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Decentralized Closed-Loop Additive Manufacturing from Post-Consumer PET Bottles: Mechanical Performance and Interpretable Stress-Response Prediction

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Abstract.

Decentralized recycling offers a promising pathway for circular additive manufacturing, yet the physical variability of local waste streams often compromises material reliability. This study evaluates the direct conversion of post-consumer polyethylene terephthalate (PET) bottles into structural feedstock for fused filament fabrication (FFF). Using a custom automated extrusion system, bottles with wall thicknesses of 0.25 mm and 0.475 mm were processed into standard 1.75 mm filament. ASTM D638 Type IV tensile specimens were printed from the recovered material and benchmarked against commercial PLA, ABS, and PETG. Results showed that process stability is highly sensitive to initial bottle geometry; continuous extrusion requires strip widths to be strictly calibrated to the source wall thickness. The optimized recycled PET (rPET) filament demonstrated highly competitive mechanical properties. It achieved an ultimate tensile strength of 45.31 MPa, retaining nearly 98% of PLA's strength, along with superior elongation at break (8.65%) and toughness (2.23 MJ/m³). The system recorded an average material recovery yield of 53.8%. To address quality-control barriers in distributed manufacturing settings, an interpretable XGBoost regression model was developed using 15,738 continuous tensile-strength data points. The model successfully predicted non-linear stress-response trajectories with a Root Mean Square Error of 0.901 MPa. SHAP analysis confirmed that these predictions were driven by physical load and yield-stress parameters rather than data leakage. By combining geometry-specific extrusion guidelines with data-driven quality assurance, this research outlines a practical method for manufacturing engineering-grade structural components directly from recovered plastics.

Keywords: Sustainable Additive Manufacturing; Fused Filament Fabrication; Filament Extrusion; Circular Economy; Mechanical Characterization; decentralized recycling

1. Introduction

The proliferation of plastic waste represents a significant sustainability challenge, primarily due to the rapid increase in polymer production outpacing the development of infrastructure for collection, sorting, and reprocessing [1,2]. Polyethylene terephthalate (PET) is a prominent component of this waste stream, as beverage bottles are extensively used, frequently discarded, and often transported over considerable distances before entering formal

recycling systems [3]. Although PET is technically recyclable, the value retained post-collection is heavily influenced by local infrastructure, contamination control, market demand, and the availability of technologies capable of converting waste into functional products [4]. In the absence of these conditions, post-consumer PET either becomes a low-value secondary material or persists as an environmental burden. This discrepancy between material recyclability and practical recovery underscores the need for developing localized manufacturing pathways that can convert municipal PET waste into products with quantifiable engineering performance.

Additive manufacturing (AM), particularly fused filament fabrication (FFF), offers a promising approach for localized polymer reuse by transforming filament directly into geometrically intricate components without the need for the tooling associated with injection or compression molding [5]. FFF is extensively utilized in laboratories, educational institutions, maker spaces, and small-scale manufacturing settings, resulting in a widespread distribution of filament demand [6]. Meeting a portion of this demand through the local recovery of PET bottles could enhance the environmental benefits of AM, transitioning it from a rapid prototyping tool to a more sustainable material platform [7]. Nonetheless, converting discarded bottles into reliable filament involves more than merely substituting one feedstock for another. This process necessitates controlled strip preparation, consistent thermal softening, synchronized pulling, precise filament diameter control, calibration of printing parameters, and verification that the printed components meet the mechanical standards expected of engineering polymers.

Existing research indicates that recycled plastic filaments can be printed effectively; however, the literature is dispersed across three partially independent domains [8]. The first domain focuses on recycling hardware, encompassing shredding, pellet extrusion, and pultrusion-style bottle-strip conversion [9–11]. These studies are significant as they establish technical feasibility, yet many systems remain costly, labor-intensive, or inadequately characterized for decentralized operation. The second domain investigates the mechanical properties of recycled FFF materials. While some studies report promising strength and ductility, results vary significantly due to the variability in feedstock origin, thermal history, moisture, additives, contamination, and printing orientation [12–14]. The third domain involves the application of machine learning to AM process prediction, with most research concentrating on metals, process monitoring, or single-value performance outcomes rather than comprehensive stress-strain trajectories of recycled polymer parts [15–17]. This research is situated at the convergence of these domains, addressing the recycling machine, the printed material, and the prediction framework as an integrated sustainable materials technology.

The primary scientific challenge lies in the fact that decentralized recycling cannot be assessed solely based on the production of filament. A sustainable materials technology must also address whether the recovered material can be consistently manufactured, whether the final product exhibits competitive mechanical performance, whether the geometry of the source material influences the processing parameters, and whether quality can be predicted with minimal destructive testing [7,18,19]. These considerations are particularly crucial for recycled polyethylene terephthalate (rPET) due to the variability in bottle wall thickness and curvature, which affect the closure, melting, and drawing of the strip through the extrusion nozzle. A strip that is too narrow may fail to form a continuous tube, while one that is too wide may overfill the thermal zone, swell at the exit, overload the winding system, or obstruct the printer. Consequently, the geometry of the source material is not a trivial operational detail; it is a critical material-processing variable that can determine the practical success of the circular recycling process.

A second scientific issue arises from the prevalent practice of reporting ultimate tensile strength, modulus, or elongation at break as isolated summary values in the mechanical characterization of recycled FFF polymers. While these metrics are essential, they fail to encompass the complete deformation trajectory through which a printed polymer stores elastic energy, yields, necks, accumulates damage, and ultimately fractures [20–22]. In brittle materials such as PLA, the stress-strain curve exhibits a rapid ascent and concludes at relatively low strain levels. Conversely, in more ductile materials, including the rPET variants examined in this study, the curve demonstrates extended deformation and energy absorption prior to rupture. A model trained solely on a final value would overlook this behavior. Consequently, this study employs high-resolution tensile records to predict the continuous engineering stress response. The aim is not merely to fit a curve but to develop a virtual testing framework that accurately reflects the physics of load, extension, and material yield behavior, while preventing data leakage from variables that directly encode the answer.

This study presents four significant innovations. First, it introduces a compact and user-friendly extrusion-winding system designed to convert post-consumer PET bottle strips into 1.75 mm filament. This system incorporates a closed-loop temperature subsystem and an automated speed-control subsystem. Second, the study quantifies the relationship between bottle-wall thickness, strip width, and filament formation quality, thereby translating feedstock geometry into a practical processing window. Third, it offers a direct mechanical comparison between custom-extruded rPET and commercial PLA, PETG, and ABS, utilizing a common ASTM D638 testing protocol and standard FFF processing conditions. Finally, the study develops an interpretable XGBoost model capable of predicting continuous non-linear stress trajectories using a minimal set of physically meaningful inputs, with validation conducted through group cross-validation on unseen specimens. This comprehensive contribution aligns with the scope of Sustainable Materials and Technologies by integrating material recovery, manufacturing system design, structure-property evaluation, and data-driven quality assurance into a single sustainable technology pathway.

2. Materials and Methods

The experimental approach integrated source material processing, filament production, specimen fabrication, mechanical testing, and data-driven modeling. The process commenced with post-consumer PET bottles, which were cleaned and subsequently cut into strips using a cutter. These strips were then thermally extruded into filament through a pulling process. The recycled PET (rPET) filament was utilized to print tensile specimens. For benchmarking purposes, commercial PLA, ABS, and PETG filaments were printed with specific geometries and conditions. The tensile data, as presented in Table 1, were transformed into engineering stress-strain curves to facilitate metric evaluation and machine-learning prediction.

Table 1. Continuous tensile data set used for machine-learning prediction.

Material type	Number of specimens	Total data points (N)	Average points per specimen
PLA	3	2,182	727.3
PETG	3	2,195	731.7
ABS	3	2,378	792.7
rPET-2 (0.475 mm)	3	3,898	1,299.3
rPET-1 (0.25 mm)	3	5,085	1,695.0

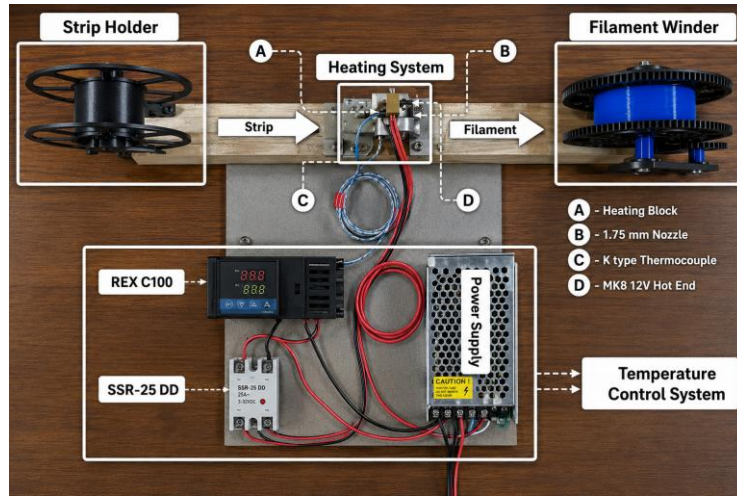


Figure 1. Developed extrusion machine showing strip holder, heating zone, control components and filament winding subsystem.

