

Objective

This study investigates the ample contribution of machine and deep learning algorithms as a predictive tool in additive manufacturing. This research aims at leveraging the high computational ability of machine learning algorithms to build predictive models that can be applied in prediction of mechanical behavior of additively manufactured components.

Introduction

Additive manufacturing (AM) and 3D printing are words that can be used interchangeably and still connote exact same thing. Additive manufacturing is a fabrication process that enables the transformation of a 3D model (CAD) designed and stored on the computer to physical object by means of layer-wise stacking of material until object is completely formed [1]. Advances in technology have ushered revolutionary development in fabrication of industrial, commercial and domestic products. 3D printing is increasingly being adopted and utilized in prototype fabrication, reverse engineering, and small run batch manufacturing. Additive manufacturing provides a rapid and cost-effective fabrication method of shaping materials like plastic, metal, ceramic, cells and tissues into design specific components. Fused Filament Fabrication (FFF) method is a well-suited manufacturing technique for reliability studies because of the different levels of input parameters and controlled performance. [2]. Fiber Reinforced Additive Manufacturing (FRAM) offers different answers for industrial application as it joins the adaptability of AM and the benefits of composite material (CM)[3].

Machine learning (ML) has emerged as a viable option in the additive manufacturing domain in recent years as a means of developing highly flexible models that describe complex relationships between material properties and printing parameters.

Most recent survey of machine learning application are set around utilization of Artificial Neural Network (ANN), Genetic Algorithm (GA), Support Vector Machines (SVM) in prediction making[4][5].

