Property Predictions of the Additively Manufactured Composites using the Machine Learning Approach

Technical Report

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I am grateful to have had the opportunity to undertake this internship.

Abstract

Although applications of additive manufacturing (AM) have significantly increased in recent years, its broad application in several industries is still under progress. AM also known as three-dimensional (3D) printing is a layer-by-layer manufacturing process that can be used for the fabrication of geometrically complex customized functional end-use products. Since AM processing parameters have significant effects on the performance of the printed parts, it is necessary to tune these parameters which is a difficult task. Today, different artificial intelligence techniques have been utilized to optimize AM parameters and predict the mechanical behavior of 3D-printed components. However, predicting the mechanical behavior of 3D-printed parts remains challenging due to their myriad processing parameters during manufacturing. To address this challenge, this research focuses on incorporating machine learning (ML) algorithms into the prediction of mechanical properties for 3D-printed composites. By leveraging historical data on materials and printing parameters, ML algorithms can be trained to predict the mechanical properties of new composite structures accurately. Ensemble and automated ML techniques offer predictive capabilities, enabling engineers to optimize composite materials without the need for extensive experimental trials. Automating the iterative tasks involved in developing ML models makes the prediction process more efficient and accessible. By demonstrating the potential of machine learning in predicting material properties, the study contributes to the growing integration of AI and ML in various engineering and manufacturing fields. This research enables the creation of a data-driven manufacturing process that helps drive the product development process in multiple industries.

Introduction

This program allows participants from both the United States and India to collaborate together on several research projects and co-lead a project in the field of additive manufacturing under the guidance of various faculty from NYU Tandon School of Engineering, CUNY New York City College of Technology, and Indian Institute of Technology, Mandi. It was a six-week internship in which first three weeks the primary emphasis was on acquiring foundational knowledge in additive manufacturing and familiarizing ourselves with essential technologies to actively engage in the given project. The technologies we learned about were Autodesk Fusion 360, Prusa Slicer, nTopology, and 3D printing which enabled us to deepen our understanding of additive manufacturing. We also engaged in comprehensive discussions regarding the existing challenges and corresponding solutions pertaining to this manufacturing technique. Concurrently, we dedicated time to meticulously examine project intricacies, conducting additional research to ensure our thorough comprehension of each topic. And, in the last three weeks, we have worked on the given project. Additionally, we learned about the printing technique employed for the polymers, primarily the AnyCubic Resin 3D printer. This process allowed us to become intimately acquainted with the technology while affording us the opportunity to print multiple lattice structures for analysis of their individual properties. Furthermore, we had the opportunity to familiarize ourselves with the Bioengineering and BioX center at IIT Mandi, where we gained valuable insights into the utilization of naturally occurring materials that offer solutions to contemporary medical challenges and also, we visited the iHub center and the IIT Mandi Catalyst, where we were introduced to the government's mandated Human-Computer Interaction initiative, broadening our knowledge in this area.

Figure 1: Screen Printing Lab Image

Figure 2: Image taken at BioX center Lab

Methodology

The methodology is to extract or create a dataset that includes experimental printing process parameters (layer height, wall thickness, infill density, infill pattern, nozzle temperature, bed temperature, print speed, material) and mechanical properties (roughness, tensile strength, elongation) of various PLA and ABS sheets from the literature. After extraction, data will be pre-processed and will be used to train different machine learning models.

