APPLICATION OF MACHINE LEARNING IN SMART MANUFACTURING

Project report submitted

In partial fulfilment of the requirement for the degree of

Bachelor of Technology

By

MD SHAMS REZA

190103056

Under the guidance of

Dr. Biranchi Panda

DEPARTMENT OF MECHANICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY, GUWAHATI

May 2022

ABSTRACT

Reliability of the 3D printed product has been the focus of many researchers. It has gained extreme importance in the field of additive manufacturing because the printed product doesn't always come out ideal and perfect. Quality problems and defects make it a less suitable mode of manufacturing, but that was before Machine Learning came into play. Machine Learning (ML) has been utilized in various AM processes to improve the quality of the printed product and reduce trial and errors to a huge extent. ML has been applied in various aspects of AM to drastically improve the manufacturing process in the era of industry 4.0. In this report, we will discuss Random Forest technique of ML and understand the AM processes, especially FDM (Fused Deposition Modeling). This report will talk in depth about the 3D printing design, process parameter optimization, applications of ML in AM. The ML algorithm RF (Random Forest) will be discussed in detail.

MD Shams Reza & Mohit Roshan

IIT Guwahati

ACKNOWLEDGEMENT

It is with great reverence that we express our sincere gratitude and appreciation towards our supervisor, Dr. Biranchi Panda, Department of Mechanical, IIT Guwahati, and thank them for their guidance and supervision throughout the project. From introducing us to the field of Machine Learning, Additive Manufacturing and applications of ML in the field to their exemplary technical advice, persistent monitoring and constant support during the course of this project, we are deeply indebted to them for giving us this opportunity.

Secondly, we are also thankful to our professors in the second semester that got us started on Computer Science, which further led to our keen interest in Machine Learning, which is the reason we requested Dr. Biranchi Panda, who is an expert in the field of Machine Learning, 3D printing and Additive Manufacturing to take us on in this project.

We would also like to thank our family and friends who helped us a lot in finalizing this project within the time frame.

MD Shams Reza and **Mohit Roshan**

IIT Guwahati

November 2021

CONTENTS

References

Chapter 1

INTRODUCTION

1.1 Additive Manufacturing

Additive manufacturing is an example of 3D Printing in which instead of molding apart or machining it, additive manufacturing uses technology that fuses the material. In the case of metal, it uses a laser to create a part layer by layer instead of being machined from the outside or molded.

Many forms are hard to manufacture through normal means. For example, there are parts with complex internal channels or parts with lattice or honeycomb structures on the inside for less material usage. With Additive Manufacturing, you can produce many complex forms quickly, layer by layer. It eliminates a lot of assembly work because a part that comes from various small components could be printed as a single piece instead. Additive manufacturing could produce many parts, including jet engine components, other precision engine parts, surgical implants, and medical devices. AM expands the range of designs that manufacturing can produce.

Using additive manufacturing as a production option is still not popular, but it is being used and applied in the real world more and more. Additive manufacturing machines will become faster, their build envelopes will get bigger, and the processing of various materials will be better understood. This process has helped change the established rules of forms that are manufacturable in many ways.

Various Additive Manufacturing fabrication techniques such as Stereolithography (**SLA**) or Vat Photopolymerization, fused filament fabrication (**FFF**) or Fused Deposition Modelling (**FDM**) or Material jetting, Selective Laser Sintering (**SLS**), Selective Laser Melting (**SLM**) or Powder Bed Fusion, Laminated Object Manufacturing (**LOM**) or Sheet Lamination, Laser Engineered Net shaping (**LENS**), Digital Light Processing (**DLP**) or Continuous Liquid Interface Production (**CLIP**)(alternative), Binder Jetting has been used to develop parts of various kinds and forms of materials.

Amongst all, Fused Deposition Modeling (FDM) also mentioned as FFF (Fused Filament Fabrication) is a popular AM technology that is utilized mainly in industries to build complex geometrical parts in a short amount of time.

