.100792.
[85] L. Ma, S. Yu, X. Xu, S. Moses Amadi, J. Zhang, Z. Wang, Application of artificial intelligence in 3D printing physical organ models, Mater. Today Bio 23 (2023) 100792, https://doi.org/10.1016/j.mtbio.2023.100792.
[86] M.T. Ho, P. Mantello, MT. Ho, An analytical framework for studying attitude towards emotional AI: the three-pronged approach, MethodsX. 10 (2023) 102149, https://doi.org/10.1016/j.mex.2023.102149.
[87] D. Mhlanga, The role of artificial intelligence and machine learning amid the COVID 19 pandemic: what lessons are we learning on 4IR and the sustainable development goals, Int. J. Environ. Res. Public Health 19 (2022), https://doi.org/10.3390/ijerph19031879.
[88] O. Mypati, A. Mukherjee, D. Mishra, S.K. Pal, P.P. Chakrabarti, A. Pal, A Critical Review On Applications of Artificial Intelligence in Manufacturing, 56, Springer, Netherlands, 2023, https://doi.org/10.1007/s10462-023-10535-y.
[89] F.H. Khan, M.A. Pasha, S. Masud, Advancements in microprocessor architecture for ubiquitous ai—an overview on history, evolution, and upcoming challenges in ai implementation, Micromachines. (Basel) 12 (2021) 1–22, https://doi.org/10.3390/mi12060665.
[90] I.H. Sarker, A.I. Khan, Y.B. Abushark, F. Alsolami, Internet of Things (IoT) security intelligence: a comprehensive overview, machine learning solutions and research directions, Mob. Networks Appl. 28 (2023) 296–312, https://doi.org/10.1007/s11036-022-01937-3.
[91] L. Zhou, S. Pan, J. Wang, A.V. Vasilakos, Machine learning on big data: opportunities and challenges, Neurocomputing. 237 (2017) 350–361, https://doi.org/10.1016/j.neucom.2017.01.026.
[92] Y. Li, R. Gupta, S. You, Machine learning assisted prediction of biochar yield and composition via pyrolysis of biomass, Bioresour. Technol. 359 (2022) 127511, https://doi.org/10.1016/j.biortech.2022.127511.
[93] F. Emmert-Streib, M. Dehmer, Taxonomy of machine learning paradigms: a data-centric perspective, Wiley. Interdiscip. Rev. Data Min. Knowl. Discov. 12 (2022) 1–24, https://doi.org/10.1002/widm.1470.
[94] T. Talaei Khoei, N. Kaabouch, Machine learning: models, challenges, and research directions, Futur. Internet 15 (2023), https://doi.org/10.3390/fi15100332.
[95] M. Belding, A. Enshaeian, P. Rizzo, A machine learning-based approach to determining stress in rails, Struct. Heal. Monit. 22 (2023) 639–656, https://doi.org/10.1177/14759217221085658.
[96] M. Mohtasham Moein, A. Saradar, K. Rahmati, S.H. Ghasemzadeh Mousavinejad, J. Bristow, V. Aramali, et al., Predictive models for concrete properties using machine learning and deep learning approaches: a review, J. Build. Eng. 63 (2023) 105444, https://doi.org/10.1016/j.jobe.2022.105444.

[97] N. Tamascelli, R. Solini, N. Paltrinieri, V. Cozzani, Learning from major accidents: a machine learning approach, Comput. Chem. Eng. 162 (2022) 107786, https://doi.org/10.1016/j.compchemeng.2022.107786.
[98] C. Zhang, J. Liu, W. Chen, J. Shi, M. Yao, X. Yan, et al., Unsupervised anomaly detection based on deep autoencoding and clustering, Secur. Commun. Netw. 2021 (2021), https://doi.org/10.1155/2021/7389943.
[99] M. Hazratifard, F. Gebali, M. Mamun, Using machine learning for dynamic authentication in telehealth: a tutorial, Sensors 22 (2022) 1–20, https://doi.org/10.3390/s22197655.