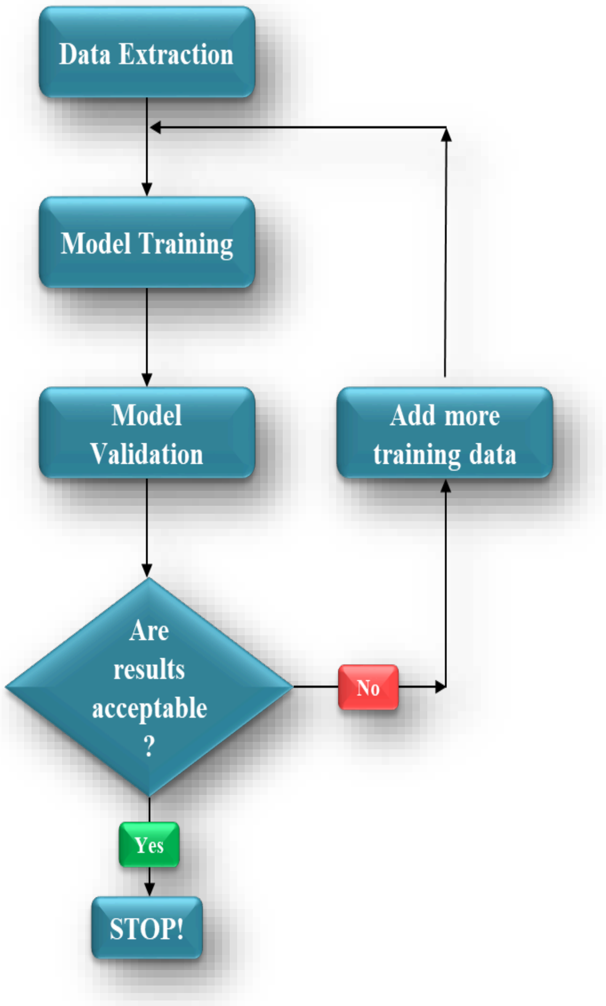

Figure 3: Workflow Chart

Material Analysis Using ML

Material Selection

For the project at hand, a variety of PLA and ABS were chosen from various sources available on the internet. PLA and ABS are two essential materials for 3D printing with FDM. As thermoplastics, both filaments enter a soft and moldable state when heated, returning to a solid state when cooled. FDM printers melt and extrude PLA and ABS filament through a nozzle to build up parts layer by layer. Each of these materials has its own unique chemical composition, which can significantly affect their properties and performance. While both materials are used for FDM, they have key differences that make each more optimal for different applications.

Material Properties

For subsequent analysis, experimental data has been gathered from various published literature sources, as indicated in the references. PLA (Polylactic Acid) is a thermoplastic derived from renewable sources such as cornstarch or sugarcane. Biodegradable under the right conditions, PLA is one of the most popular bioplastics and is perfect for various applications ranging from plastic cups to medical implants. Compared to many other 3D printing materials, PLA is quite cost-efficient, providing good value for money in exchange for high-quality components with relatively smooth surface finishes. PLA is easy to print with and has a higher stiffness than ABS (Acrylonitrile Butadiene Styrene) and other materials like nylon, though it doesn't handle high temperatures or significant stress so well. While PLA is stronger than ABS and nylon, it’s not very heat or chemical-resistant. ABS has superior mechanical properties to PLA while being lighter and more durable. However, the tradeoff is that it's harder to print with and often requires higher temperatures for effective printing.

Dataset and Comparison between Materials

The experimental data that have been collected will serve a significant purpose of establishing correlations and validating models. These correlations and models will be of great importance in providing a deeper understanding and explanation of the data obtained. Therefore, the collected experimental data will be utilized to create strong relationships between different variables and to verify the accuracy and reliability of the models that have been developed.

A	B	C	D	E	F	G	H	I	J	K	L
layer_height	wall_thickness	infill_density	infill_pattern	nozzle_temperature	bed_temperature	print_speed	material	fan_speed	roughness	tension_strenght	elongation
0.02	8	90	grid	220	60	40	abs	0	25	18	1.2
0.02	7	90	honeycomb	225	65	40	abs	25	32	16	1.4
0.02	1	80	grid	230	70	40	abs	50	40	8	0.8
0.02	4	70	honeycomb	240	75	40	abs	75	68	10	0.5
0.02	6	90	grid	250	80	40	abs	100	92	5	0.7
0.02	10	40	honeycomb	200	60	40	pla	0	60	24	1.1
0.02	5	10	grid	205	65	40	pla	25	55	12	1.3
0.02	10	10	honeycomb	210	70	40	pla	50	21	14	1.5
0.02	9	70	grid	215	75	40	pla	75	24	27	1.4
0.02	8	40	honeycomb	220	80	40	pla	100	30	25	1.7
0.06	6	80	grid	220	60	60	abs	0	75	37	2.4
0.06	2	20	honeycomb	225	65	60	abs	25	92	12	1.4
0.06	10	50	grid	230	70	60	abs	50	118	16	1.3
0.06	6	10	honeycomb	240	75	60	abs	75	200	9	0.8
0.06	3	50	grid	250	80	60	abs	100	220	10	1
0.06	10	90	honeycomb	200	60	60	pla	0	126	27	2.2
0.06	3	40	grid	205	65	60	pla	25	145	23	1.9
0.06	8	30	honeycomb	210	70	60	pla	50	88	26	1.6
0.06	5	80	grid	215	75	60	pla	75	92	33	2.1
0.06	10	50	honeycomb	220	80	60	pla	100	74	29	2
0.1	1	40	grid	220	60	120	abs	0	120	16	1.2
0.1	2	30	honeycomb	225	65	120	abs	25	144	12	1.1