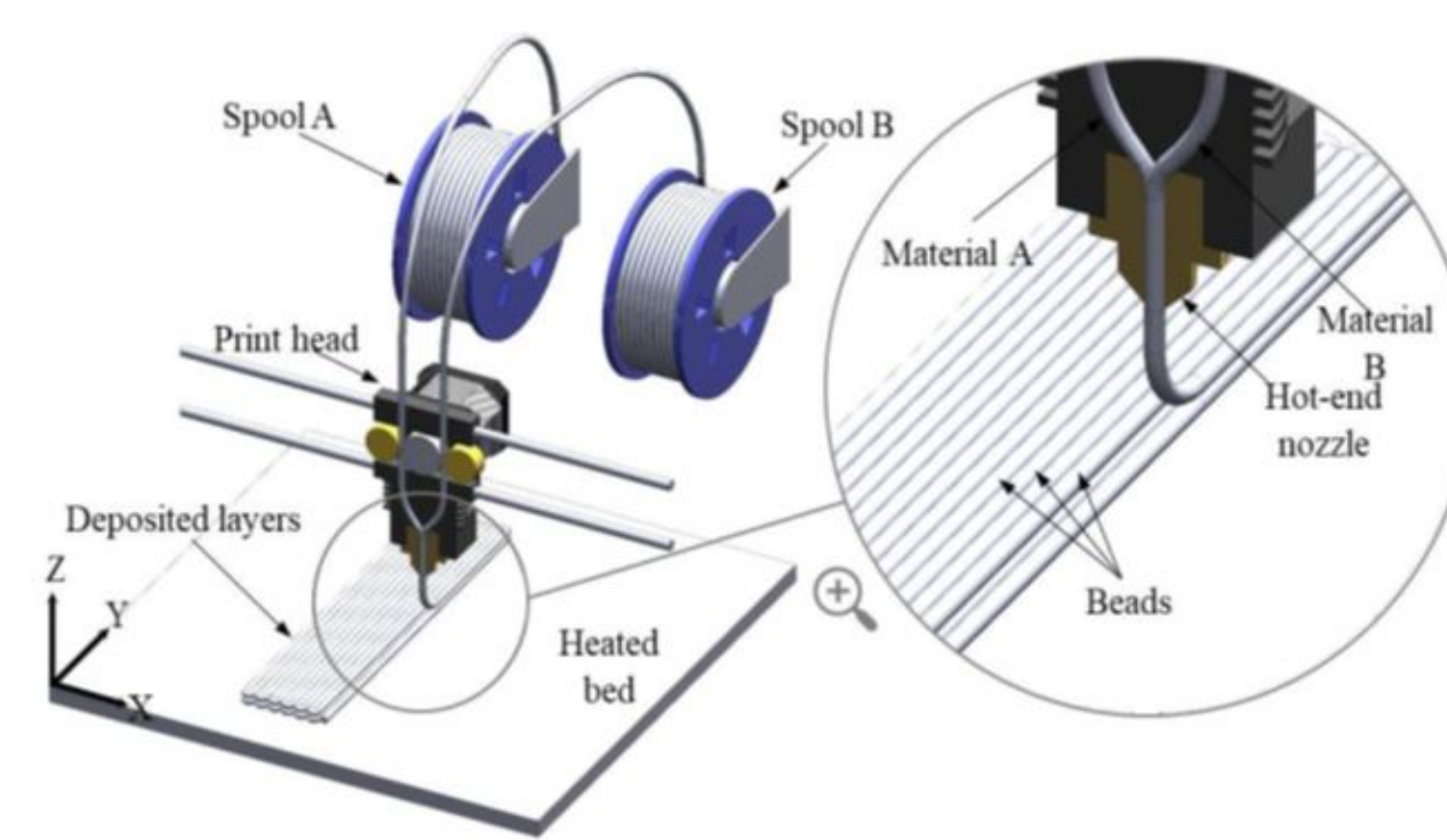


Figure 1: Fused Filament Fabrication

Methodology

Sample Development

The samples are printed according to ISO 178 standard. The computer aided diagram (CAD) geometry of the samples are designed with SOLIDWORKS. The sample has a dimension of 80mm by 10mm by 4mm. Ultimaker 4.8.0, the slicing software used converts the CAD model from stereolithography (STL) format to a G-code format which can be easily read by the printer. The printing parameters, which is an important consideration on the research are easily controlled on the slicing software, and the variation in these parameters can be easily investigated.

The test samples are printed using Ultimaker S5 dual extruder 3D printer.

All samples are printed varying three parameters this research work investigates, layer height, printing speed and infill percentage. Three different values were considered for this research. Layer heights of 0.1, 0.2- and 0.3-mm. printing speeds of 40, 55 and 70mm/s and lastly infill percentages of 90%, 95% and 100%.