Figure 1 illustrates the extrusion machine designed for decentralized use, with a focus on cost-effectiveness, modularity, and ease of repair. The machine's mechanical components include a bottle-strip cutting unit, a strip holder, a heated nozzle and block, and an automated filament winding unit. The strip width is modified by adjusting the washer spacing between parallel bolts, while a tangential blade is employed to produce a ribbon. The extrusion assembly transforms the ribbon into filament by passing it through a heated path, where the polymer softens, closes, and is drawn into a circular filament shape. Certain components are fabricated from ABS and PLA, facilitating replacement and partial self-replication.

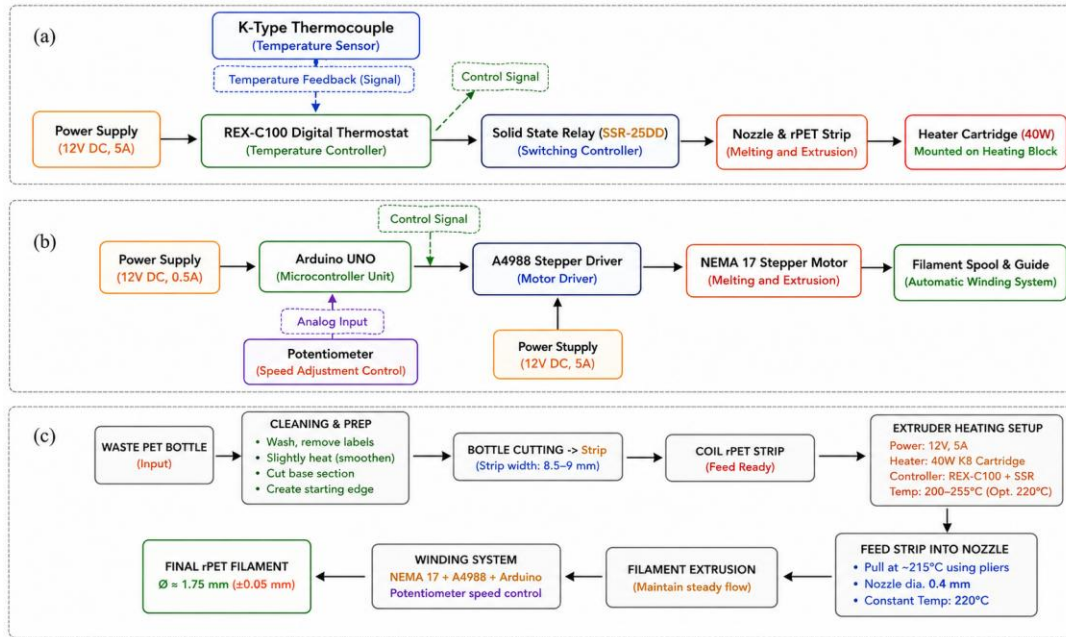


Figure 2. Electrical and process architecture of the rPET filament extrusion system: thermal regulation, automated winding and end-to-end bottle-to-filament flow.

The thermal subsystem integrated a 40 W heater cartridge and a K-type thermocouple, both connected to a digital PID thermostat, as illustrated in Figure 2. A solid-state relay was utilized to control the heating load, ensuring the maintenance of the target block temperature. The winding subsystem employed a NEMA 17

stepper motor, operated by an Arduino Uno and an A4988 driver. A potentiometer allowed for manual speed adjustment, facilitating synchronization between extrusion flow and filament take-up. This synchronization is essential, as inadequate pulling results in sagging and oversized diameters, whereas excessive pulling causes thinning, necking, and instability. The machine functioned at an extrusion temperature of 220 °C for the conversion of bottle strips, based on preliminary trials that demonstrated this condition provided suitable viscosity for the recovered PET strips. The leading edge of the strip was introduced at approximately 215 °C and manually drawn until a continuous flow was achieved, after which the automated spool-maintained filament take-up.

Two conditions of recycled polyethylene terephthalate (rPET) sources were selected to examine the effect of bottle-wall thickness. In the rPET-1 condition, bottles with a nominal wall thickness of 0.25 mm were used, requiring a strip width of 8.5-9.0 mm to produce stable filament. Conversely, the rPET-2 condition utilized bottles with a nominal wall thickness of 0.475 mm, necessitating a narrower strip width of 6.5-7.0 mm. This variation is due to volumetric differences: thicker strip material provides more polymer per unit strip width, allowing a narrower strip to adequately fill the annular path necessary for forming a 1.75 mm filament. In contrast, thinner bottle material requires a wider strip to achieve equivalent polymer volume and ensure complete closure. Failure to maintain this volume balance may result in the filament remaining partially open, expanding beyond the desired diameter, or developing surface roughness that could obstruct the fused filament fabrication (FFF) nozzle. The sequence for preparing the bottle-to-filament transition is illustrated in Figure 3. Table 2 summarizes the materials, source conditions, and fixed manufacturing parameters adopted for both comparative analysis and parametric evaluation.

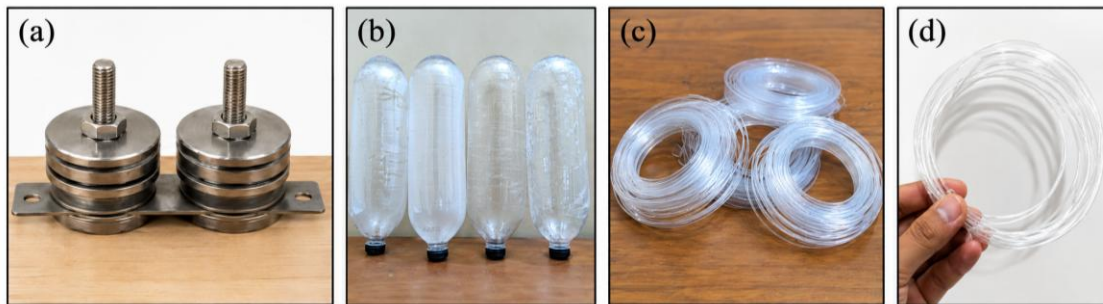


Figure 3. Bottle-to-filament preparation sequence: (a) strip cutter, (b) prepared bottles, (c) coiled rPET strips and (d) produced rPET filament.

Table 2. Materials, source conditions and fixed manufacturing parameters used for the comparative and parametric evaluations.

Category	Parameter	Value or condition	Purpose
rPET feedstock	Bottle wall thicknesses	0.25 mm (rPET-1), 0.475 mm (rPET-2)	Evaluate source-geometry influence
Strip preparation	Stable strip widths	8.5-9.0 mm for rPET-1; 6.5-7.0 mm for rPET-2	Obtain 1.75 mm filament
Extrusion	Strip-to-filament temperature	220 °C nominal block temperature	Balance melt flow and tube closure
Extrusion	Pulling speed	14 mm/s	Synchronize flow with winding
FFF printing	Printer	Bambu Lab X1 Carbon	Fabricate ASTM D638 specimens
FFF printing	Nozzle temperature for rPET	255 °C	Improve interlayer bonding

FFF printing	Bed temperature	70 °C	Improve first-layer adhesion
FFF printing	Infill and speed	100% rectilinear; 30 mm/s	Minimize porosity and standardize prints
Mechanical testing	Standard and rate	ASTM D638 Type IV; 5 mm/min	Quasi-static tensile characterization
Machine learning	Validation design	15-fold specimen-group cross-validation	Test generalization to unseen specimens

FFF specimens adhered to ASTM D638 Type IV geometry. The rPET filament, along with three commercial filaments, was printed using a Bambu Lab X1 Carbon with 1.75 mm filament. The geometry was designed in SolidWorks and processed with Bambu Lab software. To minimize porosity and uncertainty related to infill, all specimens employed 100% rectilinear infill. A consistent print speed of 30 mm/s was maintained across all materials. For rPET, a nozzle temperature of 255 °C was chosen after calibration within the 250-265 °C range, as it enhanced interlayer bonding and reduced visible interlayer gaps. The bed temperature was set at 70 °C. Specimens that were defective or dimensionally irregular were excluded prior to testing. Tensile testing was conducted under quasi-static conditions using a universal testing machine, adhering to ASTM D638 standards, with a crosshead rate of 5 mm/min. Three replicates were tested for each category. Force and displacement data were recorded, facilitating the conversion to engineering stress and strain. Engineering stress was calculated as the load divided by the original gauge cross-sectional area, while engineering strain was determined as the extension divided by the original gauge length. Ultimate tensile strength was defined as the maximum stress prior to fracture. Young's modulus was derived from the initial linear region. Yield strength was assessed using the 0.2% offset method, toughness was quantified as the area under the stress-strain curve up to fracture, and specific strength was calculated by normalizing the ultimate tensile strength by density.

The statistical analysis of the curves maintained the time-resolved mechanical response. Given that replicate tests do not conclude at identical strain values, directly averaging raw data points may distort the mean curve. Consequently, replicate curves were aligned to a standardized strain axis using cubic spline interpolation prior to calculating mean and standard deviation envelopes. This approach facilitated the visualization of average stress-strain behavior while preserving varying ductility levels and provided a consistent framework for comparing brittle and ductile responses. In the context of machine learning, the continuous data set comprised 15,738 points from 15 physical specimens and included 20 initial feature columns, such as material identifiers, dimensions, static mechanical properties, and real-time sensor variables like force and distortion. The modeling target was engineering stress. The feature-selection strategy was conservative, as tensile data contain variables that can artificially enhance accuracy if used indiscriminately. Variables prone to leakage and redundancy were systematically removed, and specimen-group cross-validation was employed to ensure evaluation on entirely unseen physical specimens. Cross-sectional area, force, material names, and specimen keys were otherwise potential sources of leakage.