Figure 4: *Dataset* (Link)

Layer Height vs. Roughness

In the dataset, all values of the Material column were converted into binary numbers of 0 and 1 where 0 denotes ABS and 1 denotes PLA. It was found that on increasing layer height, the roughness of the part also increases but PLA found to be smoother than ABS for the same value of layer height.

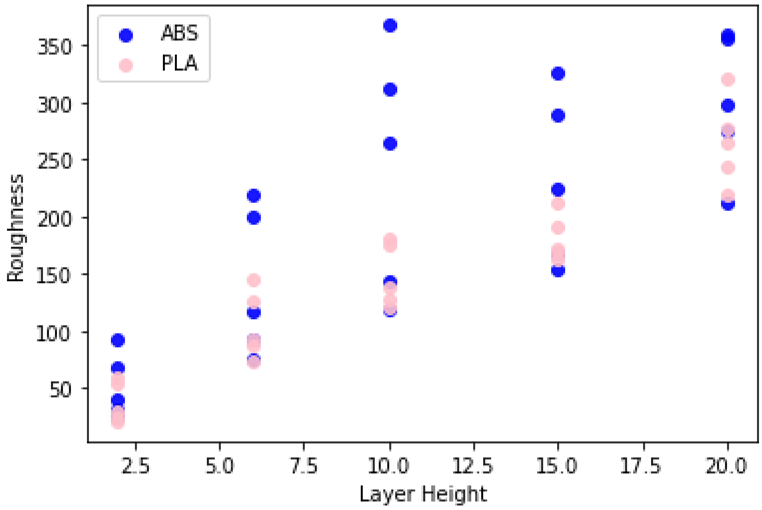

Figure 5: *Layer Height vs. Roughness*

Fan Speed vs. Tension Strength

Results using Python showed that the air circulation is not good for ABS. Tension strength of ABS tends to decrease more than of PLA on increasing the fan speed.

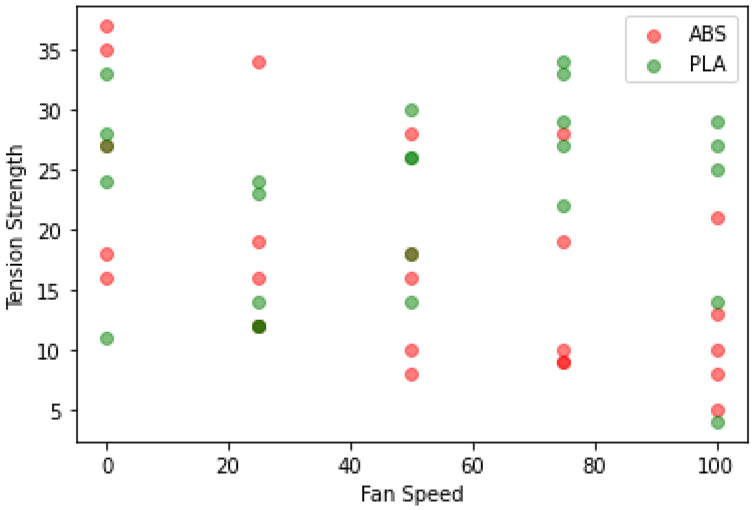

Figure 6: *Tension Strength vs. Fan speed*

Prediction of the Material

Using material as the output variable and the other columns as input features, material prediction of the printed part using the ML classification model was performed. For this, the dataset is divided into the training and test data in the ratio of 7:3. The input features were fan speed, print speed, layer height, bed temperature, normal temperature, wall thickness, roughness, tension strength, and elongation. The ML model used is KNN in which the hyper-parameter "n_neighbors" denoted by "k" is taken as 5 after fine-tuning the model. For k=5, the R^2 value was found to be maximum with the value of 0.73333.