In FDM, the thermoplastic filament is used as source material for the process. The filament is heated until it melts, and then it is extracted, layer by layer, to create a three-dimensional object. There are two aspects in this modeling. One is the material that makes the object itself; another is the support material that acts as scaffolding to support the object while it is printed.

The capabilities, limitations, processing parameters, and the technology's functioning when fabricating a part with FDM will help us achieve desired quality characteristics in the parts developed by AM process. The study of the effect of each process parameter on response characteristics of the FDM parts helps to adjust the level of the process variable leading to improvement in the quality of parts.

The computer communicates with the nozzle and the base part of the printer through numerical simulations, studies the cross-sections of the part through the CAD model's layers. Then the melted thermoplastic filament will be extruded from the nozzle as it moves over to the base to create the first layer. As each layer of the product cools and hardens, another layer is added on top of it and immediately binds to the one below it. As each layer is being printed, the base will move lower to allow more room for the layers. The produced part is ready to use immediately after the removal of support material. The figure 1 below depicts the process of FDM printer.

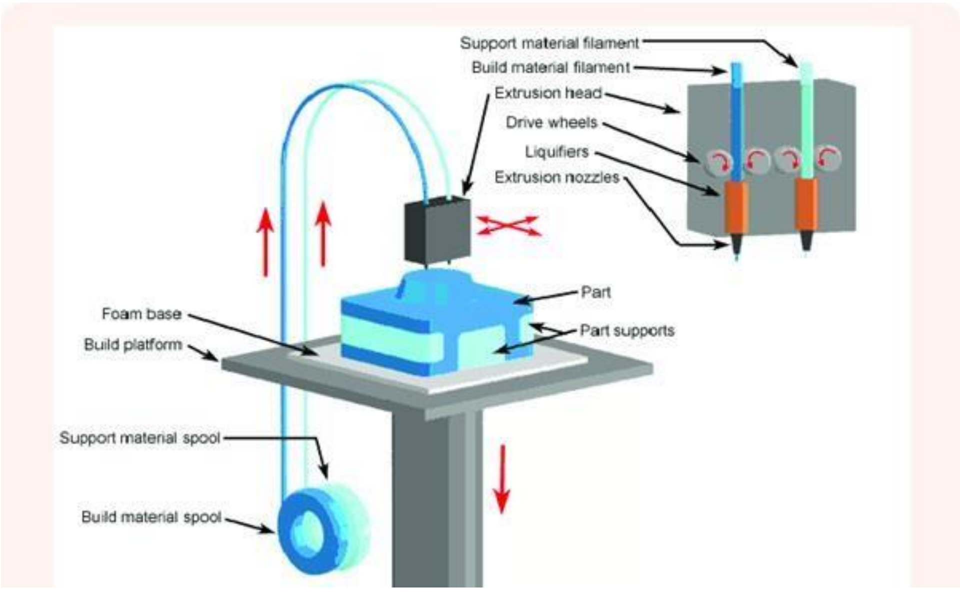


Figure 1: Fused Deposition Modeling mechanism (from link)

AM has multiple **process parameters** that can affect the quality of each AM product, like printing speed, layer thickness, solid-liquid cooling interaction, grain growth development, laser power, powder size. This is why a detailed understanding of the AM process is necessary to understand better the properties/behavior of the printed parts/product.

Chemists and engineers worldwide have researched and investigated the processing parameters *to predict the mechanical behavior* of printed items better. For example, in [1], experiments were carried out on the AM design with the input parameters, like spindle speed, feed rate, and cut depth for turning the cutting tool on the lathe machine. Output parameters like surface roughness and cutting tool vibrations were taken into account. Analysis showed the spindle speed affected surface roughness, and depth of cut + feed rate influenced the vibrations along the axes. In another investigation, [2], the porosity led to decreased fatigue life. Upon researching the various research papers and sites posted across the internet, parallel to experimental practices, different numerical models and data were used to accurately predict the mechanical properties and the entire process of manufacturing methods.