The final model employed XGBoost regression due to its capability to capture non-linear interactions among load, displacement, and material state without relying on a predetermined functional form. The input set, which was compact, included yield stress, force measured in kgf, and distortion in mm. These inputs, which are physically interpretable, correspond to applied load, extension, and a material-specific reference point for the transition from elastic to plastic behavior. Hyperparameter optimization was conducted using Bayesian

optimization, randomized search, and grid search. The evaluation metric utilized was the root mean squared error (RMSE) in MPa, with the coefficient of determination serving as an additional measure. The selection of the final model prioritized minimizing error, ensuring generalization across different specimen groups, and maintaining interpretability through SHAP analysis. The sustainability analysis concentrated on material recovery during the bottle-to-filament conversion stage for bottles of 500, 1000, and 2000 mL. For each bottle size, both the total bottle mass and the recovered filament mass were measured, and yield was calculated as the ratio of filament mass to the original bottle mass. Although this does not constitute a comprehensive life-cycle assessment, it offers a transparent indicator of material efficiency for the local conversion step, particularly for systems that claim circularity in decentralized recycling contexts. Yield was analyzed alongside processing observations to identify losses occurring at the bottle neck, base, trimming edges, and during strip-start preparation.

3. Results and Discussion

3.1 Influence of Strip Width and Bottle Wall Thickness on Filament Stability

The extrusion trials demonstrated that the production of stable filaments is contingent upon a balance among strip width, bottle-wall thickness, melt closure, and pulling speed, as depicted in Table 3 and Figure 4. For rPET-1, which is derived from a thinner 0.25 mm bottle wall, a stable 1.75 mm filament was achieved when the strip width ranged from 8.5 to 9.0 mm. Widths below this range were insufficient to provide the necessary polymer volume for complete tube closure, resulting in open seams or incomplete closure. Conversely, widths exceeding this range resulted in excess polymer volume, leading to swelling, roughness, motor overload, and clogging in downstream printers. In the case of rPET-2, produced from a thicker 0.475 mm bottle wall, stable filament was achieved at a narrower strip width of 6.5-7.0 mm. This finding confirms that the critical process variable is not solely strip width but the interaction between strip width and wall thickness. This result is practically significant, as locally available bottles may vary considerably in wall geometry; thus, a fixed strip width may not be universally applicable.

Table 3. Strip-width trade-off study and defect interpretation for rPET filament formation.

rPET-1 strip width (mm)	rPET-2 strip width (mm)	Filament diameter (mm)	Observed outcome and interpretation
7.5	5.5	n/a	Insufficient polymer volume; open seam and incomplete closure
8.0	6.0	1.60-1.68	Partial closure; discontinuous or unstable tube formation
8.5	6.5	1.75	Stable window; continuous enclosed tube
9.0	7.0	1.75	Stable window; target diameter maintained
9.5	7.5	1.77-1.78	Overfilled thermal zone; swelling and risk of nozzle clogging
10.0-10.5	8.0	1.78-1.80	Motor overload, rough filament and printer feeding instability
11.0	8.5	n/a	Filament breakage and unacceptable processing instability

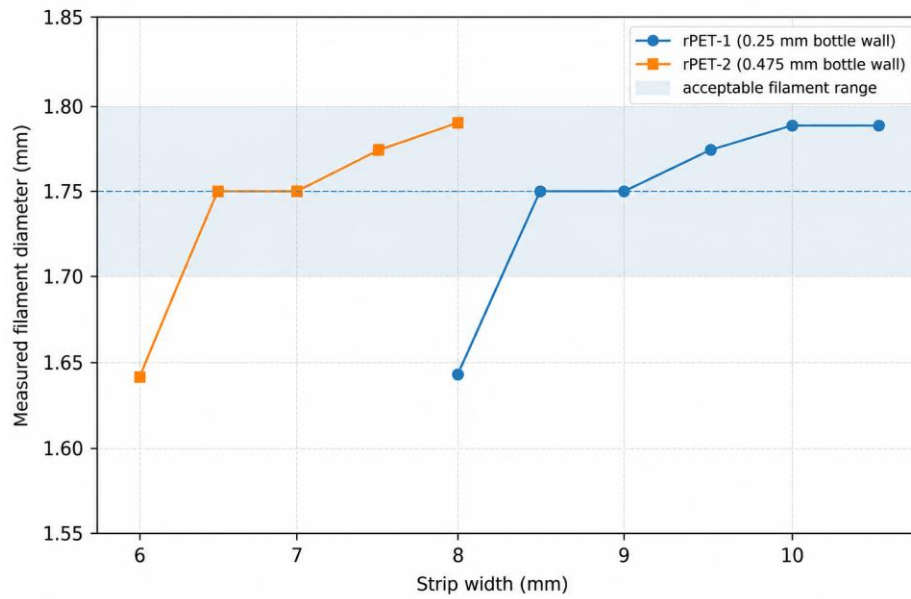


Figure 4. Process-window analysis showing the strip-width ranges that produce stable 1.75 mm filament for thin and thick bottle-wall feedstocks.

3.2 Cross-Sectional Morphology of rPET Filament in Enclosed-Tube Extrusion Process

The cross-sectional geometry of the produced filament, as illustrated in Figure 5, corresponds to an enclosed-tube mechanism. During the heating process, the strip softens and curls inward while traversing the nozzle region. When the polymer volume and pulling speed are optimally balanced, the strip edges converge and fuse, forming a closed filament with an external diameter of approximately 1.75 mm. The longitudinal seam observed in certain rPET-2 filaments is attributed to differential contraction during cooling and the increased bending stiffness of thicker strips. In contrast, rPET-1 produced smoother filament surfaces under optimized conditions, likely due to the more uniform softening of the thinner strip across its thickness. This phenomenon accounts for the higher mean strength and toughness observed in rPET-1 printed specimens, whereas rPET-2 exhibited a narrower standard deviation in ultimate tensile strength. Thin strips enhanced thermal homogeneity, while thick strips improved feeding stability.

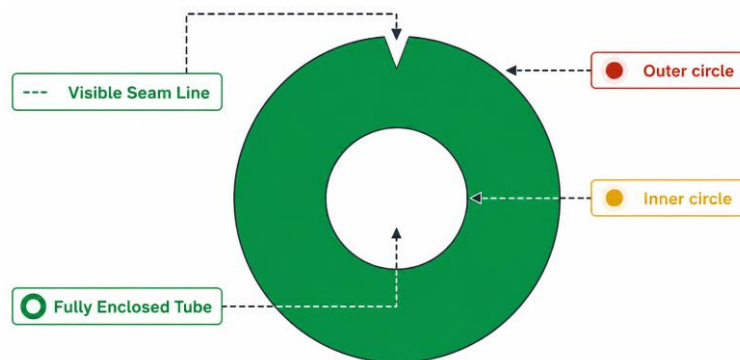


Figure 5. Cross-sectional schematic of the enclosed tube rPET filament and visible seam line formed during strip closure.

3.3 Mechanical Performance Evaluation

Table 4 presents a comparison of the mechanical properties of commercial thermoplastics, namely ABS, PETG, and PLA, with custom-extruded recycled PET variants (rPET-1 and rPET-2) in the context of decentralized closed-loop additive manufacturing. The findings indicate that recycled PET can achieve performance levels comparable to virgin polymers when extrusion conditions are optimized. PLA exhibits the highest ultimate tensile strength at 46.44 MPa and stiffness at 0.94 GPa, although it demonstrates lower ductility at 4.87% and moderate toughness at 1.19 MJ/m³, suggesting brittle behavior. ABS is characterized by the lowest strength at 27.98 MPa and toughness at 0.64 MJ/m³, whereas PETG provides moderate strength at 40.17 MPa and elongation at 6.46%. The rPET-1 variant achieves strength nearly equivalent to PLA at 45.31 MPa, with enhanced elongation at 8.65% and the highest toughness at 2.23 MJ/m³. Additionally, rPET-2 surpasses PETG in terms of the strength-ductility balance, thereby affirming the suitability of recycled PET for structural additive manufacturing, aligning with the performance of commercial FFF processes.

Table 4. Comprehensive mechanical properties of commercial and custom-extruded FFF thermoplastics.

Material	UTS (MPa)	Elongation (%)	Modulus (GPa)	Toughness (MJ/m ³)	Specific strength (MPa·cm ³ /g)	Yield stress (MPa)	Yield strain (%)
ABS	27.98 ± 0.49	4.52 ± 0.11	0.60 ± 0.00	0.64 ± 0.03	26.40 ± 0.46	27.32 ± 1.57	4.48 ± 0.10
PETG	40.17 ± 1.77	6.46 ± 1.00	0.63 ± 0.10	1.36 ± 0.25	32.13 ± 1.42	38.87 ± 1.02	6.45 ± 1.00
PLA	46.44 ± 0.95	4.87 ± 0.27	0.94 ± 0.01	1.19 ± 0.13	37.45 ± 0.77	45.97 ± 0.42	4.80 ± 0.25
rPET-1	45.31 ± 5.24	8.65 ± 2.28	0.72 ± 0.06	2.23 ± 0.87	32.83 ± 3.80	44.60 ± 6.29	6.42 ± 0.43
rPET-2	41.36 ± 2.00	7.32 ± 1.44	0.69 ± 0.02	1.65 ± 0.46	29.97 ± 1.45	39.98 ± 1.86	6.03 ± 0.23

Table 5 provides performance indices evaluating strength retention, ductility, energy absorption, and repeatability among commercial polymers and recycled PET (rPET) filaments. Polylactic acid (PLA) is used as the baseline, exhibiting 100% ultimate tensile strength (UTS) retention, high stiffness consistency, and low variability (UTS coefficient of variation [CV] = 2.0%), which confirms strong process control but limited ductility. Acrylonitrile butadiene styrene (ABS) demonstrates the weakest performance, with no UTS gain and the lowest toughness. In contrast, polyethylene terephthalate glycol (PETG) shows balanced behavior with moderate improvements in elongation and toughness. Notably, rPET-1 achieves the most significant functional enhancement, retaining 97.6% UTS, with elongation 77.6% higher than PLA, and 87.4% greater toughness, indicating superior energy absorption. However, it exhibits higher variability (CV = 11.6%), reflecting feedstock heterogeneity in decentralized recycling. rPET-2 offers a more stable response (CV = 4.8%) while maintaining strong mechanical performance. Overall, rPET materials demonstrate competitive or superior damage tolerance, supporting their suitability for circular additive manufacturing.