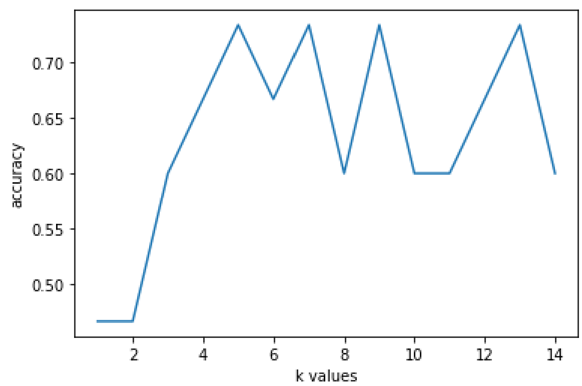

Figure 7: k values vs. accuracy

The prediction was made using the ANN model also. The ANN model has been built using five layers, with [32,64,16] units in the hidden layers respectively, and 1 unit in the output layer. The activation function used is the ReLu function in the hidden layers and the softmax activation function in the output layer for the final classification or prediction. Sparse categorical entropy was used as the loss function and the model was trained for 500 epochs.

Data Pre-Processing & Cleaning

The collected dataset, which was intended for use in training various machine learning models, underwent a thorough cleaning and pre-processing procedure before utilization. This process involved removing any outliers present in the data through data cleaning techniques and replacing any null values with the most appropriate corresponding values using data pre-processing methods. The next task was to understand the correlation of input features with each other so that feature selection can be performed. In the machine learning process, feature selection is used to make the process more accurate. It also increases the prediction power of the algorithms by selecting the most critical variables and eliminating the redundant and irrelevant ones. This was done using the Pearson-Correlation Matrix that showed that Tensile Strength and elongation are highly correlated with each other with a value of 0.96. So, the results should show the same pattern or behavior for the dependency of input features on these outputs if taken individually.

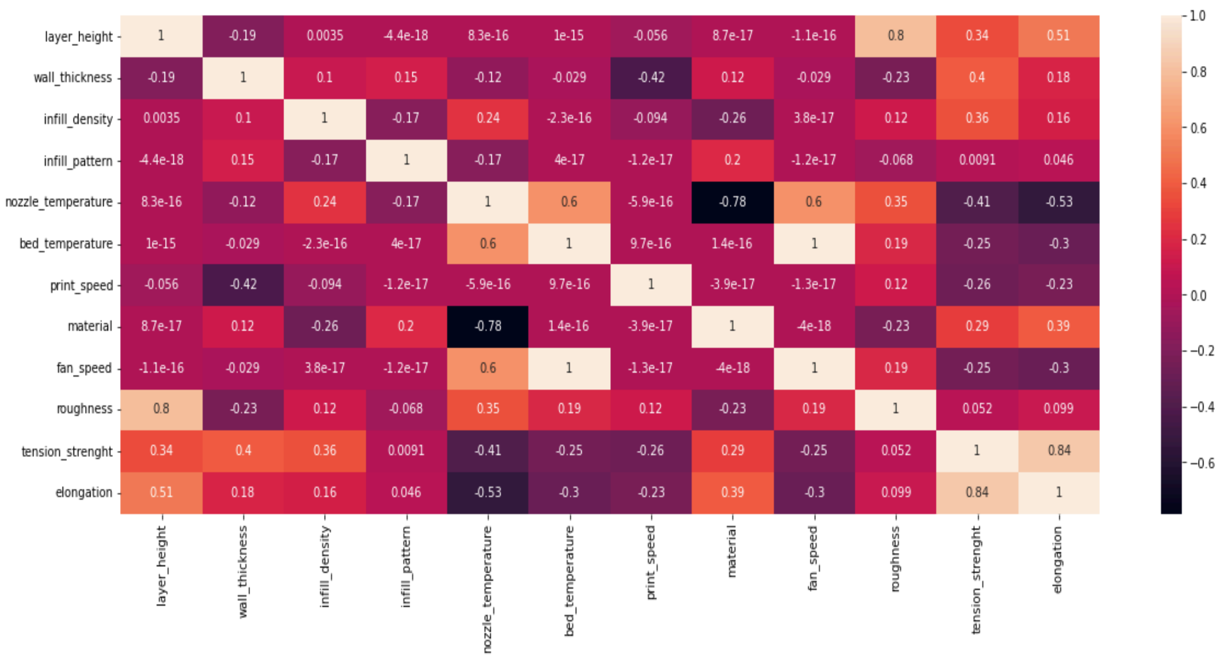

Figure 8: Pearson − Correlation Matrix
indicating correlation amongst *input features* and output variables

Furthermore, to ensure optimal performance of the machine learning models during the training and validation stages, all dataset columns used for predicting mechanical properties using these models underwent scaler normalization. This was done to account for the differences in the ranges and units of input feature values, ensuring that they were appropriately standardized before being passed through the models.