1.2 Machine Learning

ML is a part of AI which is basically *computing through algorithmic learning*. Quality and reliability of the 3D printed products were extremely important, and ML, which is a data-driven model, helped predict the shortcomings in the process and accurately print these products in realtime. It doesn't utilize various physics-based predictions and instead, **a large amount of data is collected** and processed by the various ML algorithms, helping make the final printed product more accurate and reliable by recognizing certain irregularities and patterns in the manufacturing process.

1.2.1 Random Forest Algorithms

- **RF**: Random Forest (RF) is a decision tree (a decision support tool that uses tree-like model of decisions and their possible consequences) based supervised learning algorithm used for both classification and regression (mainly classification). It creates decision trees on sample data and then gets prediction from each of them and selects the best solution by the means of voting. It is an ensemble method which is better than a single decision tree because it reduces the overfitting by averaging the result.

Chapter 2

LITERATURE REVIEW

2.1 Artificial Intelligence

Basically, AI can be thought as something with an ability to replace human intelligence in actions/decisions. Since its introduction in 1955, when it was introduced as an academic discipline, AI has poked into various aspects of our daily life. It has gotten excellent at reasoning on its own, knowledge representation, learning, perception and natural language processing beyond what we thought was possible. It has the capability to defeat grandmasters in a game of chess that one plays on computer. Over the passage of time, AI is used more and more in scientific and industrial fields. With the new era of semiconductors and transistors that made speed and computational power to tackle large datasets possible.

Machine Learning is a subset of Artificial Intelligence (AI). According to Dr. Manuela M. Veloso, the head of the Machine Learning Department at Carnegie Mellon University in the book, METAL AM [3], “Machine Learning is a fascinating field of Artificial Intelligence research and practice where we investigate how computer agents can improve their perception, cognition, and action with experience. Machine learning is about machines improving from data, knowledge and interaction.”

2.1.1 Types of Machine Learning

As different operations depend on data, Machine Learning can be classified into 4 categories:

1. Supervised Learning
2. Unsupervised Learning
3. Semi-supervised Learning
4. Reinforcement Learning

Figure 2 below is a classification of various machine learning techniques and figure 3 is