[100] IH. Sarker, Machine learning: algorithms, real-world applications and research directions, SN. Comput. Sci. 2 (2021) 1–21, https://doi.org/10.1007/s42979-021-00592-x.
[101] P. Sequeira, M. Gervasio, Interestingness elements for explainable reinforcement learning: understanding agents' capabilities and limitations, Artif. Intell. 288 (2020), https://doi.org/10.1016/j.artint.2020.103367.
[102] A.S. Polydoros, L. Nalpantidis, Survey of model-based reinforcement learning: applications on robotics, J. Intell. Robot Syst. Theory Appl. 86 (2017) 153–173, https://doi.org/10.1007/s10846-017-0468-y.
[103] H. Modares, I. Ranatunga, F.L. Lewis, DO. Popa, Optimized assistive human-robot interaction using reinforcement learning, IEEe Trans. Cybern. 46 (2016) 655–667, https://doi.org/10.1109/TCYB.2015.2412554.
[104] A.K. Pal, A.K. Mohanty, M. Misra, Additive manufacturing technology of polymeric materials for customized products: recent developments and future prospective, RSC. Adv. 11 (2021) 36398–36438, https://doi.org/10.1039/d1ra04060j.
[105] A. Mecheter, F. Tarlochan, Fused filament fabrication three-dimensional printing: assessing the influence of geometric complexity and process parameters on energy and the environment, Sustain 15 (2023), https://doi.org/10.3390/su151612319.
[106] C. Camposeco-Negrete, Optimization of printing parameters in fused deposition modeling for improving part quality and process sustainability, Int. J. Adv. Manuf. Technol. 108 (2020) 2131–2147, https://doi.org/10.1007/s00170-020-05555-9.
[107] M. Petousis, N. Vidakis, N. Mountakis, E. Karapidakis, A. Moutsopoulou, Functionality versus sustainability for PLA in MEX 3D printing: the impact of generic process control factors on flexural response and energy efficiency, Polymers. (Basel) 15 (2023), https://doi.org/10.3390/polym15051232.
[108] A.P. Golhin, R. Tonello, J.R. Frisvad, S. Grammatikos, A. Strandlie, Surface Roughness of As-Printed polymers: a Comprehensive Review, 127, Springer, London, 2023, https://doi.org/10.1007/s00170-023-11566-z.
[109] S. Singh, G. Singh, C. Prakash, S. Ramakrishna, Current status and future directions of fused filament fabrication, J. Manuf. Process. 55 (2020) 288–306, https://doi.org/10.1016/j.jmapro.2020.04.049.
[110] C.L. Druzgalski, A. Ashby, G. Guss, W.E. King, T.T. Roehling, MJ. Matthews, Process optimization of complex geometries using feed forward control for laser powder bed fusion additive manufacturing, Addit. Manuf. 34 (2020) 101169, https://doi.org/10.1016/j.addma.2020.101169.
[111] S. Kholgh Eshkalak, E. Rezvani Ghomi, Y. Dai, D. Choudhury, S. Ramakrishna, The role of three-dimensional printing in healthcare and medicine, Mater. Des. 194 (2020) 108940, https://doi.org/10.1016/j.matdes.2020.108940.
[112] S. Chinchanikar, AA. Shaikh, A review on machine learning, big data analytics, and design for additive manufacturing for aerospace applications, J. Mater. Eng. Perform. 31 (2022) 6112–6130, https://doi.org/10.1007/s11665-022-07125-4.
[113] S. Shanmugam, A. Naik, T. Sujan, S. Desai, Developing robust 3D printed parts for automotive application using design for additive manufacturing and optimization techniques, INCOSE Int. Symp. 29 (2019) 394–407, https://doi.org/10.1002/j.2334-5837.2019.00694.x.