Trends in the Data

Based on the Pearson Correlation matrix values, layer height, bed temperature, nozzle temperature, and wall thickness have showed high correlation with the elongation. That's why these 4 input features are independently used to find their variation with the minimum elongation value corresponding to the printed part. For this machine learning techniques – Linear Regression, Support Vector Regression, and Artificial Neural Network are used. All the input features are best fitted with the ANN model with an R^2 value being more than 0.65.

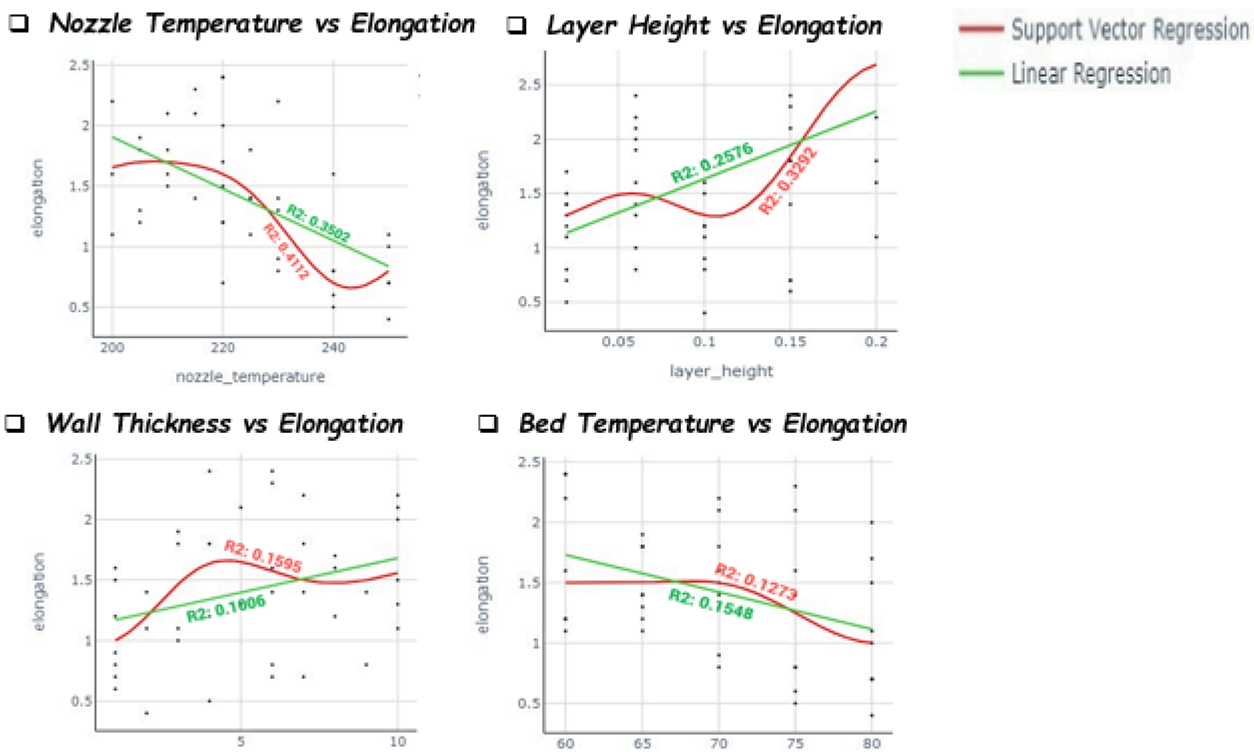

Figure 9: Variation of Input Features with Elongation

Model Architecture

The ML models that we have employed for the FLD prediction are – Linear regression, Support Vector Regression, Random Forest, Decision Tree, and Artificial Neural Network. For tuning the models, the dataset has been divided into training and testing in 80% and 20% respectively. For the ANN model, the test data has been further divided into validation data and testing in 40% and 60% respectively.

Linear Regression

Linear regression is a statistical modelling technique used to establish a relationship between a dependent variable (Y) and one or more independent variables (X) by fitting a linear equation to the observed data. The goal of linear regression is to find the best-fit line that can represent the relationship between the variables.