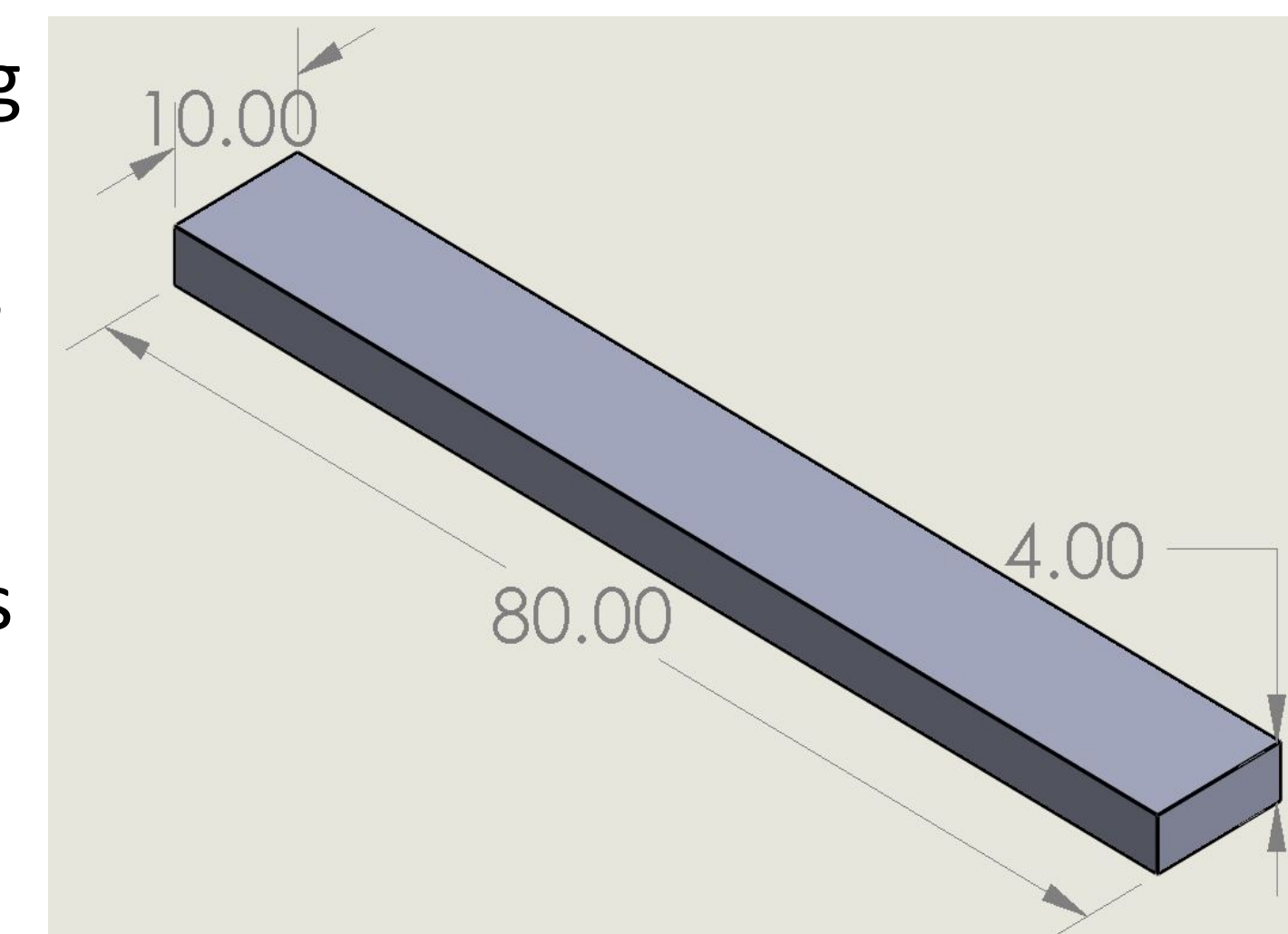


Figure 2: CAD design of the sample

Experimental Setup

Flexural tests are carried out on all samples printed, the data log from Test Resources 1000R test system are used to calculate the flexural strength and stiffness of the samples. The calibrated force range accommodates the failure point for both pure PLA and Carbon Fiber reinforced PLA, the pure PLA serves a benchmark for the material properties, as investigate CFR. The dataset collected from the experimental setup is used as an input parameter for machine learning algorithm for computational and predictive analysis.