[114] I. Rojek, D. Mikołajewski, E. Dostatni, M. Macko, Ai-optimized technological aspects of the material used in 3d printing processes for selected medical applications, Materials (Basel) 13 (2020) 1–19, https://doi.org/10.3390/ma13235437.
[115] M. Hassan, A.K. Pal, A. Rodriguez-uribe, A. Bardelcik, S. Gregori, A.K. Mohanty, et al., Creating sustainable composites from pyrolyzed burlap and ocean- recycled plastics using FDM, ACS. Sustain. Chem. Eng. (2024), https://doi.org/10.1021/acssuschemeng.3c05031.
[116] S. Oberloier, N.G. Whisman, JM. Pearce, Finding ideal parameters for recycled material fused particle fabrication-based 3D printing using an open source software implementation of particle swarm optimization, 3D. Print. Addit. Manuf. 00 (2022) 1–14, https://doi.org/10.1089/3dp.2022.0012.
[117] G.S. Ganitano, S.G. Wallace, B. Maruyama, GL. Peterson, A hybrid metaheuristic and computer vision approach to closed-loop calibration of fused deposition modeling 3D printers, Prog. Addit. Manuf. (2023), https://doi.org/10.1007/s40964-023-00480-1.
[118] S. Abdollahi, A. Davis, J.H. Miller, AW. Feinberg, Expert-guided optimization for 3D printing of soft and liquid materials, PLoS. One 13 (2018) 1–19, https://doi.org/10.1371/journal.pone.0194890.
[119] I. Rojek, D. Mikołajewski, M. Macko, Z. Szczepanski, E. Dostatni, Optimization of extrusion-based 3d printing process using neural networks for sustainable development, Materials. (Basel) 14 (2021), https://doi.org/10.3390/ma14112737.
[120] P. Kumar, P. Gupta, I. Singh, Parametric optimization of FDM using the ANN-based whale optimization algorithm, Artif. Intell. Eng. Des. Anal. Manuf. AIEDAM 36 (2022), https://doi.org/10.1017/S0890060422000142.
[121] A. Phogat, D. Chhabra, V. Sindhu, A. Ahlawat, Analysis of wear assessment of FDM printed specimens with PLA, multi-material and ABS via hybrid algorithms, Mater. Today Proc. 62 (2022) 37–43, https://doi.org/10.1016/j.matpr.2022.01.429.
[122] C.J. Yang, W.K. Huang, KP. Lin, Three-dimensional printing quality inspection based on transfer learning with convolutional neural networks, Sensors 23 (2023) 17–19, https://doi.org/10.3390/s23010491.
[123] T. Albahkali, H.S. Abdo, O. Salah, A. Fouly, Adaptive neuro-fuzzy-based models for predicting the tribological properties of 3D-printed PLA green composites used for biomedical applications, Polymers. (Basel) 15 (2023), https://doi.org/10.3390/polym15143053.
[124] A. Fouly, T. Albahkali, HS. Abdo, Investigating the mechanical properties of annealed 3D-printed PLA – date pits composite, Polymers. (Basel) (2023).
[125] M.A. Mahmood, A.I. Visan, C. Ristoscu, IN. Mihailescu, Artificial neural network algorithms for 3D printing, Materials. (Basel) 14 (2021) 1–29, https://doi.org/10.3390/ma14010163.
[126] S. Nasiri, MR. Khosravani, Machine learning in predicting mechanical behavior of additively manufactured parts, J. Mater. Res. Technol. 14 (2021) 1137–1153, https://doi.org/10.1016/j.jmrt.2021.07.004.
[127] K. Stergiou, C. Ntakolia, P. Varytis, E. Koumoulos, P. Karlsson, S. Moustakidis, Enhancing property prediction and process optimization in building materials through machine learning: a review, Comput. Mater. Sci. 220 (2023) 112031, https://doi.org/10.1016/j.commatsci.2023.112031.