Table 5. Derived performance indices from the mechanical data. Values are calculated from Table 4 and are included to clarify strength retention, damage tolerance and repeatability (CV = Coefficient of Variation).

Material	UTS retention vs PLA (%)	UTS gain vs ABS (%)	Elongation changes vs PLA (%)	Toughness change vs PLA (%)	UTS CV (%)	Yield/UTS ratio	Specific toughness (MJm ³ /g cm ⁻³)
ABS	60.2	0.0	-7.2	-46.2	1.8	0.976	0.604
PETG	86.5	43.6	32.6	14.3	4.4	0.968	1.088
PLA	100.0	66.0	0.0	0.0	2.0	0.990	0.960
rPET-1	97.6	61.9	77.6	87.4	11.6	0.984	1.616
rPET-2	89.1	47.8	50.3	38.7	4.8	0.967	1.196

Figure 6 illustrates a normalized performance envelope that compares ABS, PETG, PLA, rPET-1, and rPET-2 in terms of ultimate tensile strength (UTS), elongation, modulus, toughness, and specific strength. The radar plot emphasizes the trade-offs among stiffness, strength, and ductility. PLA exhibits the highest modulus and specific strength, making it suitable for applications where stiffness is prioritized; however, its lower elongation and toughness restrict its damage tolerance. ABS displays lower values across all metrics, indicating inferior performance. PETG occupies an intermediate position with balanced properties but lacks a dominant feature. rPET-1 presents the most comprehensive profile, characterized by high UTS, elongation, and toughness, rendering it the most versatile material. rPET-2, while showing reduced strength, offers an improved balance of ductility and stability compared to PLA and PETG. In summary, recycled PET has the potential to match or surpass traditional filaments, thereby supporting circular additive manufacturing and facilitating interpretable stress-response modeling.

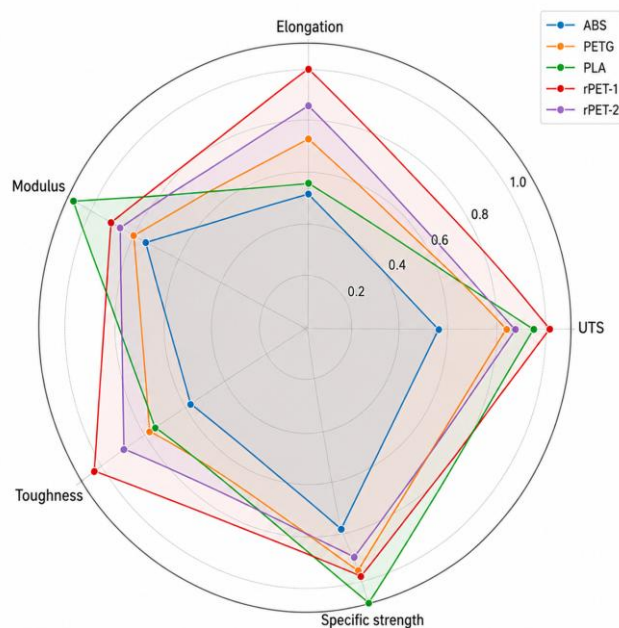


Figure 6. Normalized mechanical performance envelope for ABS, PETG, PLA and the two rPET variants. Each metric is normalized by the maximum value within the tested set.

Figure 7 illustrates a strength–ductility map with markers indicating toughness, facilitating the comparison of tensile strength and elongation for ABS, PETG, PLA, rPET-1, and rPET-2. The results reveal clustering and trade-offs within the decentralized closed-loop additive manufacturing system. PLA exhibits the highest tensile strength but limited elongation, suggesting brittle behavior with moderate toughness. ABS is positioned in the region of lowest strength and ductility, confirming its inferior performance. PETG is situated in an intermediate region, while rPET-1 occupies a favorable region, combining high tensile strength with the highest elongation and the largest toughness marker area, indicative of energy absorption and damage tolerance. rPET-2 demonstrates improved ductility compared to PLA while maintaining strength. Overall, recycled PET can match or surpass commercial filaments, supporting structural applications and stress-response prediction in circular manufacturing systems.

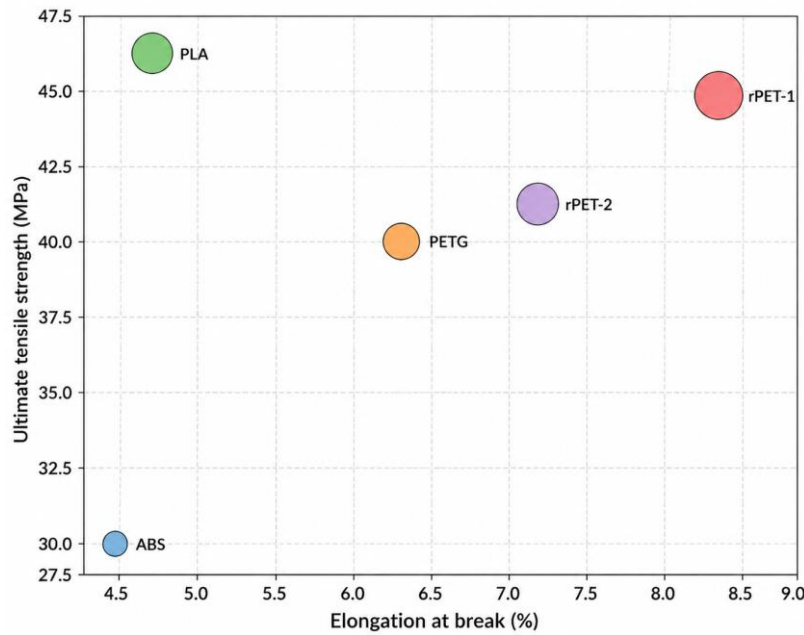


Figure. 7. Strength-ductility-toughness map showing that rPET-1 occupies a high-strength and high-energy-absorption region relative to the commercial benchmarks.

Figure 8 illustrates the average engineering stress–strain responses of PLA, ABS, PETG, rPET-1, and rPET-2, highlighting specimen variations. The results reveal differences in stiffness, yield behavior, and post-yield deformation among the materials within the decentralized closed-loop additive manufacturing system. PLA demonstrates the highest stiffness and peak stress, approximately 46–47 MPa, but fails after loading with minimal plastic deformation, indicating a brittle fracture. ABS exhibits lower strength and stiffness, characterized by early yielding and limited strain hardening. PETG undergoes an elastic-to-plastic transition, indicative of ductility. Both rPET variants display extended strain capacity; rPET-1 achieves the highest elongation and maintains stress beyond yielding, whereas rPET-2 sustains slightly lower stress levels. Overall, recycled PET demonstrates competitive ductility, which supports its use in structural applications and facilitates interpretable stress–response modeling.

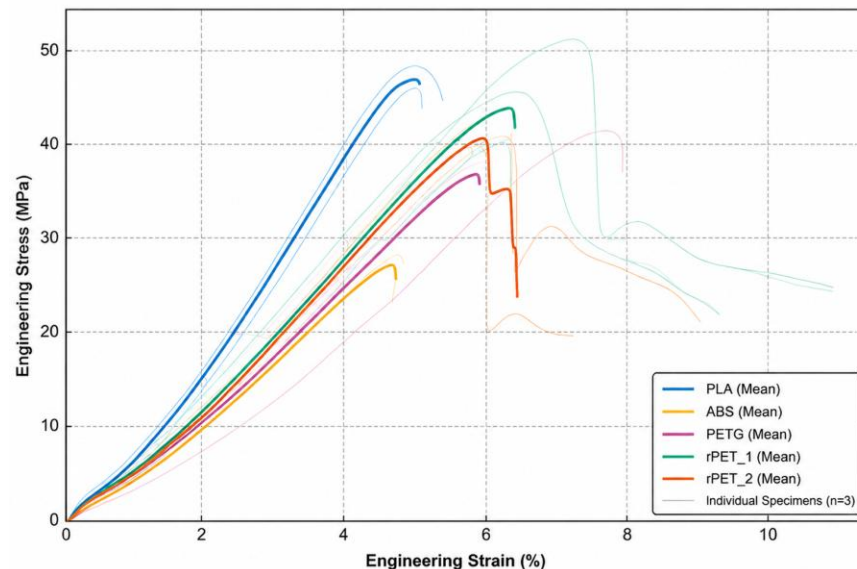


Figure 8. Average engineering stress-strain responses of the evaluated FFF thermoplastics, including individual specimen traces.

