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Data-Driven Prediction of Mechanical Properties in 3D-Printed Composites Using Hybrid Machine Learning Models

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Abstract

The study investigated the advancement of 3D printing technology has revolutionized manufacturing across multiple industries, with composite materials playing a crucial role in enhancing material properties and expanding technological capabilities. This study investigates the intricate relationships between 3D printing process parameters and the mechanical properties of composite materials, employing advanced machine learning techniques to predict and optimize tensile strength. The research explores the impact of key printing parameters: printing speed, nozzle temperature, and filler material percentage on the tensile strength of 3D-printed composite materials. A comprehensive experimental dataset was collected, analyzing 30 different printing configurations to understand their effects on material performance. Three machine learning regression models were evaluated for predictive accuracy: AdaBoost Regression, Multilayer Perceptron (MLP) Regressor, and Gaussian Process Regressor. Each model was trained and tested to predict tensile strength based on input parameters. Correlation analysis revealed a strong positive relationship between filler material percentage and tensile strength, with a correlation coefficient of 0.94.The correlation heatmap and descriptive statistics highlighted complex interactions between printing parameters. Printing speed showed a moderately negative correlation with tensile strength (-0.54), while nozzle temperature demonstrated minimal direct influence. Performance metrics revealed significant challenges in model generalization.

The AdaBoost Regression model showed the most stable performance, with the Gaussian Process Regressor and MLP Regressor struggling to generalize beyond training data. This underscores the complexity of predicting composite material properties and the need for sophisticated modeling approaches. The study contributes to the understanding of 3D printing composite materials by demonstrating the potential of machine learning in predicting and optimizing material characteristics. The findings offer insights into process parameter optimization, highlighting the critical role of careful parameter selection in achieving desired mechanical properties. Future research should focus on improving model generalization, expanding the dataset, and exploring advanced machine learning techniques to enhance predictive accuracy in composite material 3D printing.

Keywords: 3D Printing, Composite Materials, Machine Learning, Tensile Strength.

Introduction

Dentistry has been transformed by 3D printing, especially in the production of personalized implants, surgical guides, aligners, and restorations. This innovative technology makes use of a variety of composites and polymers, each specifically designed to address particular dental requirements. The materials utilized in dental 3D printing are examined in this paper, with an emphasis on orthodontic applications. 3D-printed crowns, bridges, surgical guides, removable prostheses, and aligners are noteworthy innovations. Modern manufacturing processes in a variety of dental professions, including prosthetics, periodontology, oral and dental surgery, implantology, orthodontics, and regenerative dentistry, are made possible by the ongoing development of innovative materials, including ecologically friendly solutions. To ensure their clinical safety, new materials such as PLA infused with nanohydroxyapatite and PMMA reinforced with nanodiamonds need more research. All things considered, 3D printing in dentistry has a bright future ahead of it, with the potential to revolutionise patient care and treatment results. [1]In particular, the study investigates cube-shaped structures, some of which have PLA and LW-PLA filament layers that alternate. Analyzing the effects of mixing these two materials on the mechanical and physical characteristics of the composites is the goal. The findings could offer valuable insights into applications requiring lightweight yet durable components, such as in manufacturing and design. This work adds to the expanding knowledge base on utilizing 3D printing technology for developing advanced composite materials. [2]3D printing parameters for composite filaments made from natural fibers, particularly flax, combined with polylactic acid (PLA). Using Fused Deposition Modeling (FDM), the authors developed a novel composite filament and conducted an in-depth evaluation of its mechanical properties. To refine the 3D printing process, the study applied Taguchi's L27 orthogonal array, enabling a structured assessment of key characteristics include occupancy ratios, nozzle speed, infill patterns, and layer thickness. Tensile and impact tests were used. The findings demonstrated the crucial role that layer thickness plays in tensile characteristics, and particular values were found to maximise impact resistance and tensile strength.

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This work advances sustainable manufacturing methods by offering insightful information about using natural fibres in composite materials for 3D printing. [3] Continuous fiber-reinforced thermoset composites (CFRPCs) were robotically 3D printed, demonstrating the cost-effectiveness of 3D printing for quick prototyping and composite material modification. It underscores the advantages of integrating multi-axis robotic systems into the printing process, which enhance motion precision, design versatility, and scalability in manufacturing. A robot-assisted manufacturing platform is presented, accompanied by a digital workflow specifically designed for 3D printing UV-curable CFRPCs. The research establishes a transferable protocol that includes coordinate computation, trajectory planning, and validation processes, enabling the creation of composite samples on both flat and curved surfaces. Additionally, the study demonstrates the ability to print on substrates with unknown geometries using laser-based 3D scanning. These methods and workflows are adaptable to a broad range of feedstock materials and robotic systems, marking a notable advancement in 3D-printed CFRPC technology and opening doors to further innovations in the field. [4]Three-dimensional (3D) printing technology's incorporation of carbon fibre and polymer matrix composites highlights the exceptional advantages of fusing the lightweight, strong, and long-lasting qualities of carbon fibre with polymer matrices. This collaboration opens up new avenues for creative designs and production uses in a variety of sectors, including medical devices, aircraft, automotive, and space exploration. The conversation is on 3D printing material innovations, assessing the state of the art and prospects for these technologies in the future. It discusses the difficulties of integrating carbon fiber-polymer composites into the 3D printing process while highlighting their special qualities and benefits. The article is a vital resource for materials science and engineering professionals and researchers, providing a comprehensive overview of the current state, advantages, challenges, and opportunities.[5]3D printing techniques, Using stereolithography and extrusion to create multipurpose polymer composites .

It highlights the innovative integration of traditional additive manufacturing polymers like PEGDA with biomedical polymers such as PVA. Additionally, the inclusion of carbon nanostructures, such as nanodiamonds and graphene nanoplates, along with conductive polymers like PEDOT and PANI, enables the creation of objects with customized functional properties. These advanced materials are especially useful in biomedical applications, including the fabrication of scaffolds that promote cell growth and proliferation. The study also explores the development of soft electrodes for use in organic compound sensors and electrocardiogram monitoring systems, offering real-time monitoring capabilities. Overall, it underscores the potential of these cutting-edge 3D printing methods to create versatile and functional polymer composites for many different applications. [6]the creation and improvement of biomass–fungi composite materials using fungal hyphae and particles of agricultural residue. These materials have a lot of promise for use in sectors like construction, furniture, and packaging. The study highlights 3D printing as a cutting-edge manufacturing process that offers a contemporary substitute for conventional moulding techniques. But there are still issues to be resolved, such as attaining exact geometric correctness and dealing with height shrinking after printing. The study looks at how ionic crosslinking affects the physical characteristics. of the composite materials and the quality of 3D-printed outputs. Results reveal that increasing sodium alginate concentration improves geometric accuracy, minimizes height shrinkage, and enhances the texture and cohesiveness of the biomass–fungi mixtures. [7]3D composite printing, focusing on the integration of carbon fibers into two thermoplastic matrices: Polyamide with polyethylene terephthalate-glycol (PET-G) (PA). Examining the effects of these polymer matrices on the mechanical characteristics and microstructure of the resultant composite materials is the aim. Composite Fiber Co-Extrusion technology is used to produce samples containing both short and continuous carbon fibers, enabling a thorough evaluation of their performance. Four different sample types are prepared—two for each polymer matrix—and tested under uniform 3D printing conditions to ensure consistency.