The equation for simple linear regression model is:

$$y(x) = \beta + a * x + \varepsilon$$

where:

Y is the dependent variable or the response variable.

X is the independent variable or the predictor variable.

B and α are the regression coefficients or the intercept and slope of the line, respectively.

ε is the error term or the residual, which represents the difference between the observed and predicted values.

RBF Support Vector Regression

RBF Support Vector Regression (SVR) is a variant of Support Vector Regression that uses an RBF (Gaussian Kernel Radial Basis Function) kernel function to map the input data to a high-dimensional feature space. Linear SVR aims to find a hyperplane that best separates the data into two regions - one for the target variable values that are greater than or equal to the predicted values, and one for the target variable values that are less than or equal to the predicted values. The points that lie closest to the hyperplane are called support vectors and are used to define the hyperplane.

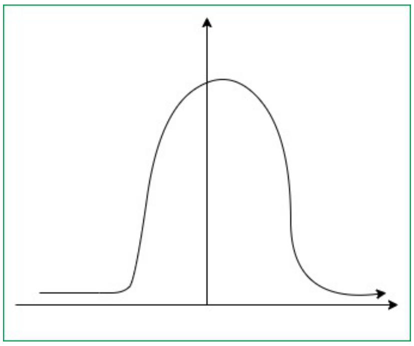

Figure 10: Gaussian kernel graph

Random Forest Regression

Random Forest Regression is a powerful and flexible algorithm that can handle a wide range of regression problems, including those with complex and non-linear relationships between the input and output variables. It is also able to handle missing data and noisy input features. It works by randomly selecting a subset of the training data and a subset of the input features to build each decision tree. This process is repeated to build multiple decision trees, each with different subsets of the data and features.

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are a type of machine learning algorithm that are inspired by the structure and function of biological neurons in the brain. ANNs consist of interconnected layers of artificial neurons that are trained to learn complex patterns and relationships between the input and output data.

An ANN typically consists of three types of layers: input layer, hidden layer(s), and output layer. The input layer receives the input data, which is then passed through the hidden layer(s) to the output layer. Each neuron in the hidden and output layers receives input from the previous layer, performs a weighted sum of the input, applies an activation function, and passes the output to the next layer.

The weights of the connections between the neurons are adjusted during the training phase using a process called backpropagation. The goal of backpropagation is to minimize the difference between the predicted output and the actual output by adjusting the weights of the connections.