[128] D. Verma, Y. Dong, M. Sharma, AK. Chaudhary, Advanced processing of 3D printed biocomposite materials using artificial intelligence, Mater. Manuf. Process. 37 (2022) 518–538, https://doi.org/10.1080/10426914.2021.1945090.
[129] W. Alhaddad, M. He, Y. Halabi, K. Yahya Mohammed Almajhali, Optimizing the material and printing parameters of the additively manufactured fiber-reinforced polymer composites using an artificial neural network model and artificial bee colony algorithm, Structures 46 (2022) 1781–1795, https://doi.org/10.1016/j.istruc.2022.10.134.
[130] M.S. Meiabadi, M. Moradi, M. Karamimoghadam, S. Ardabili, M. Bodaghi, M. Shokri, et al., Modeling the producibility of 3d printing in polylactic acid using artificial neural networks and fused filament fabrication, Polymers. (Basel) 13 (2021) 1–21, https://doi.org/10.3390/polym13193219.
[131] L. Waltersmann, S. Kiemel, J. Stuhlsatz, A. Sauer, R. Miehe, Artificial intelligence applications for increasing resource efficiency in manufacturing companies—a comprehensive review, Sustain 13 (2021), https://doi.org/10.3390/su13126689.
[132] M. Ipek, I.H. Selvi, F. Findik, O. Torkul, IH. Cedimoğlu, An expert system based material selection approach to manufacturing, Mater. Des. 47 (2013) 331–340, https://doi.org/10.1016/j.matdes.2012.11.060.
[133] A.A.A. Rahim, S.N. Musa, S. Ramesh, MK. Lim, A systematic review on material selection methods, Proc. Inst. Mech. Eng. Part L J. Mater. Des. Appl. 234 (2020) 1032–1059, https://doi.org/10.1177/1464420720916765.
[134] H.J. Bullinger, J. Warschat, D. Fischer, Knowledge-based system for material selection for design with new materials, Knowl.-Based Syst. 4 (1991) 95–102, https://doi.org/10.1016/0950-7051(91)90013-R.
[135] T. Xue, T.J. Wallin, Y. Menguc, S. Adriaenssens, M. Chiaramonte, Machine learning generative models for automatic design of multi-material 3D printed composite solids, Extrem. Mech. Lett. 41 (2020) 100992, https://doi.org/10.1016/j.eml.2020.100992.
[136] R. Teharia, R.M. Singari, H. Kumar, Optimization of process variables for additive manufactured PLA based tensile specimen using taguchi design and artificial neural network (ANN) technique, Mater. Today Proc. 56 (2022) 3426–3432, https://doi.org/10.1016/j.matpr.2021.10.376.
[137] Ali D., Huayier A.F., Enzi A. Parametric prediction of FDM process to improve tensile properties using taguchi method and artificial neural network 2023;17: 130–8.
[138] J. Deb, N. Ahsan, S. Majumder, Modeling the interplay between process parameters and part attributes in additive manufacturing process with artificial neural network, ASME Int. Mech. Eng. Congr. Expo. 86632 (2022). V02AT02A015.
[139] S.D. Grozav, A.D. Sterca, M. Kočiško, M. Pollák, V. Ceclan, Artificial neural network-based predictive model for finite element analysis of additive-manufactured components, Machines 11 (2023) 1–13, https://doi.org/10.3390/machines11050547.
[140] V.S. Jatti, M.S. Sapre, A.V. Jatti, N.K. Khedkar, VS. Jatti, Mechanical properties of 3D-printed components using fused deposition modeling: optimization using the desirability approach and machine learning regressor, Appl. Syst. Innov. 5 (2022), https://doi.org/10.3390/asi5060112.
[141] M.S. Meiabadi, M. Moradi, M. Karamimoghadam, S. Ardabili, M. Bodaghi, M. Shokri, AH. Mosavi, Modeling the producibility of 3D printing in polylactic acid using artificial neural networks and fused filament fabrication, Polymers. (Basel) 13 (2021) 3219, https://doi.org/10.20944/preprints202012.0487.v1.