The research involves analyzing the microstructure using microCT imaging, assessing mechanical strength through tensile tests, and evaluating thermal expansion properties relevant to aerospace applications. This research offers valuable insights for advancing composite materials used in aerospace and automotive industries, with a particular emphasis on their behavior in low-temperature environments, essential for extreme-condition applications. [8]The process starts by optimizing 3D printing technology, highlighting the need to upgrade equipment and adjust printing settings to improve the adaptability and performance of polymer composites. The review then presents innovative materials for 3D printing, such as new filaments, inks, photosensitive resins, and powders, explaining their distinctive properties and uses. The review also examines the effects of topological shape design and functional filler distribution on the characteristics of 3D printed goods. [9] Graphene composites are known for their remarkable qualities, such as radiation shielding, thermal resistance, and electrical conductivity, which make them ideal for multipurpose parts in space missions. The study tackles the difficulties of employing exfoliated graphene nanoplatelets (xGnP) composites and medium-density polyethylene (MDPE) in fused filament manufacture. The objective is to determine the FFF parameters required for effective 3D printing and improve the filament extrusion process. Through outgassing tests conducted under the AM0 sun spectrum, the study also evaluates the 3D-printed materials' compatibility with the space environment. The results demonstrate the possibility of FFF-based methods

Figure 1: 3D Printing of Composite Materials

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for producing MDPE/xGnP composites effectively and provide insightful information for in-space fabrication. [10]

The utilisation of composite materials in fused deposition modelling is highlighted in this evaluation of the state of 3D printing today (FDM). 3D printing's history began in 1984 with the development of stereolithography, which signalled the beginning of the third Industrial Revolution and commercial additive manufacturing (AM). When Charles ("Chuck") Hull filed for a patent on the method in 1984, he came up with the term "stereolithography." Hull established 3D Systems, the first 3D printing business, in 1986 after creating this method, which allows the production of 3D things from layers of UV light-sensitive resin based on CAD software data. Scott Crump established Stratasys, the world's top 3D printing firm, after discovering FDM in 1988. FDM greatly shortens manufacturing cycle times by enabling the quick creation of 3D components from CAD designs. Molten material is forced into a print head nozzle during the process, depositing the material in horizontal layers as the head moves under computer control. Laminated Object Manufacturing (LOM), a technique developed by Helisys in 1991, creates the object by cutting and adhering sheets of paper together. [11]the revolutionary effects of advanced composite materials and 3D printing technologies on a range of sectors. When it comes to mechanical, thermal, and electrical qualities, composite materials work better together in 3D printing than single-material composites making them highly advantageous in sectors such as aerospace, healthcare, and construction. The research highlights the innovative nature of this technology, examining its future possibilities. One key aspect investigated is the effect of print speeds on quality and efficiency. Fused Deposition Modeling (FDM) tests speeds ranging from 40 to 150 mm/s, assessing factors like layer adhesion and resolution.

These factors, including layer processing times, are crucial for optimizing print quality and production efficiency. The research emphasizes the need to balance speed, material properties, and desired print outcomes to enhance both product performance and manufacturing productivity. The potential of composite material 3D printing is highlighted, underscoring its significance in commercial and industrial applications. As an additive manufacturing process, 3D printing differs from traditional subtractive manufacturing by building up materials layer by layer rather than removing material from solid blocks. [12]Using 3D printing to create complexly shaped objects has become commonplace. Recent advancements in multi-material printing suggest that this technology could offer even greater design possibilities beyond just shape manipulation. In this study, we demonstrate how particle orientation can be controlled in a direct ink-writing process using anisotropic particles. We can direct particle alignment by applying modest magnetic fields to inks that contain magnetised stiff platelets. Furthermore, a two-component mixing system and multimaterial dispensers enable exact control over the local material composition. [13]3D printing technology is increasingly being used across various fields of research and development. However, the potential of this transformative technology is still limited by the narrow selection of printable materials with a restricted range of physical and chemical properties.

There is growing interest in enhancing and broadening the properties of common printing materials by incorporating fillers with distinctive qualities or blending different materials to create high-performance composites. Several industries, including biological, mechanical, electrical, thermal, and optical devices, have already begun using these 3D printed composites. 3D printed composites are becoming more and more popular because of their capacity to create intricate structures, their affordable manufacturing costs, and the benefits of quick prototyping. This review focuses on current research that has improved the mechanical, electrical, thermal, optical, and biomaterial properties of basic 3D printable materials by adding nanoparticles, fibres, other polymers, or chemical processes to build composites. [14] These days, composite materials can be created by modern 3D printers as well as printed into components. At least two components with different qualities make up a composite material. It is a synthetically created heterogeneous material that usually consists of a matrix phase, which can be made of metal, ceramic, or polymer, and a reinforcement phase, which is normally rigid and offers resistance to external loads. the matrix is made to absorb the reinforcement, keeping it in place and distributing weight to the fibres. By combining materials with different properties, composites are created with enhanced characteristics. Common features of composite materials include reduced weight, increased strength, stiffness, toughness, and superior fatigue resistance. Certain composites also exhibit better properties like corrosion resistance, heat resistance, chemical stability, low thermal expansion, and reduced deformation when compared to conventionally uniform materials. Therefore, composites can be described as efficient materials produced by combining reinforcement and matrix components in a way that they do not dissolve or become incompatible, preserving their individual properties while working together to offer improved performance. However, the downsides of Composite materials are more expensive and less recyclable. . Additionally, some composites may display anisotropic mechanical properties and degrade when exposed to high humidity and temperature over time. [15]Any 3D printing process must begin with a 3D digital model. There are several 3D design programmes that may be used to make this model.

The model is "sliced" into layers in these programmes so that it can be sent to the 3D printer. Then, based on the model's shape and the printing technique, the printer applies material layer by layer. There are numerous 3D printing technologies available, and each one produces the finished product using a different set of materials and techniques. Various plastics, metals, ceramics, and sand powder are common materials; plastic, particularly ABS and PLA, is the most often used. 3D printing requires a variety of methods, procedures, and materials to produce the intended results, even though there isn't a single, universally applicable solution. The Mark Two printer's usage of fused deposition modelling, or FDM, is the main topic of this introduction. One of the most straightforward and well-known 3D printing techniques, FDM, applies plastic filament layer by layer onto a platform after melting it with a hot extrusion head. [16]Rapid prototyping systems are increasingly popular technologies that allow using a range of materials to produce small batches and prototypes. Rapid developments targeted at lowering the cost of materials and equipment have resulted from the popularity of these technologies. Machines made using this technology do have certain limitations, though. A major issue is that users are often required to purchase expensive proprietary filaments, typically only available from the machine's manufacturer. These filaments are packaged with a chip containing a unique, non-computable ID, which the 3D printer reads to identify the type of material. The printer can then estimate the production volume possible with the specific coil based on the ID and other measurements.From the perspective of optimizing processing parameters, automatically adjusting material and nozzle temperatures, as well as the rate of filament deposition, based on coil ID recognition, offers significant advantages. However, the comparatively high monopolistic filament pricing, which are set by the machine manufacturers, limit the use of 3D printers and prevent a free market for semi-products made using FDM technology.