Figure 9 illustrates the fractured tensile specimens of PLA, ABS, PETG, and rPET, emphasizing their deformation and failure behaviors under uniaxial loading within a decentralized closed-loop additive manufacturing system. The PLA specimens exhibit a brittle fracture characterized by minimal plastic deformation and breakage following peak stress. PETG displays toughness, evidenced by moderate necking prior to failure, suggesting a transition in stress-strain behavior. ABS demonstrates ductile behavior, with notable elongation and energy absorption preceding fracture. Conversely, rPET specimens exhibit drawing, stress whitening, and deformation, indicating enhanced ductility relative to PLA and PETG. The whitening effect is indicative of micro-void formation and polymer chain alignment during plastic deformation, a characteristic feature of recycled PET structures. Collectively, the fracture patterns corroborate the competitive performance and improved ductility of recycled PET, thereby validating the interpretable stress-response model.

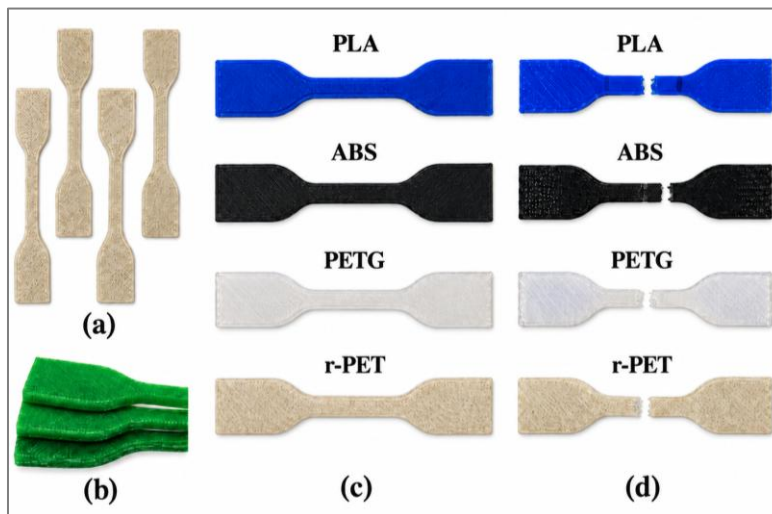


Figure 9. Printed and fractured tensile specimens. The rPET samples show visible drawing and stress whitening, consistent with higher ductility.

Figure 10 illustrates the recovery efficiency of three post-consumer PET bottle formats within a decentralized closed-loop additive manufacturing system. A non-linear relationship with bottle volume is evident. The 1000 mL bottle format achieves the highest yield at 61.3%, suggesting an optimal balance between wall uniformity and process stability. In contrast, the 500 mL format exhibits the lowest efficiency due to curvature-induced trimming losses and incomplete strip utilization. The 2000 mL bottle demonstrates intermediate efficiency, characterized by higher filament output but increased processing resistance due to thicker walls. The mean efficiency of 53.8% indicates that nearly half of the input material is lost during processing. These findings underscore the importance of geometry-driven feedstock selection, process optimization, and predictive control frameworks for circular PET manufacturing in fully decentralized systems.

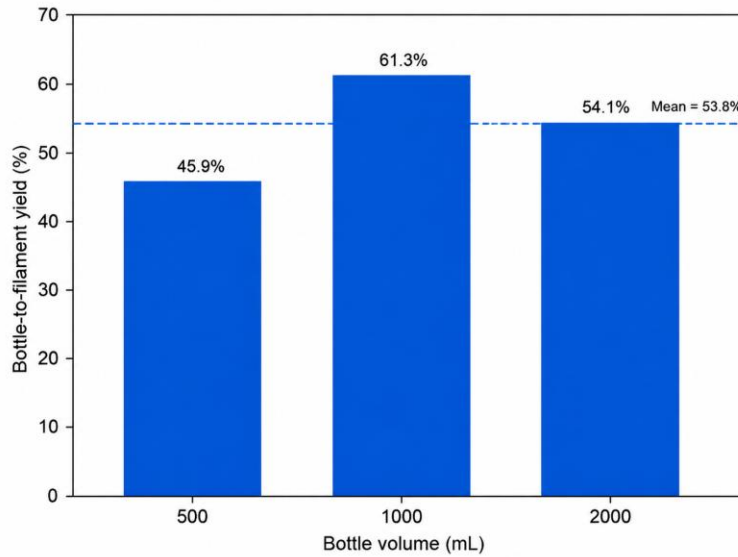


Figure 10. Bottle-to-filament material recovery yield. The 1000 mL format provides the highest measured conversion efficiency, while the 2000 mL format provides the highest absolute filament mass.

Table 6 presents the conversion efficiency from bottle to filament for post-consumer PET bottles within a decentralized closed-loop additive manufacturing system. The data indicate substantial variation in yield based on bottle size. The 1000 mL bottle exhibited the highest efficiency, with a yield of 61.3% and the lowest loss fraction of 38.7%, suggesting an optimal balance between wall uniformity and process stability. Conversely, the 2000 mL bottle showed a moderate yield of 54.1%, while the 500 mL bottle recorded the lowest yield at 45.9%, accompanied by the highest waste fraction of 54.1%. On average, the system achieved a yield of 53.8% with a material loss of 46.2%. These findings highlight that conversion efficiency is significantly influenced by bottle geometry, wall thickness, and strip processing behavior. Smaller bottles experience higher trimming losses due to curvature effects, whereas larger bottles face cutting resistance and thermal inconsistencies. Overall, the results confirm that feedstock variability substantially impacts material circularity and process efficiency in PET-based additive manufacturing systems.

Table 6. Bottle-to-filament material yield and waste fraction for representative post-consumer bottle sizes.

Bottle volume (mL)	Bottle mass (g)	Filament mass (g)	Trim/loss mass (g)	Yield (%)	Loss fraction (%)
500	12.2	5.6	6.6	45.9	54.1
1000	28.4	17.4	11.0	61.3	38.7
2000	50.6	27.4	23.2	54.1	45.9
Mean	30.4	16.8	13.6	53.8	46.2

3.4 Machine-Learning Prediction Performance and Feature Optimization

The findings presented in Table 7 and Figure 11 illustrate a leakage-aware feature reduction strategy applied to the XGBoost model for predicting stress response in a decentralized closed-loop additive manufacturing system utilizing post-consumer PET bottles. Initially, the baseline model, which was trained on all 19 extracted features, achieved a root mean square error (RMSE) of 1.336 MPa. This result indicates the presence of redundant and leakage-prone descriptors that hinder generalization across various recycled material conditions. By removing geometrical and post-fracture features, such as width, thickness, area,

elongation, and toughness, the RMSE improved to 1.208 MPa, demonstrating that geometric descriptors are not reliable predictors of variability in recycled PET-based printing. Further reduction of RMSE to 1.108 MPa was achieved by eliminating duplicated and correlated force- and strain-derived inputs, including force (N) and strain percentage, which also enhanced model stability. The exclusion of specimen keys and derived ultimate properties resulted in a more compact feature space and an RMSE of 0.907 MPa. Subsequent grid-search tuning slightly improved the RMSE to 0.901 MPa, suggesting that the primary improvements were due to informed feature selection rather than increased model complexity within this decentralized recycling-driven system.

Table 7. Leakage-aware feature reduction during XGBoost development.				
Iteration phase	Features removed	Features retained	RMSE (MPa)	Interpretation
Baseline	None	All 19 extracted features	1.336	High-dimensional model includes redundant and leakage-prone descriptors
Leakage and geometry	Width, thickness, area, elongation, toughness	Load metrics, strain metrics, material properties	1.208	Removing algebraic and post-fracture descriptors improves generalization
Multicollinearity	Force (N), strain percent	Force (kgf), distortion, material properties	1.108	Duplicate force units and correlated strain descriptors removed
Final optimization	Material, specimen key, UTS, modulus, yield strain	Yield stress, force (kgf), distortion	0.907	Compact mechanics-based feature set prevents identifier memorization

Figure 11 illustrates a progressive reduction in cross-validated prediction error (Group CV RMSE) as leakage-prone, redundant, and correlated features are systematically eliminated during the development of a model for predicting stress response in decentralized closed-loop additive manufacturing using post-consumer PET bottles. Initially, the baseline model, which includes the complete feature set, exhibits an RMSE of 1.336 MPa. This value is influenced by geometrical descriptors and post-fracture or implicitly predictive variables that enhance performance but compromise generalization. The exclusion of geometry-related leakage features reduces the error to 1.208 MPa. Further elimination of multicollinearity decreases the RMSE to 1.108 MPa. Ultimately, the final compact model achieves an RMSE of 0.907 MPa, thereby enhancing interpretability, generalizability, and robustness.