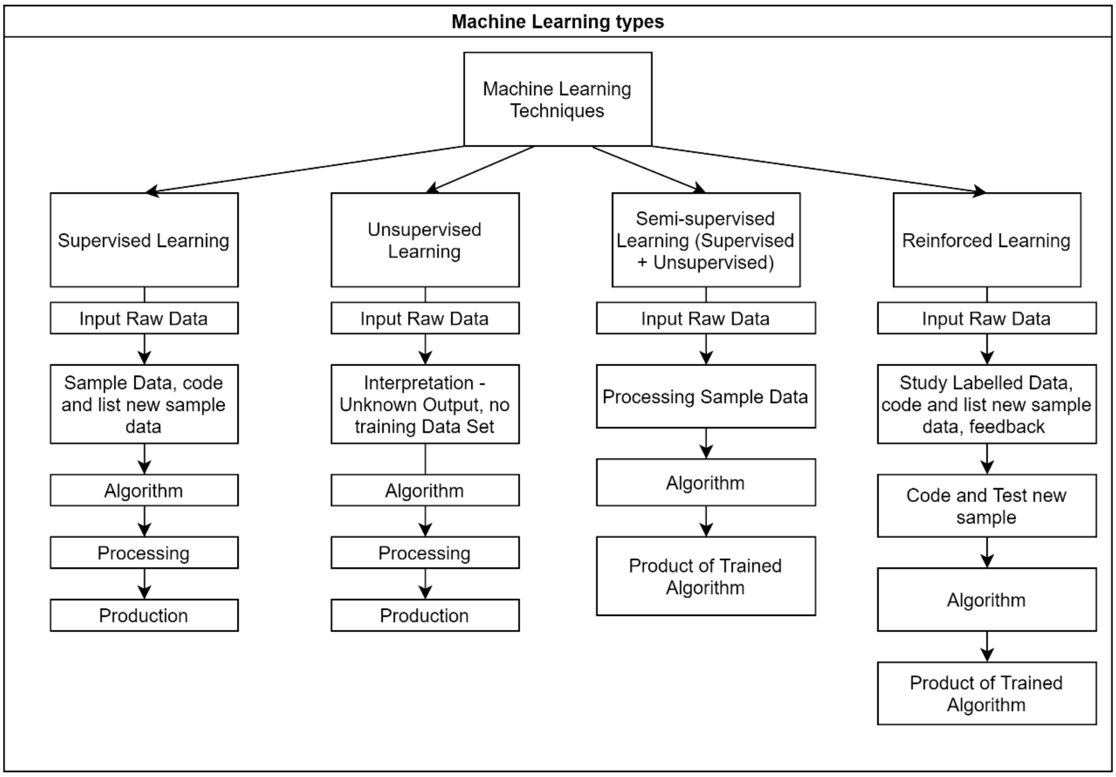


Figure 2: Types of Machine Learning

Supervised Learning:

Supervised Learning algorithms involve training an algorithm on a group of data. They fit hypotheses to training datasets which are labelled, meaning they have known input (e.g., a vector) and output (e.g., a signal). The trained algorithm is then applied to unlabeled data cases to predict the corresponding label. This label tells us which class the training point belongs to. The interesting part is that by identifying the decision boundaries that split the datasets, **SL Algorithms match the dots between the input and the labeled outputs.** This is how it can predict input features for desired outputs, giving us the ability to predict the output for unseen situations.

Supervised learning can be classified into 2 categories: **classification** and **regression:** in classification, the algorithm tries to figure out the qualitative labels, e.g. is the image of a horse? Whereas in regression, the algorithm tries to figure out the quantitative labels, e.g. What is the age of the horse based on the image?

Neural networks (NNs) are a wildly popular tool for supervised learning, especially with large datasets. These algorithms seek to emulate a brain by enforcing layers of connected neurons. NNs collude an input space onto an affair space, which is generally of different confines. The perpetuation of NNs allows for non-linear decision boundaries to be inferred in a computationally effective manner. Further specialized NNs also live for specific operational areas. For illustration, convolutional neural networks (CNNs) use convolutional layers to identify features present throughout the input space. CNNs are often in computer vision tasks, where analogous features, for illustration perpendicular lines, may do anywhere in the input space.

Support vector machines (SVMs) are used in traditional bracket supervised learning tasks, but they can retrogress. They calculate connections between data in an advanced dimensional space using a kernel function and placing a hyperplane decision boundary between classes to maximize the perimeters. In retrogression tasks, the hyperplane is named to stylish fit the data. SVMs perform well for high-dimensional data, but with far more features than training exemplifications, they're prone to overfitting the training data. Still, can frequently overcome this through careful selection of a useful kernel function or regularization.

We can see supervised learning being utilized in AM field in Naïve bayes[4], CNN[5]. It is also used in decision trees, linear regression, genetic programming.

Unsupervised Learning:

Unsupervised learning problems attempt to infer patterns from unlabeled data. Since labels are not attached to the data, they are often more difficult to evaluate. There are various types of unsupervised learning algorithms, with the two most common types being clustering and association rules. Clustering, also called data segmentation, algorithms group data into clusters. The data within each cluster are such that they are more closely related to each other than any data in a different cluster. Association rule analysis, also known as market basket analysis, seeks to identify prototype values for a feature set such that the probability density at those values is relatively large.

We can see unsupervised learning being utilized in AM field in K-means clustering[6].

Semi-supervised Learning:

Semi-supervised learning is a combination of supervised and unsupervised learning algorithms. Semi-supervised learning algorithms are applied when dealing with a large volume of data that makes labeling veritably impracticable and expensive. Thus the data fed to the learning algorithms is an admixture of labeled and unlabelled data. These models use the two sets of data (labeled and unlabelled) and generally perform better than unsupervised learning because of the presence of the small quantum of labeled data. They're further cost-effective and more straightforward to train than supervised learning.