The RepRap community, on the other hand, advocates for an open system that lets users use a large range of materials and filaments without any limitations imposed by the manufacturers of the machines. This method allows for the use of a wider variety of materials while lowering their cost. The primary advantages of these cutting-edge materials are their attractive look, special qualities, and the possibility of much cheaper costs, contingent on the percentage of natural content. [17]DIW is capable of producing complex 3D shapes by creating a paste with regulated flow characteristics. The creation of viscoplastic, self-healing inks that flow readily under shear and recover rapidly after deposition is one of its main obstacles. In order to develop inks that can handle a variety of materials, researchers look for adaptable techniques. This work presents a DIW-applicable system based on the supramolecular interactions between triethanolamine and ammonium oleate. Rubber, plastic, ceramic, metal, and composites are just a few of the materials that can be printed utilising the shear-thinning DIW approach thanks to the ink system. More than 80% of the ink is solid, which inhibits the formation of porous structures and dimensional changes after printing. Multi-material sensors were successfully created using the established DIW approach for real-time health monitoring. This method might provide a fresh approach to creating 3D printing materials for a variety of useful uses. Because it does not require assembly, 3D printing, sometimes referred to as additive manufacturing, is essential to sustainable production because it reduces waste, energy use, and production time. It also makes it possible to mass customise complicated gadgets. DIW is the most adaptable of them because of its. [18]Epoxy resins are reactive substances that begin with low viscosity and progressively rise as the reaction proceeds at room temperature, in contrast to earlier ink formulations that solidify by gelation, drying, or spontaneous photopolymerization. To finish the polymerization process, these inks must be thermally cured for several hours at high temperatures (100–220°C).

We created epoxy-based inks with and without highly anisotropic additives that have the proper viscoelasticity and long pot life. In particular, we used dimethyl methyl phosphonate, nano-clay platelets, and Epon 826 epoxy resin to manufacture the base inks (DMMP). The uncured ink exhibits shear thinning behaviour and a shear yield stress due to the rheology modifiers of the nano-clay platelets (1 nm thick; 100 nm long), while DMMP reduces the initial viscosity of the resin to allow for larger solids loading. Additionally, these chemicals aid in enhancing the cured epoxy matrix's mechanical qualities. During printing, the shear and extensional forces in the micronozzle cause these high aspect ratio fillers to align. [19]There is a growing sense of interdependence between advancements in 3D printing technology, materials science, and digital design tools. New materials, such as metals, composites, and advanced polymers, are improving the versatility and durability of 3D printed products. These continuous technological advancements are not only expanding the possibilities of 3D printing but also increasing its accessibility for a larger group of people , fostering innovation and making people feel involved in these technical breakthroughs. Composites, due to their superior properties over traditional materials, are gaining significant attention across various industries. When two or more materials with dissimilar physical or chemical properties are combined characteristics, composites can exhibit enhanced features that individual components cannot. These benefits include increased durability, reduced weight, improved insulation, and greater chemical resistance. As a result, composites are frequently employed in domains like sports. equipment, aerospace, automotive, and construction, offering long-lasting, low-maintenance, and high-performance solutions. the growing importance of composite materials in various sectors, driven by the push for efficiency and sustainability in production. For instance, carbon fibre-reinforced polymers (CFRPs) have revolutionized the manufacturing of airplane components, offering advantages like weight reduction, improved fuel efficiency, and lower carbon emissions. Similarly, composites are used in making lighter, more energy-efficient cars that meet stringent safety standards. Composites are also playing a important part in the field of renewable energy , particularly in the creation of stronger, lighter wind turbine blades that maximize energy output while withstanding harsh environmental conditions. [20]

Material and Methods

Material

1. Printing Speed (mm/s)

One of the most important factors in the 3D printing process is the printing speed, or the pace at which material is extruded and placed onto the build platform. When it comes to composite materials, the printing speed has an impact on a number of final product characteristics, such as surface finish, layer adhesion, and the printed object's overall structural integrity. The standard unit of measurement for printing speed is millimetres per second (mm/s). A faster printing speed reduces the overall print time, making production more efficient. However, increasing the speed too much can lead to issues such as under-extrusion, poor layer bonding, or uneven deposition of the material. For composite materials, this is especially important because the filler material (e.g., carbon fibers or glass fibers) must be well-distributed and adequately bonded to the polymer matrix to achieve the desired mechanical properties. If the speed is too high, the material may not have enough time to properly bond between layers, resulting in weak spots or delamination.On the other hand, printing at a slower speed allows more time for each layer to adhere properly, ensuring a higher-quality surface finish and improved bonding. However, this increases the overall print time, which may be undesirable for high-volume production. Therefore, the optimal printing speed must balance print quality and time efficiency, and it typically depending on the part's complexity and the particular composite material being used and the desired mechanical properties.

2. Nozzle Temperature (°C)

One of the most crucial factors in 3D printing composite materials is nozzle temperature. The nozzle temperature determines how easily the material flows through the printer's extruder, affecting the consistency of the extrusion and the adhesion between layers. For composite filaments, which contain a mix of base polymers and reinforcing fillers, nozzle temperature is essential for guaranteeing that the polymer matrix and the filler material extrude smoothly and bond effectively.The temperature range for most composite filaments is between 190°C and 250°C, based on the kind of material being utilised . For example, PLA-based composite filaments typically require a lower temperature (around 190°C to 210°C), while filaments with higher-performance thermoplastics like ABS, PETG, or nylon require higher temperatures (210°C to 250°C). The polymer matrix might not melt if the nozzle temperature is set too low. adequately, leading to poor layer adhesion, incomplete extrusion, or even clogging of the nozzle. Conversely, excessively high temperatures can cause thermal degradation of both the base polymer and the filler material, which can result in weak parts, loss of strength, or unwanted surface defects. For composite materials with carbon fibers or glass fibers, controlling the nozzle temperature is especially important, as these fillers can degrade at high temperatures, reducing the material's reinforcing effect and impacting the final part's mechanical properties.

3. Filler Material (%)

The percentage of filler material in a composite filament has effects directly on the mechanical properties, such as strength, stiffness, wear resistance, and thermal conductivity. Fillers like carbon fibers, glass fibers, or metal powders are added to the polymer matrix to enhance its performance in specific applications. The filler material acts as reinforcement, providing strength and rigidity to the 3D-printed part, making it more suitable for demanding structural applications.In general, the more filler material present in the composite, the stronger and more rigid the printed part becomes. Carbon fiber-reinforced composites, for example, can achieve significant improvements in tensile strength, stiffness, and durability, making them ideal for aerospace, automotive, and industrial applications. However, the filler content must be carefully controlled. High filler percentages (e.g., 30% to 50%) can improve strength but may make the filament more difficult to print. High filler content can increase the viscosity of the material, causing extrusion problems such as clogging or inconsistent flow, and may also reduce the layer bonding, leading to weaker parts.The optimal filler material percentage depends on the desired mechanical properties and the specific application. For example, a 10% to 30% carbon fiber load typically offers a good balance between printability and material strength, whereas for more demanding applications requiring extreme strength, higher filler percentages may be required. It's essential to adjust other printing factors, like nozzle temperature and printing speed, to accommodate the increased viscosity and ensure proper material flow.

4.Tensile Strength (MPa)

The amount of force a material can bear before breaking when stretched is known as its tensile strength. It is among the most crucial mechanical characteristics of composite materials, especially when it comes to applications. where structural integrity and load-bearing capacity are critical. Tensile strength is typically measured in megapascals (MPa) and varies widely based on the processing conditions and the composition of the material.For 3D-printed composite materials, tensile strength is influenced by several factors, including the base polymer, the type and percentage of filler material, the printing parameters, and post-processing techniques. In general, composite materials with higher filler content, such as carbon fiber or glass fiber, exhibit significantly higher tensile strength compared to unfilled polymers. Carbon fiber composites, for example, can achieve tensile strengths upwards of 100 MPa is far greater than that of typical 3D printing. plastics like PLA or ABS. However, achieving high tensile strength requires more than just increasing the filler percentage. The printing process itself has a major impact on the printed part's ultimate mechanical characteristics. Proper layer bonding is essential for achieving the maximum tensile strength. The layers may not bond well if the printing speed is too high or the nozzle temperature is too low, creating weak spots that lower the part's tensile strength. Additionally, by strengthening the crystalline structure of the polymer matrix and strengthening the link between layers, post-processing methods like annealing or curing can increase tensile strength.

