An Examination of the Utilization of Machine Learning in Fused Deposition Modeling.

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***Abstract*— Fused deposition modeling (FDM) is a type of additive manufacturing (AM) that creates components by layering material in a sequential manner. Compared to traditional manufacturing techniques, FDM can produce complex geometries and intricate details more quickly, without the need for a fixed process plan or specialized tooling, and requires minimal human intervention. FDM parts exhibit excellent heat and chemical resistance, along with impressive strength-to-weight ratios. However, challenges remain with the consistency, reliability, and accuracy of FDM-produced parts. To ensure consistent quality and process reliability, real-time monitoring of the FDM process is essential. Recent research indicates that machine learning (ML) models offer a powerful computational approach to help AM processes achieve high-quality standards, maintain product consistency, and optimize process outcomes. Despite its potential, the integration of ML with FDM remains relatively unexplored. While existing research is limited, there is a lack of review-based studies on the application of ML in the FDM process, which could guide future research. This paper aims to fill that gap by providing a comprehensive overview of the use of ML in FDM. Keywords: Fused Deposition Modeling, Machine Learning**

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I. INTRODUCTION

In today's customer-focused product development environment, the demand for lightweight structures that exhibit high strength, stiffness, and energy absorption is paramount. Due to their ability to precisely control mechanical properties, a variety of structures have recently garnered significant attention across multiple fields (Joshi et al., 2010; Ingrole et al., 2017; Yu et al., 2018). Metamaterials, which are among the most popular lightweight structures, are artificially engineered with complex geometries that impart unique, counterintuitive properties. These properties are defined by three elastic constants: Young's modulus, shear modulus, bulk modulus, and a dimensionless parameter, Poisson's ratio (Yu et al., 2018). Metamaterials possess distinctive mechanical characteristics such as negative Poisson's ratio (NPR), high shear modulus, negative compressibility, and negative stiffness, which set them apart from conventional structures. Specifically, auxetic or NPR structures are notable for their exceptional mechanical properties, including high indentation resistance, impact resistance, bending stiffness, fracture toughness, vibration damping, hardness, and superior shock absorption, outperforming conventional structures with a positive Poisson's ratio (Elipe and Lantada, 2012; Zhang and Yang, 2016). Auxetic structures find extensive use in industries such as automotive (e.g., car bumpers and instrument panels), aerospace (e.g., fuselage and seat structures), protective equipment (e.g., helmets and pads), and biomedical devices (e.g., implants and stents) due to their high strength, stiffness, and specific energy absorption (SEA).

Fused deposition modeling (FDM), also known as fused filament fabrication (FFF), is a well-established additive manufacturing (AM) technique renowned for its ability to produce complex products with reduced cycle times. FDM does not require specialized tooling or a fixed process plan and involves minimal human intervention, making it widely applicable in various engineering and medical fields. However, despite the broad application of FDM products, the process faces challenges related to consistency in part properties, process reliability, and part accuracy. Recent advancements in computing technology have enabled the use of machine learning (ML) techniques to enhance FDM reliability and part accuracy. Nonetheless, the significance of ML in the FDM process has yet to be fully recognized. Therefore, this proposed work will conduct an experimental investigation on complex parts manufactured by FDM. Regression and ML models will be developed to predict key responses, including surface roughness, dimensional accuracy, and fabrication time (Joshi et al., 2010; Ingrole et al., 2017; Yu et al., 2018; Elipe and Lantada, 2012; Zhang and Yang, 2016).

II. LITERATURE

The methodology for the proposed literature review on FDM is depicted in Figure 1. Due to the heat produced by the ME extruder, each hot layer bonds by fusion to the previously deposited layer. Bellehumeur et al. (1996) examined how various factors affect the porosity and compressive strength of porous structures. They developed a model to predict the impact of the air gap on the structure's porosity. Too et al. (2002) investigated the influence of process parameters on the compressive strength and stiffness of tissue engineering scaffolds fabricated by ME, finding that air gap and raster width were the most significant factors. Ang et al. (2006) explored gradient auxetic structures as cores in aero-engine fan blades, analyzing their natural frequencies and mode shapes for the first three fundamental modes. The optimized configuration led to a reduction in the mass of the fan blade, a decrease in dynamic modal displacement, and a lowering of the first three natural frequencies.