[142] J. Singh, K.K. Goyal, R. Kumar, V. Gupta, Development of artificial intelligence-based neural network prediction model for responses of additive manufactured polylactic acid parts, Polym. Compos. 43 (2022) 5623–5639, https://doi.org/10.1002/pc.26876.
[143] I. Rojek, D. Mikołajewski, P. Kotlarz, K. Tyburek, J. Kopowski, E. Dostatni, Traditional artificial neural networks versus deep learning in optimization of material aspects of 3d printing, Materials. (Basel) 14 (2021) 1–18, https://doi.org/10.3390/ma14247625.
[144] M. Jayasudha, M. Elangovan, M. Mahdal, J. Priyadarshini, Accurate estimation of tensile strength of 3D printed parts using machine learning algorithms, Processes 10 (2022) 1–16, https://doi.org/10.3390/pr10061158.
[145] A.D. Tura, H.G. Lemu, H.B. Mamo, AJ. Santhosh, Prediction of tensile strength in fused deposition modeling process using artificial neural network and fuzzy logic, Prog. Addit. Manuf. 8 (2023) 529–539, https://doi.org/10.1007/s40964-022-00346-y.

[146] P. Charalampous, N. Kladovasilakis, I. Kostavelis, K. Tsongas, D. Tzetzis, D. Tzovaras, Machine learning-based mechanical behavior optimization of 3D print constructs manufactured via the FFF process, J. Mater. Eng. Perform. 31 (2022) 4697–4706, https://doi.org/10.1007/s11665-021-06535-0.
[147] R. Cai, W. Wen, K. Wang, Y. Peng, S. Ahzi, F. Chinesta, Tailoring interfacial properties of 3D-printed continuous natural fiber reinforced polypropylene composites through parameter optimization using machine learning methods, Mater. Today Commun. 32 (2022) 103985, https://doi.org/10.1016/j.mtcomm.2022.103985.
[148] J. Mountstephens, J. Teo, Progress and challenges in generative product design: a review of systems, Computers 9 (2020) 1–23, https://doi.org/10.3390/computers9040080.
[149] L. Barbieri, M. Muzzupappa, Performance-driven engineering design approaches based on generative design and topology optimization tools: a comparative study, Appl. Sci. 12 (2022), https://doi.org/10.3390/app12042106.
[150] M. Brossard, G. Gatto, A. Gentile, T. Merle, C. Wlezien, How Generative Design Could Reshape the Future of Product Development, Mckinsey Co, 2020.
[151] Ai G.. Harnessing harnessing the value of the value of top use cases across industries 2023.
[152] Vora L.K., Gholap A.D., Jetha K., Thakur R.R.S., Solanki H.K., Chavda VP. Artificial intelligence in pharmaceutical technology and drug delivery design. vol. 15. 2023. https://doi.org/10.3390/pharmaceutics15071916.
[153] S. Oh, Y. Jung, S. Kim, I. Lee, N. Kang, Deep generative design: Integration of topology optimization and generative models, J. Mech. Des. Trans. ASME 141 (2019), https://doi.org/10.1115/1.4044229.
[154] Yao X., Moon S.K., Bi G. A hybrid machine learning approach for additive manufacturing design feature recommendation. vol. 23. 2017. https://doi.org/10.1108/RPJ-03-2016-0041.
[155] X. Yao, S.K. Moon, G. Bi, A cost-driven design methodology for additive manufactured variable platforms in product families, J. Mech. Des. Trans. ASME 138 (2016) 1–12, https://doi.org/10.1115/1.4032504.
[156] A. Kumar, D. Chhabra, Parametric topology optimization approach for sustainable development of customized orthotic appliances using additive manufacturing, Mech. Adv. Mater. Struct. 0 (2023) 1–14, https://doi.org/10.1080/15376494.2023.2214908.