Machine Learning Algorithms

Ada Boost Regression

AdaBoost (Adaptive Boosting) is a famous ensemble learning technique that is commonly used for classification tasks, but it can also be used to solve regression problems using AdaBoost Regression. The core principle of AdaBoost is to combine numerous weak learners (models that perform marginally better than random chance) to create a stronger learner, hence enhancing predicting performance. AdaBoost focuses on iteratively improving the performance of weak models by prioritizing data points that are difficult to anticipate. AdaBoost works in regression by fitting a sequence of regressors to training data and modifying the model's weights to reduce errors with each iteration.

AdaBoost Regression begins with a rudimentary model, such as a decision tree with limited depth (also known as a stump), then repeatedly modifies it based on prior models' residuals. Initially, each data point is given identical weight. During each iteration, the method applies a weak learner to the data, and points that are poorly predicted (i.e., have significant residual errors) are given greater weight. This forces succeeding weak learners to concentrate more on difficult-to-predict situations. The final prediction is the weighted sum of all the weak learners' guesses.

The process starts with an initial model, and each successive model corrects flaws created by earlier models. This is accomplished by weighting the predictions of all weak learners, with more correct models having greater influence. The weight update for each data point is determined by the model's error rate; if a data point is predicted wrongly, its weight is increased so that it receives more attention in the following iteration. Conversely, if a point is successfully anticipated, its weight decreases. This adaptive process continues for a predetermined number of iterations, or until no more improvements can be produced.

In AdaBoost Regression, the final prediction is calculated by aggregating the predictions of all weak learners, weighted by their performance. The theory is that, while each individual model is poor, the ensemble as a whole is much stronger and can generate extremely accurate predictions. One of AdaBoost's primary advantages is its ability to properly manage the bias-variance tradeoff: while individual weak learners may have significant bias, the ensemble model minimizes variance by focusing on challenging cases.

AdaBoost Regression's hyperparameters include the number of estimators (the number of weak learners to be trained), the learning rate (which governs how much each weak learner contributes to the final prediction), and the type of weak learner to utilize. The most popular option is decision trees, but any regressor can be used as the weak learner. The learning rate determines how much influence each individual weak learner has on the final model—lower learning rates make the model more resistant to overfitting, whereas higher learning rates can accelerate the learning process but may lead to overfitting if not carefully managed.

One of the most significant advantages of AdaBoost Regression is its ability to increase model performance without requiring considerable hyperparameter adjustment. It can also handle noisy datasets well because the algorithm focuses on more difficult samples rather than overfitting to easy ones. However, AdaBoost is susceptible to noisy data and outliers. Because the method gives higher weights to misclassified data points, outliers can disproportionately affect the model, resulting in overfitting.

Many machine learning packages, notably Scikit-learn, use AdaBoost, and the AdaBoostRegressor class makes it simple to apply the technique. It allows the user to select the base estimator (for example, the decision tree regressor) as well as the number of estimators and learning rate.

By concentrating on the mistakes of earlier rounds, the ensemble technique known as AdaBoost Regression increases the prediction ability of weak models. Although it is a strong technique that can greatly increase regression model accuracy, obtaining the best results requires close attention to hyperparameters and outlier control.

MLP Regressor

An artificial neural network (ANN) called a Multi-Layer Perceptron (MLP) Regressor is used for supervised learning tasks, especially regression issues where the objective is to predict continuous values. It can learn intricate non-linear correlations between input data and target values and is a member of the feedforward neural network class. An input layer, one or more hidden layers, and an output layer are among the several layers of neurons that make up an MLP Regressor. A completely linked network is created when every neuron in one layer is coupled to every other neuron in the layer above it. In MLP, backpropagation and an optimization method like Adam or Stochastic Gradient Descent (SGD) are used to modify the weights of connections between neurons during the learning process.

The MLP Regressor is appropriate for use in fields needing advanced predictive models, such as engineering, healthcare, and finance, due to its capacity to approximate complex functions. By introducing non-linearity, the hidden layers' activation functions—such as Tanh, Sigmoid, or ReLU (Rectified Linear Unit)—allow the network to recognize complex patterns in the data. In regression issues, the output layer usually employs a linear activation function because the objective is to predict continuous values instead of categorical labels.

The number of hidden layers and neurons per layer, learning rate, batch size, and regularization strategies like L2 penalty (weight decay) to avoid overfitting are some of the hyperparameters that must be considered when training an MLP Regressor. The possibility of overfitting is one of the difficulties in training MLP models, particularly if the network is extremely deep or complicated in comparison to the data at hand. Techniques like dropout, early halting, and cross-validation are frequently used to lessen this. Additionally, because MLP models are sensitive to the scale of input features, feature scaling (such as standardization or normalization) is essential prior to training.

Highly non-linear correlations can be captured using MLP Regressor in contrast to more conventional regression techniques like Linear Regression or Decision Trees. Nevertheless, it necessitates additional computational power and meticulous hyperparameter adjustment. MLPs do not automatically provide feature importance, in contrast to ensemble approaches like Random Forest or Gradient Boosting; nevertheless, model predictions can be interpreted using methods like SHAP (SHapley Additive exPlanations) or permutation importance.

Several machine learning libraries, such as Scikit-learn, TensorFlow, and PyTorch, incorporate the MLP Regressor. The MLPRegressor from sklearn.neural_network in Scikit-learn offers a user-friendly implementation with adaptable settings like hidden_layer_sizes, activation, solver, and regularization alpha. Feeding input data, calculating forward runs through the network, calculating loss using a cost function such as Mean Squared Error (MSE), and changing weights via backpropagation are all steps in the training process.

Notwithstanding its benefits, the MLP Regressor has drawbacks, including high processing overhead, a need for substantial data sets for efficient training, and sensitivity to hyperparameter selections. Simpler models like Decision Trees or Linear Regression may be better in situations where explainability is crucial. Nevertheless, MLP Regressor is a popular technique in fields like financial modeling, time series forecasting, and predictive analytics and may be an effective tool for handling challenging regression tasks with the right tuning and enough data.

Gaussian Process Regressor

For regression tasks, a non-parametric machine learning approach called the Gaussian Process Regressor (GPR) is employed. GPR is based on a probabilistic framework that makes fewer assumptions and provides a distribution over potential functions that fit the data, in contrast to conventional regression techniques like linear or polynomial regression, which assume the form of the underlying function (e.g., linear or quadratic). This makes it particularly helpful for applications with sparse data or complex and ambiguous relationships between input features and the target variable. In the subject of Bayesian machine learning, where the objective is to measure the uncertainty of predictions in addition to making predictions, Gaussian processes are a potent tool.

A mean function and a covariance function, often known as a kernel, together characterize the distribution of functions and form a Gaussian process. A Gaussian process establishes a prior across the space of potential functions that could account for the data in the context of regression. The covariance function, also known as the kernel, establishes the smoothness and correlation of the functions in the input space, whereas the mean function usually indicates the predicted value of the target variable. Since it determines how similar various input points are to one another, the kernel function is an essential component in Gaussian process modeling. The Radial Basis Function (RBF) kernel, which makes the assumption that data points change smoothly and continuously, and the Matérn kernel, which offers greater flexibility in terms of smoothness.