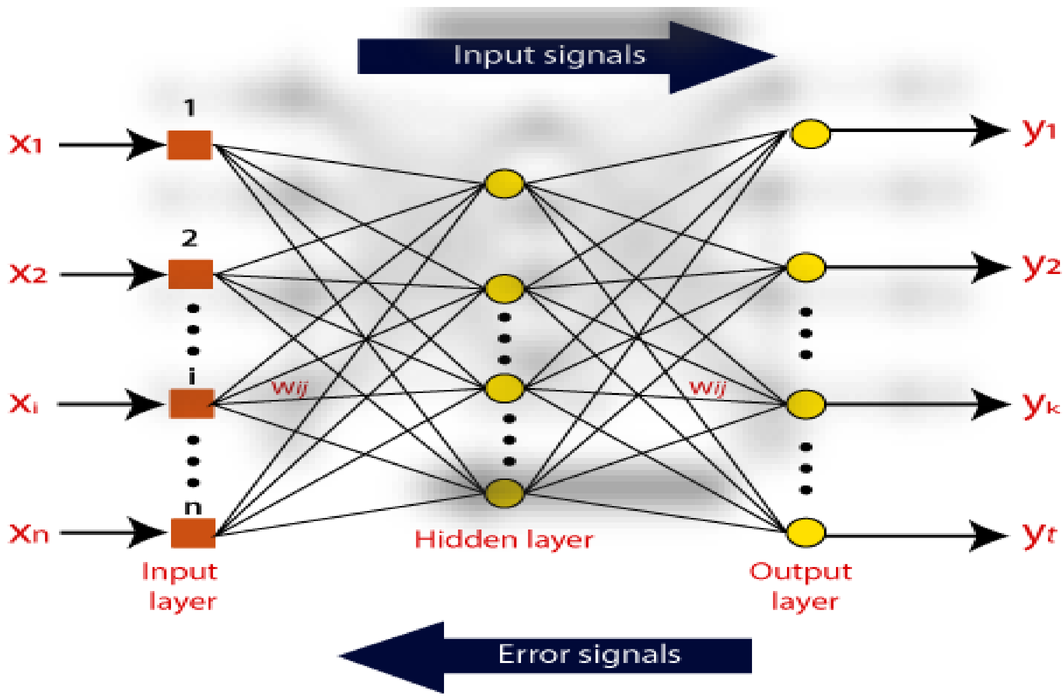

Figure 11: ANN Architecture

For this project, the ANN model has been built using four layers, with 32 units in two hidden layers and 3 units in the output layer. The activation function used is the ReLu function in the first two layers and the Linear activation function in the output layer.

$f(x) = \max(0, x)$ -> ReLu activation function

$f(x) = x$ -> Linear activation function

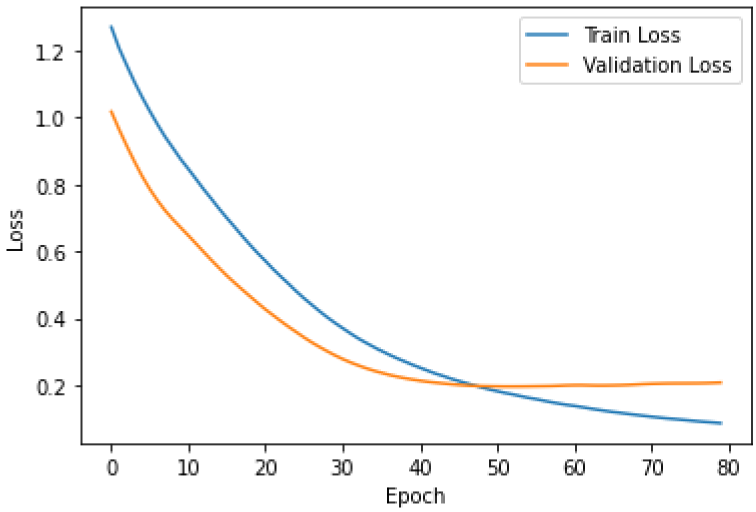

Figure 12: Relationship between loss and epoch

Results

1. Multi-Variate Linear Regression gave a R^2 value of 0.8558 on the test data for predicting the values of the roughness of the printed part.
2. The Random Forest Regressor model which works by building multiple decision trees, showed a much better R^2 value of 0.6372 on the test data.
3. The ANN was trained for 80 epochs and on the test data the mean squared error was 0.2051 and the R^2 value was found to be 0.7682.
4. Decision Tree Regression gave a R^2 value of 0.9645 for predicting the output parameter labeled "Roughness" using all the input process parameters on the test data.

Based on the R^2 value, it is found that:

$$ANN \gg Random\ Forest\ (Multiple\ Outputs)$$

$$Decision\ Tree > Linear\ Regression$$
$$(Predicting\ Roughness\ as\ the\ output\ only)$$

Conclusions

Although 3D printing techniques have been widely employed in different industries in the past few years, they are still developing and face various problems in production. In this context, different experimental investigations have been performed to determine the effects of printing process parameters on the mechanical behavior of final products. Since experimental practices are time-consuming and costly methods, other techniques have been applied in this field that are accurate and cost-effective. In recent years, ML has attracted a lot of research interest in 3D printing due to its superior properties and we have used ML to predict the mechanical properties of 3D printed parts using ML as well as analyze the dependencies of each process parameter on the tensile strength of the printed part. The results have been proven to be consistent with the experimental results and the accuracy of the algorithms and models can be improved more with the more amount of data collection. Performances of some ML algorithms are directly related to the amount of accessible data. In some areas, there are big datasets for training, and ML algorithms proved their power in these areas, but in some fields of 3D printing there is no huge dataset. Therefore, the accuracy of the obtained results can be reduced. In this case, with limited data further attempts in data augmentation are required. To this aim, different generative models such as generative adversarial nets can be used.

All the code Jupyter Notebooks activity details along with assignments can be found here: Link

Learnings

Through this Internship, I got to learn about the culture of the foreign students and was able to engage with them in discussions of the fields I love the most. I got to know about AM and Image processing while working on this project along with other big technologies and was able to complete the internship using my prior knowledge of ML and those concepts have become stronger after this internship.

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