Lira et al. (2011) studied the in-plane mechanical behavior of graded honeycomb structures, observing greater deformation at the loading end as impact velocity increased. Shen et al. (2013) found that specimens with a sandwich deposition configuration (raster angle ± 45º) exhibited higher stiffness than those with the default configuration (zero raster angle). Magalhaes et al. (2014) conducted a parametric analysis on how Poisson’s ratio (cell angle) and relative density (wall thickness) influence the mechanical properties of auxetic structures, concluding that ultimate strength is scale-dependent when Poisson’s ratio and relative density remain constant. Zhang et al. (2016) carried out an experimental study to assess the effect of geometric parameters on mechanical properties, developing models using genetic programming (GP), automated neural networks (ANN), fuzzy logic, and response surface methodology (RSM). They found that ANN models performed best, followed by GP and RSM. Panda et al. (2018) proposed a novel design for energy-dissipating structures using a gradient auxetic configuration and performed optimization to minimize the mass of a crash box while meeting constraints on crash resistance and energy absorption. Hou et al. (2018) studied cylindrical structures with triangular and hexagonal configurations under impact loading, discovering that normalized plastic energy absorption is influenced by relative density, and that the ratio of cell wall to skin thickness is a key factor in determining specific energy absorption (SEA) and deformation mode. They also found that maintaining a positive density gradient along the crushing direction improves energy absorption at an early stage. Chen et al. (2018a) proposed a workflow for the simultaneous integration of material design, structural design, and product fabrication of functionally graded materials (FGMs), which they validated on FGM tensile structures with varying material gradients.

Ituarte et al. (2019) identified infill density as the most significant process parameter for the compressive strength of tissue engineering scaffolds. Dave et al. (2019) compared the compressive performance of regular, auxetic, and hybrid honeycomb structures, concluding that the hybrid structure, which combines regular and auxetic designs, offered the best performance. Raeisi et al. (2019) derived relationships for the mechanical properties of Aux-Hex structures under different loading directions, finding that energy absorption capacity increased by 38% in the X-direction with uniform and stable deformation of unit cells. Xu et al. (2019) concluded that extruder temperature has a greater effect on the cooling rate of material than other process parameters, such as support temperature, speed, and layer height. Vanaei et al. (2020) conducted a comparative study on re-entrant chiral (RCA) and regular re-entrant structures under compression loading, using the Multi-jet Fusion (MJF) technique with polyamide 12 (PA12) to fabricate specimens. They found that RCA structures outperformed regular auxetic structures in terms of strength and specific energy absorption (SEA). Alomarah et al. (2020) validated a mathematical approach to parameterize lattices into Bezier surfaces and fabricated non-planar lattices via curved-layer fused deposition. They observed that lattices with higher auxeticity resulted in less energy dissipation under cyclic loading.

McCaw and Cuan-Urquizo (2020) investigated star-chiral auxetic structures both numerically and experimentally, discovering that the Poisson’s ratio depended on the ratio of thickness to ligaments. Attard et al. (2020) developed theoretical nonlinear models of 2D and 3D Double-V microstructures to predict normalized Young’s modulus and Poisson’s ratio as functions of strain, finding that geometrical parameters significantly affected mechanical properties. Gao et al. (2020) studied the crushing performance of a novel auxetic hierarchical crash box, finding it superior in energy absorption compared to traditional crash boxes. They also employed multi-objective optimization techniques, including the archive-based micro genetic algorithm (AMGA), which outperformed other methods.

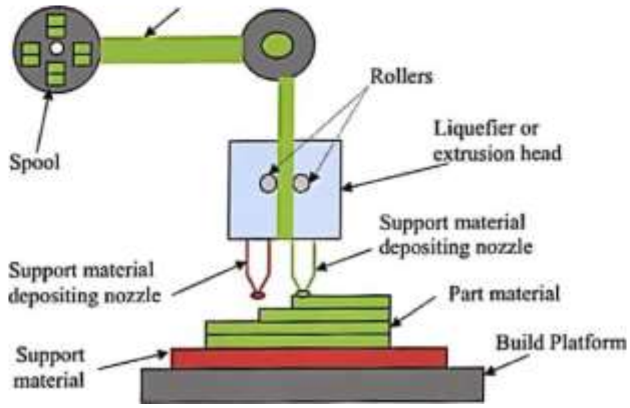

Fig 1.FDM machine

III. FINDINGS

After thoroughly reviewing the existing literature, several key insights have emerged:

1. The reviewed literature highlights the interdisciplinary nature of the research, encompassing both additive manufacturing (AM) and machine learning (ML) techniques.
2. Additive manufacturing proves to be an efficient and cost-effective method for fabricating complex parts. Furthermore, the integration of ML techniques can enhance the characteristics of the parts produced.