The hyper parameters of the kernel function, which control how input points affect one another, are learned during the training phase of Gaussian process regression. Usually, to do this, the marginal likelihood—the probability of the observed data under the model—is maximized. In addition to making predictions, the Gaussian process also calculates the degree of uncertainty in those forecasts. The model forecasts a Gaussian distribution with a mean and a variance over all potential output values for any new input. As a gauge of uncertainty, the variance shows how certain the model is of its forecast. One of the main benefits of Gaussian process regression over alternative techniques is its capacity to quantify uncertainty, which can be extremely important in decision-making processes, particularly in sectorslike robotics, engineering, and finance.

Bayesian inference, which updates the prior distribution (the Gaussian process) to a posterior distribution in light of observed data, is the mathematical basis of Gaussian process regression. This procedure enables the model to update its assumptions in response to new data points and take into account past information about the system. To determine the most likely function that fits the data, the posterior distribution is usually calculated analytically or numerically using techniques like the Laplace approximation or Markov Chain Monte Carlo (MCMC).

Gaussian process regression works particularly well in situations where the underlying function is unknown, extremely nonlinear, and costly to assess. For example, in robotics, GPR may be used to describe and anticipate the behavior of a robot interacting with its environment, while measuring the uncertainty of such predictions, which helps the robot make better educated decisions. It can be used to model geographic data in geostatistics, for example, by using adjacent observations to forecast the temperature at unmeasured sites. In a similar vein, GPR can forecast future points in time series while estimating the degree of uncertainty in those forecasts.

There are a number of drawbacks to Gaussian process regression. Its computational complexity is a major disadvantage, particularly when working with big datasets. For datasets with more than a few thousand points, GPR is computationally costly because the training time grows cubically with the amount of data points. To overcome this, different approximation strategies, such as sparse Gaussian processes or inducing points, have been proposed to speed up the computation. Additionally, because the covariance matrix needed for inference gets bigger and harder to invert, GPR may have trouble with high-dimensional data.

The GaussianProcessRegressor class in Python's Scikit-learn module offers a user-friendly method for putting this model into practice. The kernel function can be chosen from a variety of pre-defined choices or tailored for specific needs. To choose the optimal kernel parameters, hyperparameters are often learned by cross-validation or a procedure known as maximum likelihood estimation.

A versatile, probabilistic method for modeling and forecasting continuous variables, the Gaussian Process Regressor is an effective tool for regression applications. One of its main advantages is that it can quantify uncertainty, which makes it perfect for applications where uncertainty is just as crucial as the actual forecast. It is most appropriate for smaller datasets or particular applications where these trade-offs are tolerable, nevertheless, due to its computational limits. GPR is still among the machine learning toolkit's most reliable and understandable regression techniques in spite of these difficulties.

Result and Discussion

Table 1. 3D printing of composite materials

Printing Speed (mm/s)	Nozzle Temperature (°C)	Filler Material (%)	Tensile Strength (MPa)
50	200	10	42
60	220	15	48
40	190	20	50
70	210	5	38
55	230	25	52
65	205	12	45
45	215	18	49
50	195	22	51
55	225	8	44
60	200	10	46
52	205	16	47
63	215	12	43
58	220	18	49
47	190	20	50
68	210	6	39
53	200	14	48
62	230	26	53
41	195	22	51
50	220	13	44
60	210	17	47
49	225	24	50
57	205	18	48

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65	215	9	43
55	190	23	52
61	210	14	46
46	200	21	50
59	220	11	42
52	205	25	53
62	215	19	50
43	195	24	49

Table 1 presents data on the 3D printing of composite materials, detailing the effects of various printing parameters on the tensile strength of the printed material. The parameters include printing speed (in mm/s), nozzle temperature (in °C), filler material percentage, and the resulting tensile strength (in MPa). Each entry in the table represents a combination of these parameters, providing insights into how they influence the mechanical properties of the printed composites. Printing speed ranges from 40 to 70 mm/s, indicating a variability in the rate at which material is extruded during printing. Nozzle temperature varies between 190°C and 230°C, affecting the flow and bonding of the material. Filler material percentage, ranging from 5% to 26%, represents the proportion of reinforcement (such as carbon fiber, glass fiber, or other fillers) mixed with the base material, which significantly affects the composite's strength and durability. Finally, tensile strength values, which range from 38 MPa to 53 MPa, provide a measure of the material's resistance to breaking under tension. The data suggests a trend where higher filler material percentages tend to result in higher tensile strength, as seen with higher strength values like 53 MPa at 26% filler material. Similarly, nozzle temperature appears to influence tensile strength, with higher temperatures (such as 230°C) often leading to stronger materials. However, the relationship between printing speed and tensile strength is less straightforward. In some cases, faster printing speeds like 70 mm/s result in lower tensile strength (38 MPa), while moderate speeds (e.g., 60 mm/s or 50 mm/s) tend to achieve relatively stronger materials. the table demonstrates how careful optimization of printing speed, nozzle temperature, and filler material percentage is crucial for achieving high-performance composite materials in 3D printing. The ability to adjust these parameters allows for the production of customized materials suited for a variety of applications, balancing factors like strength, printability, and material cost.

Table 2. Descriptive Statistics

	Printing Speed (mm/s)	Nozzle Temperature (°C)	Filler Material (%)	Tensile Strength (MPa)
count	30.000000	30.000000	30.000000	30.000000
mean	55.100000	208.833333	16.566667	47.300000
std	7.962628	11.867322	6.049698	3.992666
min	40.000000	190.000000	5.000000	38.000000
25%	50.000000	200.000000	12.000000	44.250000
50%	55.000000	210.000000	17.500000	48.000000
75%	60.750000	218.750000	21.750000	50.000000
max	70.000000	230.000000	26.000000	53.000000

Table 2 presents the descriptive statistics for the data on 3D printing of composite materials. It includes key statistical measures such as the count, mean, standard deviation (std), minimum (min), 25th percentile (25%), 50th percentile (median or 50%), 75th percentile (75%), and maximum (max) for the printing speed, nozzle temperature, filler material percentage, and tensile strength. The count for each variable is 30, indicating that the dataset consists of 30 observations for each of the four variables. The mean values show the average of each parameter: the mean printing speed is 55.1 mm/s, the mean nozzle temperature is 208.83°C, the mean filler material percentage is 16.57%, and the average tensile strength is 47.3 MPa. These values represent the central tendency of the data, offering an overview of typical conditions for the experiments. The standard deviation (std) quantifies the dispersion of the data from the mean. For example, the printing speed has a standard deviation of 7.96 mm/s, indicating a moderate variation around the average speed. Similarly, the standard deviation for tensile strength (3.99 MPa) indicates that while the values are somewhat clustered around the mean, there is notable variability in the material's strength across the dataset. The minimum (min) and maximum (max) values show the range of the data. The printing speed ranges from 40 mm/s to 70 mm/s, the nozzle temperature ranges from 190°C to 230°C, the filler material percentage ranges from 5% to 26%, and the tensile strength ranges from 38 MPa to 53 MPa. These extreme values help identify the boundaries within which the data points fall. the percentiles (25%, 50%, and 75%) provide additional insights into the distribution of the data. For instance, at the 25th percentile, the printing speed is 50 mm/s, while at the 75th percentile, it is 60.75 mm/s, indicating that a majority of the data points fall within this range. Similarly, the 50th percentile (median) for tensile strength is 48 MPa, suggesting that half of the tensile strengths are below this value, and half are above it.