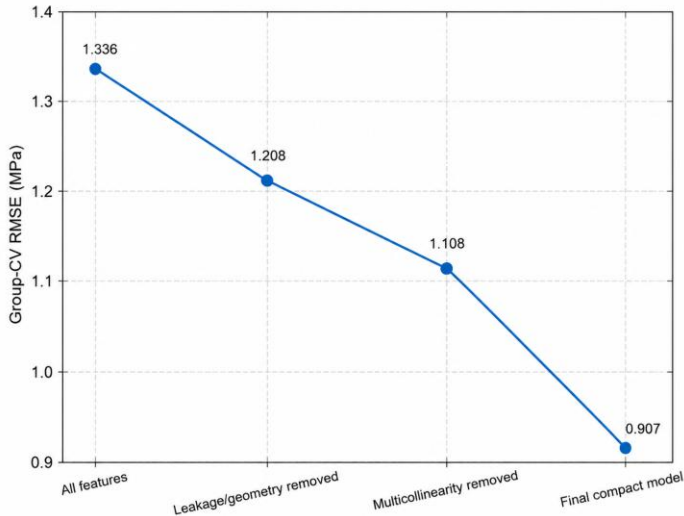


Figure 11. Cross-validation error decreases as leakage-prone and redundant variables are removed, demonstrating the value of physically constrained feature selection.

Table 8 and Figure 12 present a comparison of hyperparameter optimization strategies for the XGBoost-based stress-response prediction model in decentralized closed-loop additive manufacturing using post-consumer PET bottles. The base model, configured with 200 estimators, a maximum depth of 6, and a learning rate of 0.1, achieves an average RMSE of 0.907 MPa, establishing a robust baseline through leakage-aware feature selection. Bayesian optimization, despite exploring a broader parameter space with 548 estimators, a depth of 3, and adjustments to gamma and subsampling, results in a higher RMSE of 1.003 MPa. This suggests over-regularization and a diminished capacity to capture nonlinear stress–strain relationships in recycled PET. Grid search yields the best performance, achieving an RMSE of 0.901 MPa with a simpler configuration of 100 estimators, a depth of 6, and full feature subsampling, indicating that constrained exploration is more effective than probabilistic search. Randomized search performs the worst, with an RMSE of 1.065 MPa, reflecting instability due to a reduced learning rate of 0.0627 and lower subsampling ratios. Overall, hyperparameter tuning provides only marginal gains once meaningful features are established, with grid search offering the most stable improvement. Performance is more significantly influenced by physically informed feature engineering than by hyperparameter complexity.

Table 8. Hyperparameter optimization summary for the XGBoost stress-prediction model.

Hyperparameter	Base model	Bayesian optimization	Grid search	Randomized search
n_estimators	200	548	100	316
max_depth	6	3	6	4
learning_rate	0.1	0.1134	0.1	0.0627
subsample	-	0.9920	1.0	0.6405
colsample_bytree	-	0.7891	1.0	0.8737
min_child_weight	-	1	-	-
gamma	-	0.0026	-	-
Average RMSE (MPa)	0.907	1.003	0.901	1.065

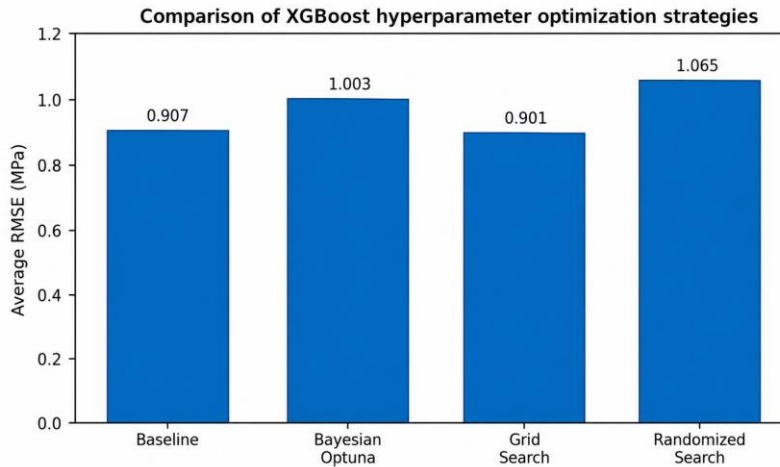


Figure 12. Hyperparameter search comparison. Grid search provided the lowest average group-cross-validation RMSE.

Table 9 and Figure 13 present a comparison between the ultimate tensile strength (UTS) and the UTS predicted by the XGBoost model for filament materials. This comparison demonstrates the model's capability across both commercial and recycled polymers, with prediction errors remaining below 5%. Polylactic acid

(PLA) exhibits the highest experimental UTS at 46.44 MPa, compared to a predicted value of 46.75 MPa, resulting in a 0.67% error. For recycled polyethylene terephthalate (rPET), the experimental UTS values for rPET-1 and rPET-2 are 45.31 MPa and 41.36 MPa, respectively, while the predicted values are 43.28 MPa and 39.86 MPa, with errors of 4.49% and 3.61%. These discrepancies reflect the variability in post-consumer PET feedstock. Polyethylene terephthalate glycol (PETG) demonstrates reliable prediction, with an experimental UTS of 40.17 MPa and a predicted value of 38.97 MPa, resulting in a 2.99% error. Acrylonitrile butadiene styrene (ABS), the material with the lowest strength, is predicted with high accuracy, showing a 0.26% error and a root mean square error (RMSE) of 0.087 MPa. Overall, the data confirm the model's accuracy across different polymer classes and support its suitability for closed-loop monitoring and quality control in decentralized additive manufacturing using post-consumer PET bottles.

Table 9. Experimental versus predicted ultimate tensile strength and category-specific prediction error.

Material type	Experimental UTS (MPa)	Predicted UTS (MPa)	Error (%)	Category RMSE (MPa)
PLA	46.44	46.75	0.67	1.386
rPET-1	45.31	43.28	4.49	1.354
rPET-2	41.36	39.86	3.61	1.248
PETG	40.17	38.97	2.99	0.700
ABS	27.98	27.91	0.26	0.087

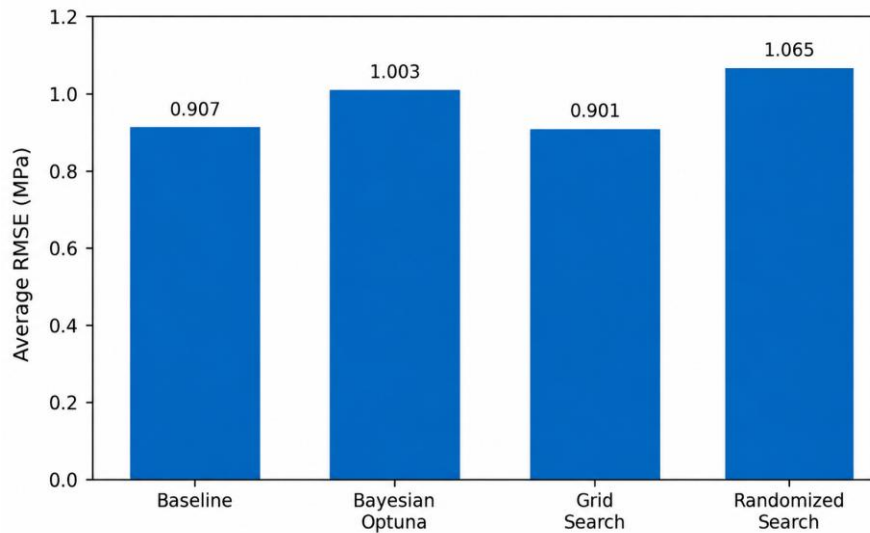


Figure 13. Category-specific RMSE values. Higher errors for rPET indicate the greater material and process variability of decentralized recycled feedstock.

Figure 14 illustrates the parity between the measured and model-predicted ultimate tensile strength (UTS), thereby validating the stress-response model for decentralized closed-loop additive manufacturing utilizing PET bottles. The 45° reference line signifies agreement, with clustering near this line indicating high fidelity and minimal bias. The PLA material demonstrates near-ideal concordance. In contrast, recycled PET variants (rPET-1 and rPET-2) exhibit greater deviation, suggesting increased uncertainty due to feedstock variability, degradation history, and inconsistencies during recycling and extrusion-based printing. PETG maintains alignment with the reference line, while ABS displays the closest agreement, confirming the model's accuracy across both virgin and recycled polymers.

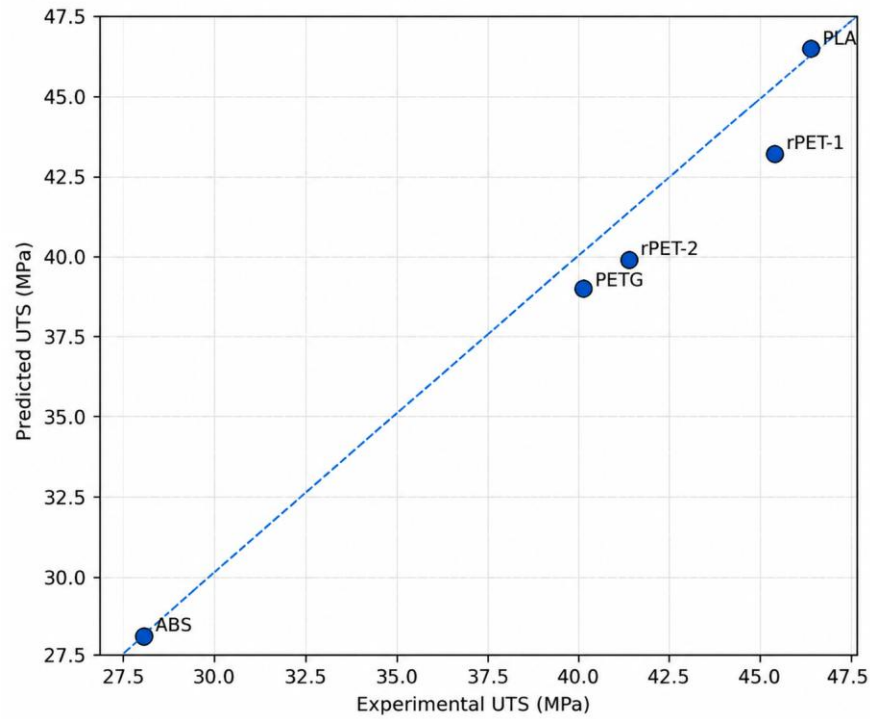


Figure 14. Experimental-predicted UTS parity plot. Points near the dashed line indicate accurate recovery of material-level strength from the continuous stress-prediction model.