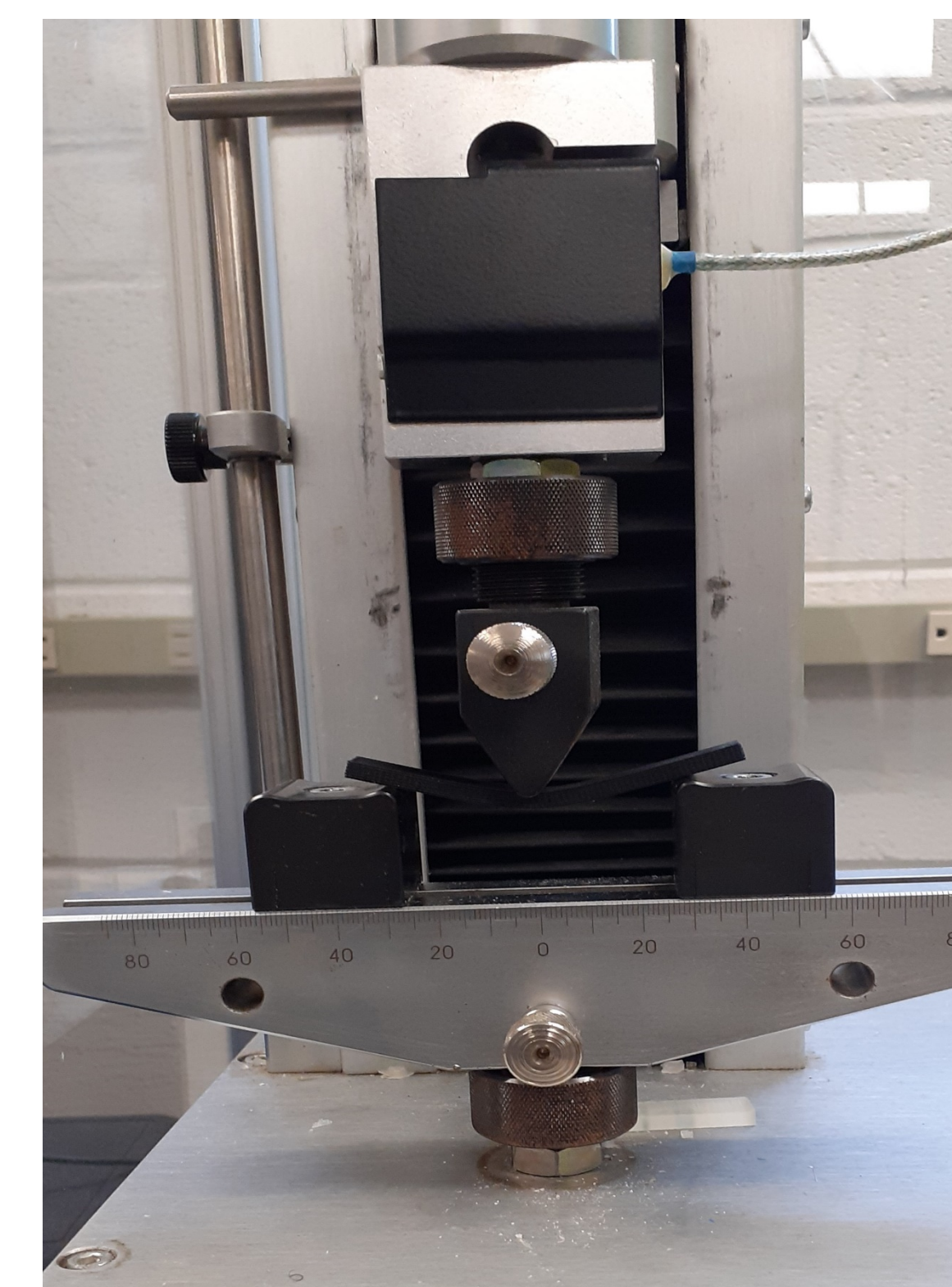


Figure 3: Sample in flexural test position

Preliminary Result

The effect of printing parameters on the stiffness on pure PLA and Carbon Fiber PLA is investigated. The printing speed seems not to have noticeable effect on the stiffness of the material, when compared to effects of layer height and infill percentage. Although the parameters are close in value, machine learning algorithm will be used to justify the distinguishable effects of all the printing parameter and its effect on mechanical properties. Prediction will also be made from the ML model on the mechanical behavior due to the changes in printing parameters investigated.