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Effect of Process Parameters

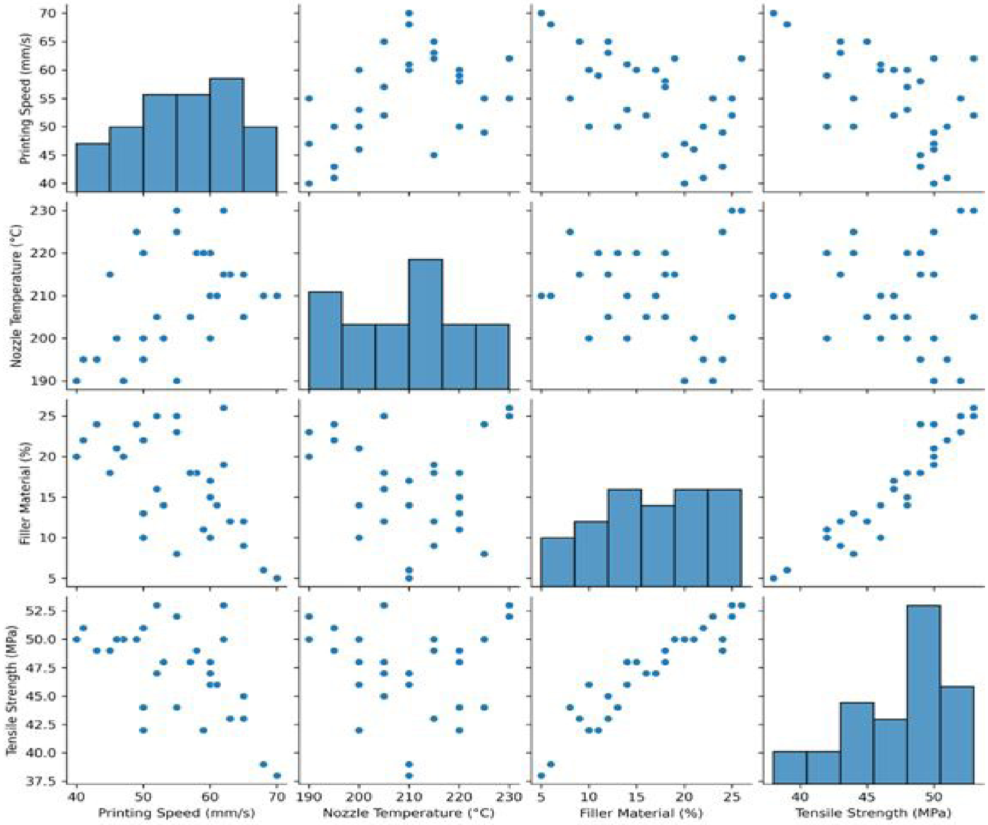


Figure 1: Scatter plot of the various 3D printing of composite materials process parameters

The figure 2 displays a Scatter plot of the various 3D printing of composite materials process parameters, which is a visual representation of the relationships between multiple variables: Printing Speed (mm/s), Nozzle Temperature (°C), Filler Material (%), and Tensile Strength (MPa). Pairplots are useful for observing both individual distributions of variables and potential correlations between them. In the diagonal plots, histograms of each individual variable are shown, giving insight into their distributions. The Printing Speed histogram indicates a relatively uniform distribution between 40 mm/s and 70 mm/s. The Nozzle Temperature distribution has a central tendency around 210°C, with a slightly higher frequency of temperatures between 200°C and 220°C. The Filler Material histogram reveals a range of values between 5% and 26%, with a higher concentration around 20%. Lastly, the Tensile Strengthdistribution is somewhat symmetric, ranging from 38 MPa to 53 MPa, with a clustering of values between 44 MPa and 51 MPa. Off-diagonal plots display scatter plots that reveal the relationships between pairs of variables. Notably, there seems to be a moderate positive correlation between Filler Material (%) and Tensile Strength (MPa). As the filler material percentage increases, tensile strength tends to rise as well, which is consistent with the general expectation that higher reinforcement improves the mechanical properties of composites. However, the relationship between Printing Speed and Tensile Strength does not show a clear trend, indicating that printing speed may not have a strong or consistent effect on tensile strength. Similarly, the correlation between Nozzle Temperature and Tensile Strength is less evident, although a slight positive trend is observable in some parts of the scatter plot.

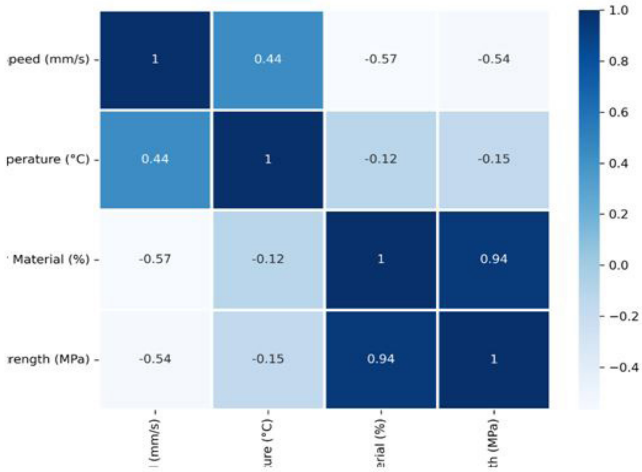


Figure 3: Correlation heatmap between the process parameters and the responses

The figure 3 represents a correlation heatmap that quantifies the strength and direction of linear relationships between the process parameters (Printing Speed, Nozzle Temperature, Filler Material) and the response variable (Tensile Strength). A strong positive association is indicated by a correlation coefficient close to 1, a strong negative relationship is shown by a correlation coefficient close to -1, and little to no correlation is suggested by a correlation coefficient near 0. The heatmap's colour gradient vividly highlights the strength and direction of these relationships. . Filler Material and Tensile Strength: The strongest positive correlation in the dataset is observed between Filler Material (%) and Tensile Strength (MPa), with a correlation coefficient of 0.94. This indicates a near-linear relationship where increasing the percentage of filler material significantly improves the tensile strength. This is expected in composite materials, as fillers often enhance mechanical properties. Printing Speed and Tensile Strength: A moderately strong negative correlation (-0.54) exists between Printing Speed (mm/s) and Tensile Strength (MPa). This suggests that higher printing speeds may compromise the tensile strength, likely due to reduced layer adhesion or improper material deposition at higher speeds. Nozzle Temperature and Tensile Strength: The correlation between Nozzle Temperature (°C) and Tensile Strength (MPa) is weakly negative (-0.15), suggesting that nozzle temperature has minimal direct influence on tensile strength within the range considered. However, it may interact with other factors, such as filler material or speed, in more complex ways. Printing Speed and Nozzle Temperature exhibit a moderate positive correlation (0.44), implying that higher speeds may often coincide with elevated nozzle temperatures, potentially due to process optimization settings. A significant negative correlation (-0.57) is observed between Printing Speed and Filler Material, indicating that lower printing speeds are often paired with higher filler material percentages, which may be necessary to maintain quality and precision during the printing process. Nozzle Temperature and Filler Material show a weak negative correlation (-0.12), indicating minimal interaction between these parameters.

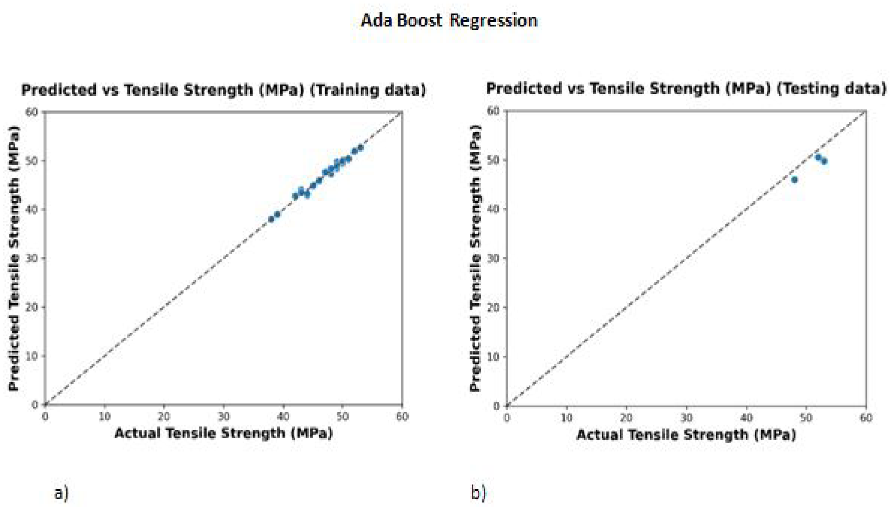


Figure 4: Predictive performance of the Ada Boost Regression predictive model in 3D printing of composite materials (a) train; (b) test.