Figure 15 presents a comparative analysis of the stress–strain responses for ABS, PETG, PLA, rPET-1, and rPET-2. In this figure, solid curves denote experimental data, while dashed curves represent AI-predicted responses derived from the interpretable stress–response model. The close alignment between experimental and predicted trajectories for most materials indicates the model's efficacy in capturing both elastic deformation and nonlinear plastic behaviour, despite the variability in recycled feedstock. PLA demonstrates the highest stress response, with predicted curves accurately reflecting hardening and peak stress, suggesting robust generalization for virgin thermoplastics. PETG exhibits stable agreement, indicative of the consistent viscoelastic–plastic transition behaviour effectively captured by the learning framework. For rPET-1 and rPET-2, the model accurately tracks overall stress evolution, although minor deviations are observed near yield and post-yield softening due to microstructural heterogeneity, degradation, and extrusion-induced crystallinity variability. ABS displays lower stress levels and smoother alignment, signifying reliable predictions for homogeneous polymer behaviour. Overall, the figure substantiates that the AI-driven framework consistently predicts tensile strength and reconstructs the complete stress–strain response, supporting decentralized additive manufacturing.

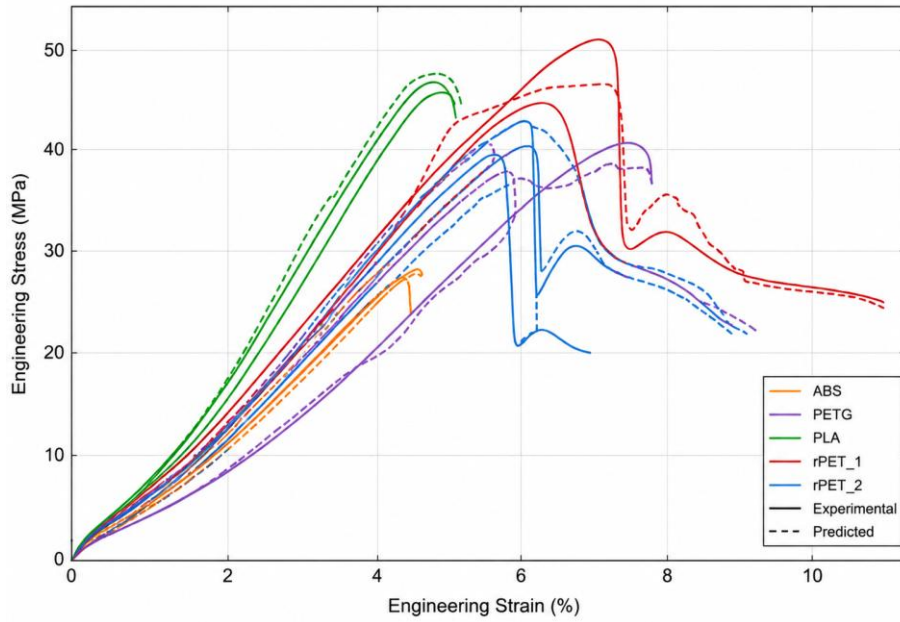


Figure 15. Experimental and predicted stress-strain profiles for all material categories. Dashed curves represent model predictions.

SHAP interpretation (Figure 16) revealed that force was the primary determinant in stress prediction, consistent with engineering stress principles. Yield stress was identified as a significant feature, serving as a material reference point. Distortion provided strain context for deformation. This hierarchy indicates that the model relied on load, extension, and material-yield information in accordance with mechanical principles, rather than arbitrary identifiers or hidden leakage. Such interpretability is essential for materials technologies, where black-box accuracy is insufficient for heterogeneous materials, decentralized processes, and structural decision-making.

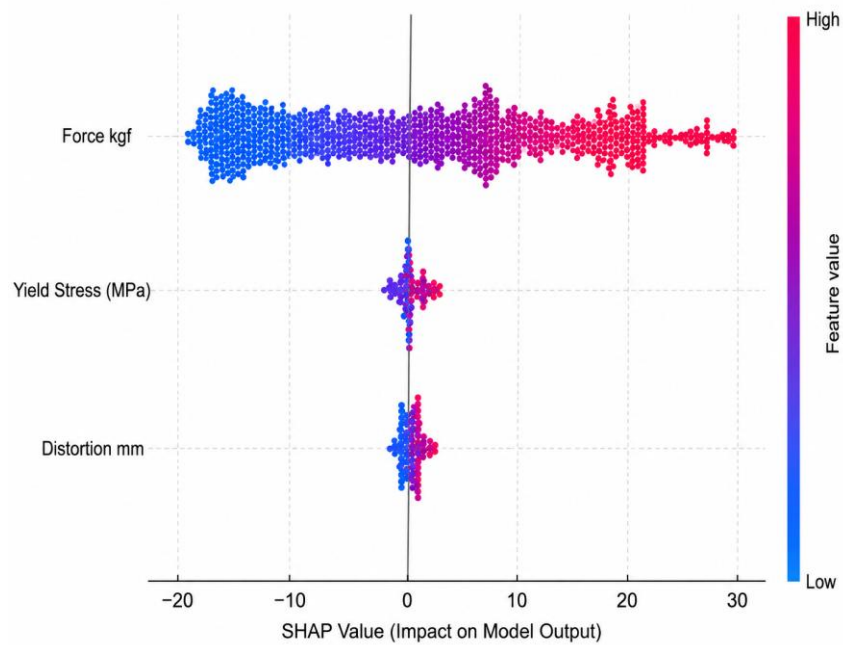


Figure 16. SHAP summary plot showing the global feature impact on stress prediction. Force dominates prediction, followed by yield stress and distortion.

Both experimental and computational findings indicate a quality-control framework for circular additive manufacturing (AM). The extrusion apparatus generates filament from polyethylene terephthalate (PET) waste, while mechanical testing determines the material properties and process parameters. Yield analysis evaluates efficiency, and the interpretable machine learning model facilitates monitoring. This framework demonstrates greater robustness compared to individual print or tensile values. It underpins a technology where operators adjust strip width, oversee filament formation, print test coupons, and employ models for batch assessment.

4. Implications for Sustainable Materials and Technologies

The primary implication for the design of sustainable materials is that recycled polyethylene terephthalate (rPET) should be assessed as a processing-sensitive engineering polymer, rather than as undifferentiated recycled waste. The same polymer can yield varying filament surfaces, seam quality, mechanical variability, and fracture responses, contingent upon the source-bottle wall thickness and strip width. Consequently, decentralized recycling protocols should incorporate straightforward feedstock characterization. Utilizing a caliper to measure wall thickness and selecting an appropriate strip width can minimize trial-and-error processes. Future machine designs should incorporate adjustable strip-width control and filament-diameter sensor feedback to automatically compensate for variations in feedstock geometry. Furthermore, comparisons with commercial filaments provide additional insights into sustainability. Although polylactic acid (PLA) is frequently regarded as environmentally preferable due to its bio-based nature, its environmental benefit is contingent not only on its origin but also on the waste stream it displaces, its service performance, and the durability of printed parts. rPET-1 demonstrated nearly equivalent peak strength to PLA and exhibited greater toughness, thereby supporting a performance-based perspective on circularity: recycled material is sustainable when it can substitute virgin material in a specific function without significant loss in performance or process reliability.

The analysis elucidates the limitations of reporting only Ultimate Tensile Strength (UTS). While Polylactic Acid (PLA) appears optimal when evaluation is confined to peak strength and modulus, the inclusion of elongation and toughness highlights recycled Polyethylene Terephthalate (rPET-1) as the more damage-tolerant option. Considering process repeatability, rPET-2 emerges as a viable choice despite its lower strength. In terms of specific strength, PLA maintains a high ranking due to its lower density, yet rPET remains competitive. These trade-offs are crucial for guiding application selection. rPET is appropriate for models, fixtures, brackets, low-load structural components, replacement parts, and applications where energy absorption is advantageous. Conversely, PLA is preferable for components requiring high stiffness and dimensional stability. Acrylonitrile Butadiene Styrene (ABS) is beneficial when heat resistance and post-processing are priorities; however, under tensile testing conditions, its strength was inferior to that of the rPET variants. The machine learning component facilitates the transition from batch demonstration to batch qualification in decentralized environments, where batch sizes may be small and feedstock quality may vary frequently. A predictive model based on continuous tensile response can mitigate the need for destructive

testing, and group cross-validation demonstrates generalization to unseen specimens, with a Root Mean Square Error (RMSE) below 1 MPa.