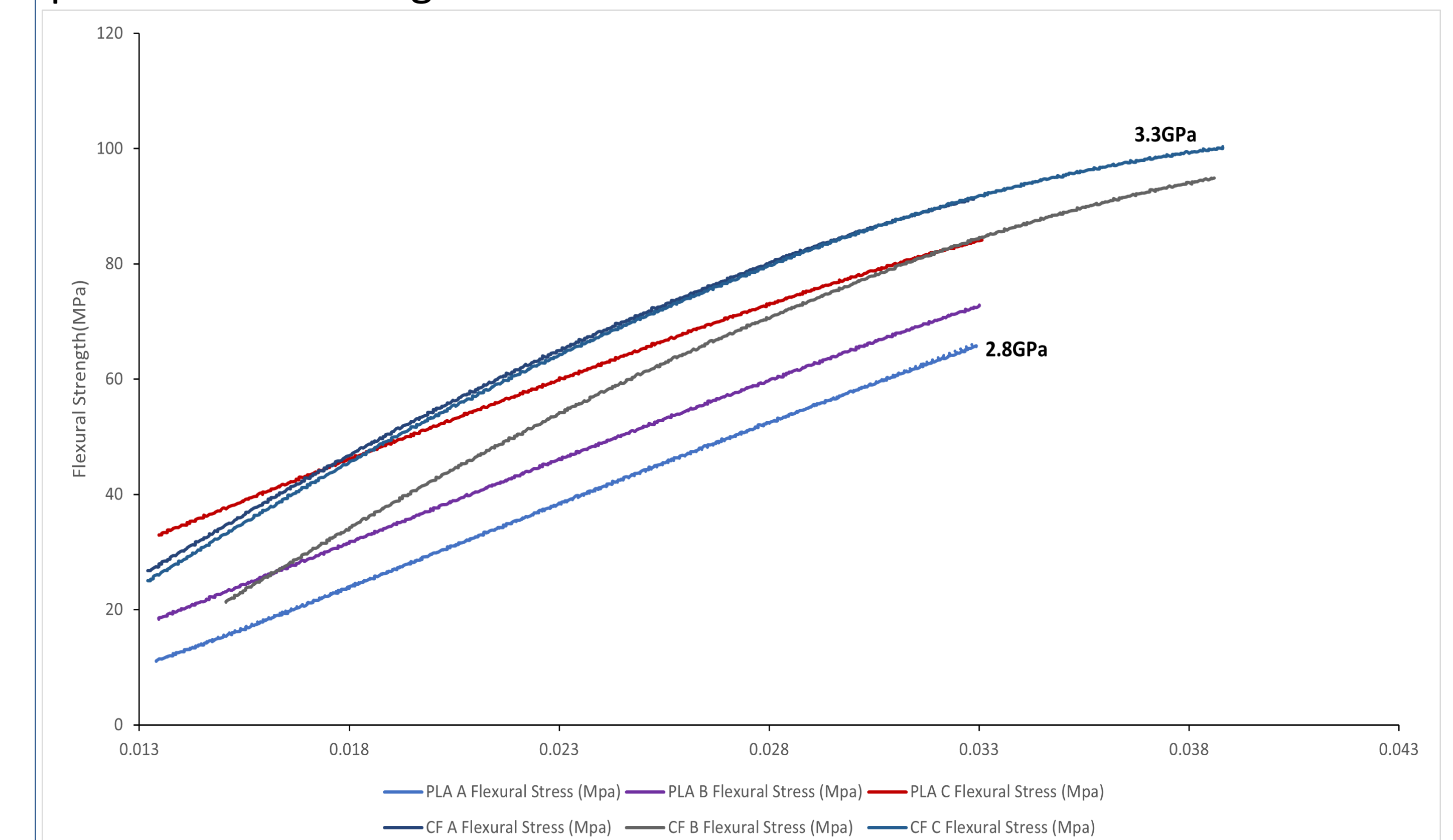


Table 1: Graph of stiffness for samples of pure PLA and Carbon Fiber PLA

The graph above shows the stiffness curve for three samples each for pure PLA and Carbon fiber PLA (CF PLA). The stiffness are been compared, the sample are printed at 0.1-layer height, 40mm/s printing speed and 90% infill. It can be observed that the CF PLA showed a higher value of stiffness, they deflect at minimum value and deflection inversely related to stiffness.

Conclusion/Future Work

- The current setup investigate the effect on printing parameters on the mechanical properties of 3D printed samples.
- Future work into predicting mechanical properties of printed samples using trained machine learning algorithms.

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