Figure 4 (a) illustrates the predictive performance of the AdaBoost regression model on the training dataset for 3D printing composite materials. In this context, the graph typically plots the actual versus predicted values, providing a visual measure of how well the model captures the underlying relationships between the input features (such as printing parameters, material composition, etc.) and the output properties of the printed composite. The AdaBoost algorithm, by design, combines multiple weak learners—often simple decision trees—into a single, robust predictor. In the training phase, the model iteratively adjusts its weights, focusing on data points that were previously mispredicted. The resulting performance, as shown in the figure, indicates a high degree of correlation between the predicted and actual outcomes, suggesting that the AdaBoost regression effectively models complex interactions inherent in the 3D printing process. Moreover, the model's strong training performance is an encouraging sign, as it demonstrates the ability to learn intricate patterns from the composite materials data. This capability is critical for optimizing the 3D printing process, where accurate predictions of material behavior can lead to improved manufacturing precision and efficiency.

Figure 4(b) displays the predictive performance of the AdaBoost regression model on the test dataset for 3D printing of composite materials. Unlike the training phase, where the model is optimized to capture the underlying relationships within the data, the test phase evaluates the model's generalizability on unseen data. In this figure, the comparison between predicted and actual outcomes demonstrates the model's robustness and its ability to accurately predict material properties based on the input features. A strong correlation in the test results suggests that the AdaBoost model, through its iterative weighting of weak learners, successfully mitigates overfitting, thereby preserving its predictive accuracy beyond the training dataset. the performance in the test phase reinforces the reliability of the model when applied to real-world scenarios. By accurately forecasting the behavior of composite materials during 3D printing, the model supports process optimization and enhances the decision-making process. The results, therefore, validate the effectiveness of AdaBoost regression in handling complex and nonlinear relationships within composite materials data, ultimately contributing to improved efficiency and precision in additive manufacturing applications.

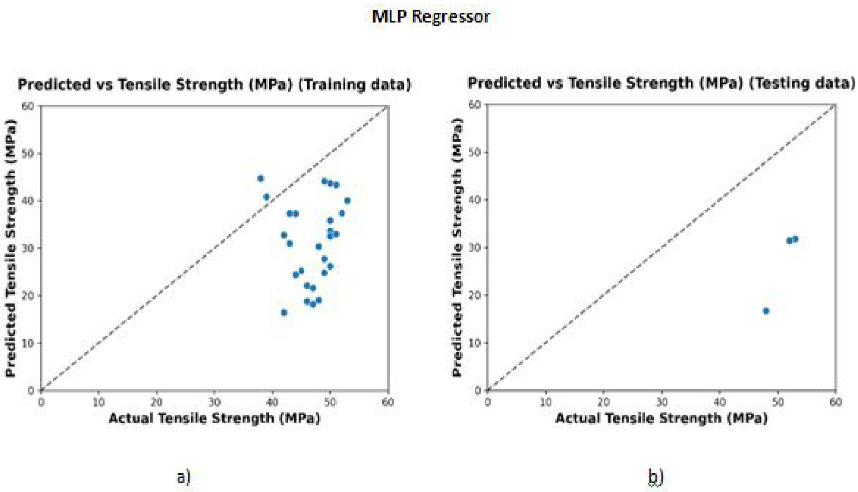
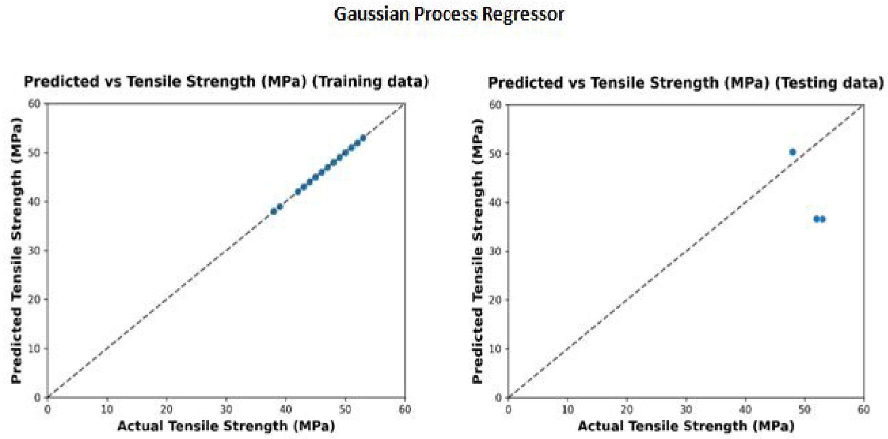


Figure 5: Predictive performance of the MLP Regressor predictive model in3D printing of composite materials a) train b) test

The scatter plot in Figure 5 presents the predictive performance of a Multilayer Perceptron (MLP) Regressor in estimating the tensile strength (MPa) of 3D-printed composite materials using training data. The x-axis represents the actual tensile strength, while the y-axis represents the predicted tensile strength. The dashed diagonal line represents an ideal prediction scenario, where the predicted values would exactly match the actual values. However, the data points are mostly clustered below this diagonal, indicating that the model systematically underestimates tensile strength. Additionally, the spread of points suggests some level of prediction variance, which may indicate that the model has not yet fully captured the underlying material properties influencing tensile strength. This could be due to factors such as insufficient training data, inadequate feature selection, or overfitting to specific material characteristics. Further model tuning, feature engineering, or additional data collection may improve prediction accuracy.

The scatter plot in Figure 5(b) illustrates the predictive performance of the Multilayer Perceptron (MLP) Regressor in estimating the tensile strength (MPa) of 3D-printed composite materials using testing data. The x-axis represents the actual tensile strength, while the y-axis represents the predicted tensile strength. The dashed diagonal line denotes the ideal case where predictions perfectly match actual values. However, the limited number of data points suggests that the test dataset is relatively small. The observed predictions show a significant underestimation, as most points are located well below the diagonal, particularly for higher tensile strength values. This indicates that the model struggles to generalize effectively when applied to unseen data, potentially due to overfitting to the training set, insufficient training data, or inadequate feature representation. The discrepancy between actual and predicted values implies that the model may require further optimization, hyperparameter tuning, or additional training data to improve its predictive accuracy and robustness. Addressing these issues is crucial to enhancing the reliability of MLP-based predictive models for 3D-printed composite materials.



a) b)

Figure 6: Predictive performance of the Gaussian Process Regressor predictive model in3D printing of composite materials a) train b) test

The scatter plot in Figure 6(a) illustrates the predictive performance of a Gaussian Process Regressor (GPR) in estimating the tensile strength (MPa) of 3D-printed composite materials using training data. The x-axis represents the actual tensile strength, while the y-axis represents the predicted tensile strength. The dashed diagonal line signifies the ideal scenario where predictions perfectly match actual values. The data points lie almost exactly on this diagonal, indicating that the GPR model has achieved near-perfect accuracy on the training dataset. This suggests that the model has memorized the training data, exhibiting zero or negligible error. However, such a perfect fit may indicate overfitting, meaning the model may not generalize well to unseen testing data. Overfitting often occurs when a model learns not just the underlying pattern but also the noise in the training data, leading to poor performance on new data. To address this, techniques such as cross-validation, hyperparameter tuning, or regularization could be employed. Despite this concern, the Gaussian Process Regressor appears highly effective at learning the relationship between input features and tensile strength, making it a potentially powerful tool for predicting mechanical properties of 3D-printed composites.