[157] J. Rade, A. Jignasu, E. Herron, A. Corpuz, B. Ganapathysubramanian, S. Sarkar, et al., Engineering applications of artificial intelligence deep learning-based 3D multigrid topology optimization of manufacturable designs, Eng. Appl. Artif. Intell. 126 (2023) 107033, https://doi.org/10.1016/j.engappai.2023.107033.
[158] J. Rasulzade, Y. Maksum, M. Nogaibayeva, S. Rustamov, B. Akhmetov, Reduction of material usage in 3D printable structures using topology optimization accelerated with u-net convolutional neural network, Eurasian Chem. J. 24 (2022) 277–286, https://doi.org/10.18321/ectj1471.
[159] M. Saleh, S. Anwar, A.M. Al-Ahmari, AY. AlFaify, Prediction of mechanical properties for carbon fiber/PLA composite lattice structures using mathematical and ANFIS models, Polymers. (Basel) 15 (2023), https://doi.org/10.3390/polym15071720.
[160] M. Pollák, J. Török, Use of Generative design tools in the production of design products using 3D printing technology, TEM J. 11 (2022) 249–255, https://doi.org/10.18421/TEM111-31.
[161] Y. Fu, A.R.J. Downey, L. Yuan, T. Zhang, A. Pratt, Y. Balogun, Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review, J. Manuf. Process. 75 (2022) 693–710, https://doi.org/10.1016/j.jmapro.2021.12.061.
[162] R.G. Kim, M. Abisado, J. Villaverde, GA. Sampedro, A survey of image-based fault monitoring in additive manufacturing: recent developments and future directions, Sensors 23 (2023) 1–30, https://doi.org/10.3390/s23156821.
[163] G.L. Chen, K. Yanamandra, N. Gupta, Artificial neural networks framework for detection of defects in 3D-printed fiber reinforcement composites, Jom 73 (2021) 2075–2084, https://doi.org/10.1007/s11837-021-04708-9.
[164] A. Selot, RK. Dwivedi, Machine learning and sensor-based approach for defect detection in MEX additive manufacturing process- a review, J. Brazilian Soc. Mech. Sci. Eng. 45 (2023) 1–25, https://doi.org/10.1007/s40430-023-04425-1.
[165] G.D. Goh, S.L. Sing, WY. Yeong, A Review On Machine Learning in 3D printing: applications, potential, and Challenges, 54, Springer, Netherlands, 2021, https://doi.org/10.1007/s10462-020-09876-9.
[166] K. Paraskevoudis, P. Karayannis, EP. Koumoulos, Real-time 3d printing remote defect detection (Stringing) with computer vision and artificial intelligence, Processes 8 (2020) 1–15, https://doi.org/10.3390/pr8111464.
[167] P. Sharma, H. Vaid, R. Vajpeyi, P. Shubham, K.M. Agarwal, D. Bhatia, Predicting the dimensional variation of geometries produced through FDM 3D printing employing supervised machine learning, Sensors Int. 3 (2022) 100194, https://doi.org/10.1016/j.sintl.2022.100194.
[168] E. Westphal, H. Seitz, Machine learning for the intelligent analysis of 3D printing conditions using environmental sensor data to support quality assurance, Addit. Manuf. 50 (2022) 102535, https://doi.org/10.1016/j.addma.2021.102535.
[169] V. Kadam, S. Kumar, A. Bongale, S. Wazarkar, P. Kamat, S. Patil, Enhancing surface fault detection using machine learning for 3d printed products, Appl. Syst. Innov. 4 (2021), https://doi.org/10.3390/asi4020034.
[170] R.M. Scheffel, A.A. Fröhlich, M. Silvestri, Automated fault detection for additive manufacturing using vibration sensors, Int. J. Comput. Integr. Manuf. 34 (2021) 500–514, https://doi.org/10.1080/0951192X.2021.1901316.