IV. RESEARCH GAP

Researchers worldwide have made significant strides in improving the surface characteristics and mechanical properties of parts and structures produced using the material extrusion (ME) technique. The literature review has led to the following conclusions:

Many studies have focused on optimizing the ME process to improve surface finish, dimensional accuracy, and minimize fabrication time for simple geometrical parts. However, there is a need for further research into the ME process for parts with more complex geometries, such as pyramidal and conical features. While some efforts have been made to study the mechanical properties of standard ASTM components, there is limited literature on the impact of geometric and gradient parameters of auxetic structures on mechanical properties such as strength, stiffness, and specific energy absorption (SEA) under compressive, shear, and flexural loading. Additionally, although some research has investigated the influence of ME process parameters on the mechanical properties of standard ASTM components, more research is needed to explore how these parameters affect ME-fabricated auxetic structures under various loading conditions.

Therefore, there is significant potential for experimental studies focused on improving the surface characteristics and mechanical properties of ME-fabricated auxetic structures

V. MACHINE LEARNING AND THEIR MODELS

Machine learning (ML) is a branch of artificial intelligence (AI) where machines are initially trained by humans and subsequently learn from their experiences. After initial training, human involvement is minimal. The ability of machines to learn from past data allows for quick, accurate, and effective analysis. While ML models typically require large datasets for training, they can start with moderate datasets and do not need to wait for extensive data collection. This section will provide a brief overview of ML fundamentals and associated models. As illustrated in Figure 3, ML can be divided into three main categories: (1) Supervised learning, (2) Unsupervised learning, and (3) Reinforcement learning. Additionally, there is a semi-supervised algorithm, which combines supervised and unsupervised methods, though it is less commonly used. The categorization of supervised and unsupervised learning is detailed in Figure 2. A brief discussion of the different learning algorithms is provided below.

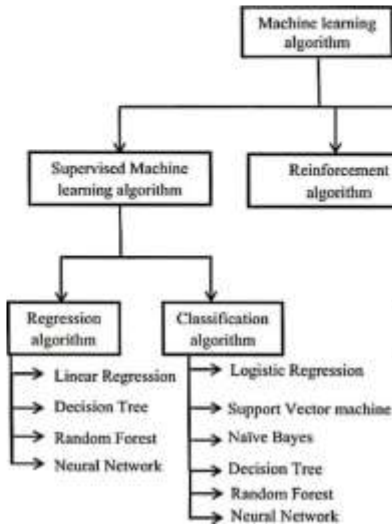

Fig 2 Machine Learning and Their Models

VI. DISCUSSIONS AND FUTURE SCOPE

Fused deposition modeling (FDM), also known as fused filament fabrication (FFF), is a well-established AM technique capable of producing complex products with reduced cycle times. This method does not require specialized tooling or a fixed process plan and allows for minimal human intervention. As a result, FDM is widely applied across various engineering and medical fields. However, despite its widespread use, the FDM process struggles with consistency in part properties, process reliability, and accuracy. Advances in computing technology have facilitated the integration of ML techniques to enhance FDM reliability and part accuracy. However, a comprehensive review highlighting the significance of ML in the FDM process has yet to be established.

Reference

[1] Alomarah, A., Masood, S. H., Sbarski, I., Faisal, B., Gao, Z. & Ruan, D. 2020. Compressive properties of 3D printed auxetic structures: experimental and numerical studies. *Virtual and Physical Prototyping,* 15**,** 1-21.

[2] Ang, K. C., Leong, K. F., Chua, C. K. & Chandrasekaran, M. 2006. Investigation of the mechanical properties and porosity relationships in fused deposition modelling-fabricated porous structures. *Rapid Prototyping Journal*.