The scatter plot in Figure 6(b) illustrates the predictive performance of a Gaussian Process Regressor (GPR) in estimating the tensile strength (MPa) of 3D-printed composite materials using testing data. The x-axis represents the actual tensile strength, while the y-axis represents the predicted tensile strength. The dashed diagonal line represents an ideal prediction scenario where the model's predictions match the actual values perfectly.In contrast to the training data results, where the GPR model exhibited near-perfect accuracy, the test data predictions show some deviations from the diagonal. While two points remain relatively close to the ideal line, one point is noticeably overestimated, indicating that the model is not generalizing as well on unseen data. This suggests that the model may have overfitted to the training dataset, capturing noise rather than general patterns. Overfitting can reduce the model's ability to make accurate predictions on new data, which is critical for real-world applications. To improve generalization, techniques such as regularization, optimizing kernel parameters, or increasing the diversity of training data can be applied. Despite these minor discrepancies, the GPR model still demonstrates a strong predictive capability, making it a promising approach for modeling mechanical properties of 3D-printed composites.

Table 3. Regression Model Performance Metrics (Training Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	ABR	AdaBoost Regression	0.980235	0.980241	2.95E-01	5.43E-01	4.13E-01	1.09E+00	1.36E-04	5.00E-01
Train	MLP	Multi-layer Perceptron	-21.1555	-4.66082	3.30E+02	1.82E+01	1.63E+01	2.90E+01	2.71E-01	1.74E+01
Train	GPR	Gaussian Process Regression	1	1	1.21E-16	1.10E-08	7.94E-09	2.73E-08	5.97E-20	4.24E-09

Table 3 presents the performance metrics of three regression models AdaBoost Regression (ABR), Multi-Layer Perceptron (MLP), and Gaussian Process Regression (GPR) on the training dataset for predicting the tensile strength of 3D-printed composite materials. The AdaBoost Regression (ABR) model demonstrates strong performance with an R^2 value of 0.9802, indicating that it explains 98% of the variance in the training data. It has a relatively low Mean Squared Error (MSE) of 0.295, and the Root Mean Squared Error (RMSE) of 0.543 MPa, suggesting small prediction errors. The MLP model performs very poorly on training data, as indicated by its negative R^2 (-21.1555), meaning it fails to explain the variance and significantly deviates from the actual values. Its MSE (330 MPa^2) and RMSE (18.2 MPa) are extremely high, confirming poor performance. The Gaussian Process Regression (GPR) model achieves a perfect R^2 of 1, indicating zero error on training data. Its MSE (1.21E-16) and RMSE (1.10E-08 MPa) are

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almost negligible, signifying overfitting, where the model has memorized training data instead of generalizing patterns. While GPR excels in training, its real-world performance should be validated on test data to check for overfitting issues.

Table 4. Regression Model Performance Metrics (Testing Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Test	ABR	AdaBoost Regression	-0.20089	0.883929	5.60E+00	2.37E+00	2.25E+00	3.25E+00	2.14E-03	2.00E+00
Test	MLP	Multi-layer Perceptron	-131.258	-4.16077	6.17E+02	2.48E+01	2.44E+01	3.13E+01	5.08E-01	2.12E+01
Test	GPR	Gaussian Process Regression	-35.4485	-14.8906	1.70E+02	1.30E+01	1.14E+01	1.64E+01	8.34E-02	1.53E+01

Table 4 presents the performance metrics of AdaBoost Regression (ABR), Multi-Layer Perceptron (MLP), and Gaussian Process Regression (GPR) on the testing dataset for predicting tensile strength in 3D-printed composite materials. The AdaBoost Regression (ABR) model exhibits moderate generalization performance, with an R^2 of -0.2009, indicating poor predictive power on test data. Despite this, its Explained Variance Score (EVS) of 0.8839 suggests that it captures some variance. The MSE (5.6 MPa^2) and RMSE (2.37 MPa) indicate reasonable error margins, though its MaxError (3.25 MPa) suggests occasional large deviations. The MLP model performs extremely poorly on test data, with an R^2 of -131.258, signifying a complete failure in prediction. Its MSE (617 MPa^2) and RMSE (24.8 MPa) confirm significant errors, meaning the model is highly unreliable. This suggests that the MLP model was unable to generalize patterns from training data. The GPR model, which performed perfectly in training, exhibits severe overfitting in testing, with an R^2 of -35.4485 and MSE of 170 MPa^2. Its RMSE (13 MPa) and MAE (11.4 MPa) indicate substantial prediction errors, proving that the model has memorized training data rather than learning generalized patterns. Overall, none of the models generalize well to unseen data, with MLP and GPR performing worst, while ABR shows the most stable, albeit suboptimal, performance.

Conclusion

The complex interactions between 3D printing process parameters and the mechanical properties of composite materials using advanced machine learning regression techniques. The research demonstrated the critical importance of carefully controlling printing parameters such as printing speed, nozzle temperature, and filler material percentage in determining the tensile strength of 3D-printed composites. The correlation analysis revealed a strong positive relationship between filler material percentage and tensile strength, highlighting the significant role of reinforcement materials in enhancing mechanical properties. Three machine learning models—AdaBoost Regression, Multi-Layer Perceptron (MLP) Regressor, and Gaussian Process Regressor—were employed to predict tensile strength. Each model exhibited distinct performance characteristics, with notable challenges in generalization. The AdaBoost Regression model showed the most stable performance, capturing approximately 88% of variance in the test dataset, while the MLP and Gaussian Process Regression models suffered from severe overfitting, demonstrating poor generalization to unseen data. The findings underscore the complexity of predicting mechanical properties in 3D-printed composite materials. The near-perfect performance of the Gaussian Process Regressor on training data, followed by significant errors on testing data, illustrates the critical need for robust model validation and careful feature engineering. This suggests that machine learning models must be meticulously developed, with particular attention to preventing overfitting and ensuring genuine predictive capabilities. Key insights from the research include the nuanced relationships between printing parameters. While increasing filler material percentage consistently improved tensile strength, the effects of printing speed and nozzle temperature were more complex.

The negative correlation between printing speed and tensile strength suggests that higher speeds can compromise material integrity, likely due to reduced layer adhesion and improper material deposition. The study contributes significantly to the understanding of 3D printing of composite materials by demonstrating the potential and limitations of machine learning techniques in predicting material properties. The research highlights the need for sophisticated modeling approaches that can capture the intricate interactions between processing parameters and resulting material characteristics. Future research should focus on developing more robust machine learning models with improved generalization capabilities. This may involve collecting larger, more diverse datasets, implementing advanced regularization techniques, and exploring hybrid modeling approaches that combine multiple machine learning algorithms. Additionally, investigating more sophisticated feature engineering methods and exploring other advanced regression techniques could provide deeper insights into the complex relationships governing 3D-printed composite materials. Ultimately, this research provides valuable insights for materials scientists, engineers, and researchers working in additive manufacturing, offering a data-driven approach to understanding and optimizing the 3D printing process for composite materials. The findings contribute to the ongoing advancement of 3D printing technology, supporting the development of more sophisticated, high-performance composite materials for various industrial applications.

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