[171] U. Delli, S. Chang, Automated process monitoring in 3D printing using supervised machine learning, Procedia Manuf. 26 (2018) 865–870, https://doi.org/10.1016/j.promfg.2018.07.111.
[172] J. Straub, Physical security and cyber security issues and human error prevention for 3D printed objects: detecting the use of an incorrect printing material, Dimens. Opt. Metrol. Insp. Pract. Appl. VI 10220 (2017) 102200K, https://doi.org/10.1117/12.2264578.
[173] R. Nascimento, I. Martins, T.A. Dutra, L. Moreira, Computer vision based quality control for additive manufacturing parts, Int. J. Adv. Manuf. Technol. 124 (2023) 3241–3256, https://doi.org/10.1007/s00170-022-10683-5.
[174] J. Lyu, S. Manoochehri, Online convolutional neural network-based anomaly detection and quality control for fused filament fabrication process, Virtual. Phys. Prototyp. 16 (2021) 160–177, https://doi.org/10.1080/17452759.2021.1905858.
[175] L. Chen, X. Yao, P. Xu, S.K. Moon, G. Bi, Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning, Virtual. Phys. Prototyp. 16 (2021) 50–67, https://doi.org/10.1080/17452759.2020.1832695.
[176] M.R. Sarabi, M.M. Alseed, A.A. Karagoz, S. Tasoglu, Machine learning-enabled prediction of 3D-printed microneedle features, Biosensors 12 (2022) 1–16, https://doi.org/10.3390/bios12070491.
[177] P. Charalampous, I. Kostavelis, C. Kopsacheilis, D. Tzovaras, Vision-based real-time monitoring of extrusion additive manufacturing processes for automatic manufacturing error detection, Int. J. Adv. Manuf. Technol. 115 (2021) 3859–3872, https://doi.org/10.1007/s00170-021-07419-2.
[178] K. Kiran Kumar, V. Srikanth, G.N.R. Prasad, B. Hazela, A. Kumar Tamrakar, Fault detection on the 3-D printed objective surface by using the SVM algorithm, Mater. Today Proc. (2023), https://doi.org/10.1016/j.matpr.2023.06.016.
[179] S.M. Rachmawati, M.A.P. Putra, J.M. Lee, DS. Kim, Digital twin-enabled 3D printer fault detection for smart additive manufacturing, Eng. Appl. Artif. Intell. 124 (2023) 106430, https://doi.org/10.1016/j.engappai.2023.106430.
[180] R. Kumar, K.S. Sangwan, C. Herrmann, R. Ghosh, M. Sangwan, Development and comparison of machine-learning algorithms for anomaly detection in 3D printing using vibration data, Prog. Addit. Manuf. (2023), https://doi.org/10.1007/s40964-023-00472-1.
[181] R. Kumar, R. Ghosh, R. Malik, K.S. Sangwan, C. Herrmann, Development of machine learning algorithm for characterization and estimation of energy consumption of various stages during 3D printing, Procedia CIRP. 107 (2022) 65–70, https://doi.org/10.1016/j.procir.2022.04.011.
[182] M.A. El youbi El idrissi, L. Laaouina, A. Jeghal, H. Tairi, M. Zaki, Modeling of energy consumption and print time for FDM 3D printing using multilayer perceptron network, J. Manuf. Mater. Process. 7 (2023), https://doi.org/10.3390/jmmp7040128.
[183] I. Rojek, D. Mikołajewski, J. Kopowski, P. Kotlarz, M. Piechowiak, E. Dostatni, Reducing waste in 3D printing using a neural network based on an own elbow exoskeleton, Materials (Basel) 14 (2021), https://doi.org/10.3390/ma14175074.
[184] R. Kumar, P.G. Padma Vilochani, S. Kahnthinisha, O. Patil, F. Cerdas, K. S. Sangwan, et al., Live life cycle assessment implementation using cyber physical production system framework for 3D printed products, Procedia CIRP. 105 (2022) 284–289, https://doi.org/10.1016/j.procir.2022.02.047.