The model functions as a foundational tool rather than a comprehensive predictor. It is trained on 15 specimens across five categories under a fixed protocol, demonstrating optimal performance within this specific domain. Future variations in parameters such as nozzle temperature, raster orientation, layer height, moisture, annealing, or chemical composition necessitate updates to the model. The integration of tensile data with extrusion signals, including filament diameter, heater duty cycle, and pulling speed, could facilitate direct prediction of mechanical properties, thereby reducing the need for extensive testing. Material-yield analysis requires careful consideration. A recovery rate of 53.8% is promising but does not fully represent system-wide circularity. The remaining mass, which includes bases, necks, and trimming waste, could potentially be repurposed. Consequently, the yield reflects only the fraction of recovered filament, not the total recoverable PET. Future designs could enhance yield by processing curved sections, employing multiple strip widths, or incorporating preheating and flattening techniques. Economically, the machine is appealing due to its low-cost, modular components, such as heater cartridges, thermostats, and Arduino controllers, which lower adoption barriers in resource-constrained regions. However, its viability is contingent upon factors such as labor, cleaning, electricity, maintenance, and print success. This research refrains from asserting universal cost savings beyond material recovery and potential filament replacement. A comprehensive techno-economic assessment must compare the cost per kilogram of rPET filament with commercial alternatives, taking into account local labor and waste handling costs.

Environmental interpretation necessitates a disciplined approach to scope. This study illustrates material diversion and recovery yield; however, it does not encompass a comprehensive life-cycle assessment. The environmental benefits identified include a reduction in the demand for virgin filament, the elimination of transportation for low-density bottles, and the promotion of circular material usage. Future research should focus on quantifying the energy required for cleaning, cutting, extrusion, and printing processes. Although the literature indicates reductions in embodied energy for recycled polymers, precise values are contingent upon local electricity sources, machine operation, and yield. This work provides a foundation for technology and material performance, while subsequent studies should assess system-level impacts. The experimental limitations offer valuable insights. Only tensile behavior was assessed using 100% rectilinear infill, whereas actual applications may involve varying densities, angles, or geometries. Factors such as moisture content, the chemical condition of rPET, and thermal properties like glass transition and crystallinity were not characterized. These measurements would elucidate differences in strength and ductility. Despite these limitations, this study offers a robust initial demonstration by integrating process optimization, mechanical comparison, yield quantification, and predictive modeling.

The subsequent phase involves converting the platform into a closed-loop adaptive system. Sensors would be employed to measure filament diameter, identify surface defects, and adjust speed or temperature accordingly. The XGBoost model would evolve from a post-test predictor to an in-process quality estimator. By training the model with controlled variations in temperature, speed, and moisture, it would be possible to map

process-property relationships. This system addresses the primary challenge of decentralized recycling: variability. Rather than presuming that waste behaves like virgin pellets, the technology would adapt to fluctuations in feedstock. Overall, the findings confirm that post-consumer PET bottles can be transformed into filament with adequate performance for structural FFF applications. The primary contribution is the comprehensive evidence that local recycling can be engineered, optimized, and modeled, signifying the transition from a sustainability concept to a functional technology.

5. Implementation and Quality-Control Pathway

Defining acceptance criteria for recycled filament is a key implementation challenge. Unlike conventional purchasing, where users assume dimensional consistency and predictable behavior, decentralized recycling requires local verification. A minimum protocol should include four checks: filament diameter, surface continuity, printability, and tensile coupon performance. Diameter ensures drive system compatibility, surface checks identify defects, printability verifies hot-end passage, and tensile tests quantify properties. Once established, machine learning can reduce required coupons by identifying batches matching expected profiles. A practical quality-control strategy uses a tiered workflow. Tier 1 involves visual and dimensional inspection, rejecting sections with seams or swelling. Tier 2 requires printing a standardized coupon from each batch. Tier 3 compares load-displacement responses against model-predicted envelopes. Batches within the trajectory are released for low-risk applications; deviations prompt adjustments to extrusion parameters. This workflow suits university labs and small manufacturers by avoiding complex instrumentation. The technology's primary value lies in localized retention rather than mass production. Converting bulky beverage bottles near the point of use reduces transport costs and creates a visible link between waste and reuse, which is particularly valuable for education. It also supports prototyping in resource-constrained environments by reducing reliance on imported filament. However, this is a complementary pathway for local additive manufacturing, not a replacement for industrial recycling.

The data indicate that product design should consider the balance of properties in rPET. Given that rPET-1 exhibits high toughness and elongation, it is suitable for components where minor deformation prior to failure is permissible, such as covers, clips, housings, supports, brackets, and prototypes exposed to impact. Due to its lower modulus compared to PLA, thin rPET parts may experience greater deflection under identical loads; designers can mitigate this by increasing thickness, incorporating ribs, or altering infill patterns. This approach adapts the geometry to leverage strengths and mitigate limitations. Additionally, process-window results influence machine scalability. A fixed strip width is unlikely to be optimal across different bottle brands, volumes, and wall geometries. Future machine generations should incorporate an adjustable strip-width guide, a thickness measurement station, and a look-up table or software prompt to recommend an initial width. Implementing a low-cost optical diameter sensor between the nozzle and spool could enable the controller to adjust pulling speed, maintaining filament within tolerance and enhancing the machine's utility as a sustainable manufacturing tool. The research also benefits from integrating experimental and predictive evidence, as recycled materials often face credibility challenges. While the interpretable model should not replace mechanical

testing, it can inform testing frequency, identify unusual batches, support future closed-loop control, and enhance overall technical credibility. Table 10 summarizes the design implications, limitations, and proposed future experiments for advancing decentralized rPET additive manufacturing systems.

Table 10. Design implications, limitations and recommended next experiments for advancing decentralized rPET additive manufacturing.

Finding or limitation	Implication	Recommended next step
Source bottle thickness controls strip-width requirements	Feedstock geometry must be measured before extrusion	Develop a strip-width selection chart based on wall thickness and target diameter
rPET-1 maximizes strength and toughness but has higher variation	Thin bottles improve melting but reduce repeatability	Add filament diameter sensing and moisture control to reduce scatter
rPET-2 improves repeatability but lowers mean UTS	Thicker strips feed more consistently but may develop thermal gradients	Evaluate preheating or slower thermal residence time for thicker strips
Yield analysis is limited to filament mass recovery	Whole-system circularity requires energy and emissions accounting	Perform cradle-to-gate LCA with measured electricity, cleaning and failed-print data
Tensile testing used one infill and print orientation	Application performance will depend on print architecture	Test raster angle, layer height, infill density, impact, fatigue and creep
Machine-learning model trained within one experimental domain	Prediction may not generalize to untested printers or processing conditions	Expand the data set with process sensors and retrain using transfer learning
Chemical and thermal degradation were not measured directly	Mechanistic explanation of rPET variability remains incomplete	Add DSC, TGA, FTIR, intrinsic viscosity and rheology measurements

6. Conclusions

This study developed and evaluated a decentralized approach for converting post-consumer PET bottles into functional rPET filament suitable for fused filament fabrication. The results indicated that stable filament production is significantly affected by the interaction between the bottle wall thickness and the strip width. Specifically, bottle walls with a thickness of 0.25 mm required wider strips of 8.5-9.0 mm, whereas thicker bottle walls of 0.475 mm necessitated narrower strips of 6.5-7.0 mm to produce stable 1.75 mm filament. This processing window provides practical guidance for local operators and highlights the importance of considering source geometry as a controllable process variable. Mechanical testing confirmed that the optimized rPET filament is competitive with standard commercial FFF materials. The rPET-1 condition achieved an ultimate tensile strength of 45.31 MPa, which is 97.6% of the measured strength of PLA, while also offering the highest elongation at break and toughness among the materials tested. The rPET-2 condition demonstrated slightly lower strength but improved repeatability. These findings indicate that rPET is not merely a cost-effective alternative; it offers a favorable balance of strength, ductility, and toughness for applications where damage tolerance and energy absorption are critical.

The evaluation of material recovery demonstrated an average yield of 53.8% in converting bottles to filament, with the 1000 mL bottle format achieving the highest yield at 61.3%. This suggests that a substantial portion of local PET waste can be transformed into printable filament. However, future research should address the remaining losses attributed to trimming and geometry. The machine-learning analysis indicated that continuous stress response can be accurately predicted using a leakage-aware and interpretable XGBoost model. The final model achieved a root mean square error (RMSE) of 0.901 MPa under specimen-group cross-validation, with SHAP interpretation showing that predictions were primarily influenced by force, yield stress, and distortion. The integration of hardware, mechanical, sustainability, and machine-learning evidence provides

a practical foundation for circular additive manufacturing using recovered PET bottles. Future research should expand material characterization to include thermal, rheological, chemical, fatigue, and impact properties; assess additional print orientations and infill structures; evaluate energy consumption for a comprehensive life-cycle assessment; and incorporate real-time sensing into the extrusion system for adaptive quality control.

Author Contributions

J. Banarjee: Conceptualization, Methodology, Writing - original draft. **M.H. Miah:** Validation, Writing – review & editing. **H.P. Himel:** Investigation, Dataset Creation. **T.W. Opol:** Software, Visualization. **T.A. Anny:** Resources, Writing – review & editing. **S. Khan:** Supervision, Funding acquisition.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper. The generative AI tool Grammarly was used to improve grammar and academic writing standards. The authors retain full responsibility for the final scientific content and data overlays.

Data Availability

The machine learning datasets, feature optimization logs, and Python scripts used in this study are available on GitHub at: <https://github.com/jolok-banarjee/rPET-Stress-Strain-Prediction>

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Clinical Trial Registration

Not applicable.

Consent to Publish

Consent to Publish declaration: not applicable.

Ethics and Consent to Participate

Ethics and Consent to Participate declarations: not applicable.

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