[3] Attard, D., Farrugia, P., Gatt, R. & Grima, J. 2020. Starchirals–a novel class of auxetic hierarchal structures. *International Journal of Mechanical Sciences,* 179**,** 105631.

[4] Bellehumeur, C., Bisaria, M. & Vlachopoulos, J. 1996. An experimental study and model assessment of polymer sintering. *Polymer Engineering & Science,* 36**,** 2198-2207.

[5] Boldrin, L., Hummel, S., Scarpa, F., Di Maio, D., Lira, C., Ruzzene, M., Remillat, C. D., Lim, T.-C., Rajasekaran, R. & Patsias, S. 2016. Dynamic behaviour of auxetic gradient composite hexagonal honeycombs. *Composite Structures,* 149**,** 114-124.

[6] Chen, L., Zhang, J., Du, B., Zhou, H., Liu, H., Guo, Y., Li, W. & Fang, D. 2018a. Dynamic crushing behavior and energy absorption of graded lattice cylindrical structure under axial impact load. *Thin-Walled Structures,* 127**,** 333-343.

[7] Chen, Y., Li, T., Jia, Z., Scarpa, F., Yao, C.-W. & Wang, L. 2018b. 3D printed hierarchical honeycombs with shape integrity under large compressive deformations. *Materials & Design,* 137**,** 226-234.

[8] Dave, H. K., Rajpurohit, S. R., Patadiya, N. H., Dave, S. J., Sharma, K. S., Thambad, S. S., Srinivasn, V. P. & Sheth, K. V. 2019. Compressive strength of PLA based scaffolds: effect of layer height, infill density and print speed. *Int. J. Mod. Manuf. Technol.,* 11**,** 21-27.

[9] Elipe, J. C. Á. & Lantada, A. D. 2012. Comparative study of auxetic geometries by means of computer-aided design and engineering. *Smart Materials and Structures,* 21**,** 105004.

[10] Gao, D., Sun, Q., Hu, B. & Zhang, S. 2020. A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles. *Sensors,* 20**,** 1487.

[11] Hou, W., Yang, X., Zhang, W. & Xia, Y. 2018. Design of energy-dissipating structure with functionally graded auxetic cellular material. *International Journal of Crashworthiness,* 23**,** 366-376.

[12] Ingrole, A., Hao, A. & Liang, R. 2017. Design and modeling of auxetic and hybrid honeycomb structures for in-plane property enhancement. *Materials & Design,* 117**,** 72-83.

[13] Ituarte, I. F., Boddeti, N., Hassani, V., Dunn, M. L. & Rosen, D. W. 2019. Design and additive manufacture of functionally graded structures based on digital materials. *Additive Manufacturing,* 30**,** 100839.

[14] Joshi, S., Ju, J., Berglind, L., Rusly, R., Summers, J. D. & Desjardins, J. D. Experimental Damage Characterization of Hexagonal Honeycombs Subjected to In-Plane Shear Loading. International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2010. 35-41.

[15] Li, X., Lu, Z., Yang, Z. & Yang, C. 2018. Anisotropic in-plane mechanical behavior of square honeycombs under off-axis loading. *Materials & Design,* 158**,** 88-97.

[16] Lira, C., Scarpa, F. & Rajasekaran, R. 2011. A gradient cellular core for aeroengine fan blades based on auxetic configurations. *Journal of Intelligent Material Systems and Structures,* 22**,** 907-917.

[17] Magalhães, L., Volpato, N. & Luersen, M. 2014. Evaluation of stiffness and strength in fused deposition sandwich specimens. *Journal of the Brazilian Society of Mechanical Sciences and Engineering,* 36**,** 449-459.

[18] Mccaw, J. C. & Cuan-Urquizo, E. 2020. Mechanical characterization of 3D printed, non-planar lattice structures under quasi-static cyclic loading. *Rapid Prototyping Journal*.

[19] Panda, B., Leite, M., Biswal, B. B., Niu, X. & Garg, A. 2018. Experimental and numerical modelling of mechanical properties of 3D printed honeycomb structures. *Measurement,* 116**,** 495-506.

[20] Raeisi, S., Tapkir, P., Ansari, F. & Tovar, A. 2019. Design of a hybrid honeycomb unit cell with enhanced in-plane mechanical properties.