We can see semi-supervised learning being utilized in AM field in Gaussian Mixture[7]. It has also been used in Boltzmann Machine.

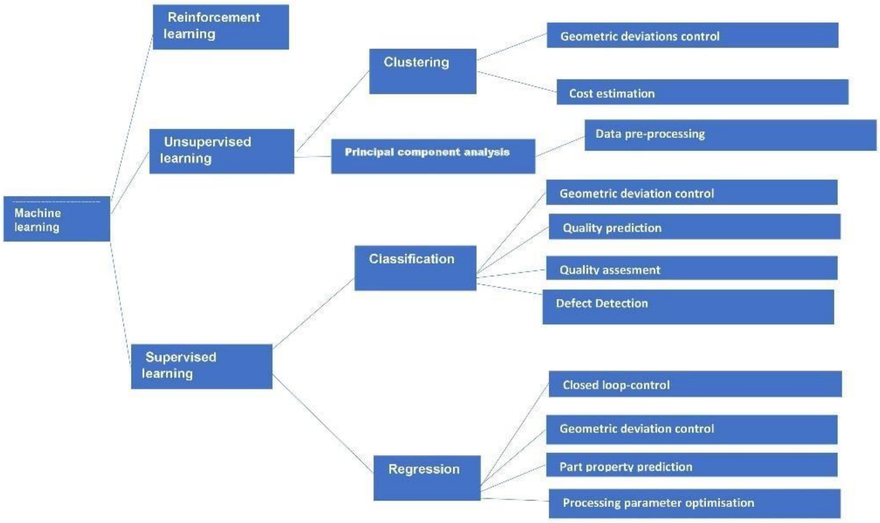


Figure 3: Machine Learning Workflow

Reinforcement Learning:

Unlike supervised literacy with labeled data, training data for corroborated literacy algorithms can only suggest whether they're correct or not. They learn "good" behavior by interacting with their terrain. They learn through principles analogous to supervised literacy. Instead of using large datasets, the model interacts with the terrain, which produces a favorable price or a negative discipline. This feedback reinforces the aspect of the model, therefore giving it the name Reinforcement Learning.

2.1.2 A review of Random forest Algorithms

Machine Learning algorithms are a big help in AM processes. Having predictive control over the AM processes is always a major help during the 3D printing processes, according to many research scientists and users. There could be an anomaly or defect which could impact the quality of the product, system flags the incident and notifies the user. The operator then tunes the parameter, using the recommended settings to mitigate such future incidents. And re-melt the laid layer to remove the pores. This is one of many such examples that ML helps in the 3D Manufacturing. It helps govern the product quality and throughput of the manufacturing. Postmanufacture analysis could also be done with ML programs.

ML programs use training data before processing real-time parameters. Training dataset, also known as learning datasets is used to help a ML program understand how to apply technologies like NNs (neural networks) to learn and produce sophisticated results. It helps them know how to take input and weigh them through algorithms and help us in the process.

- ## Random Forest Algorithm or RF

DEFINITION: It is supervised machine learning technique. It is used to solve for regression and classification of problems. It consists of many decision trees. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression.

It is a method that operates by constructing multiple decision trees during training phase. The decision of the majority of tree is chosen by random forest as the final decision.

<u>HOW IT WORKS</u>: Random Forest builds multiple decision trees and merges them together to get a more accurate and stable prediction.

ensemble technique. **Ensemble** simply means combining multiple models. Thus, a collection of models is used to make predictions rather than an individual model.

There (ensembles) are two types :

1. **Bagging**– It creates a different training subset from sample training data with replacement & the final output is based on majority voting. For example, Random Forest.
2. **Boosting**– It combines weak learners into strong learners by creating sequential models such that the final model has the highest accuracy. For example, ADA BOOST, XG BOOST

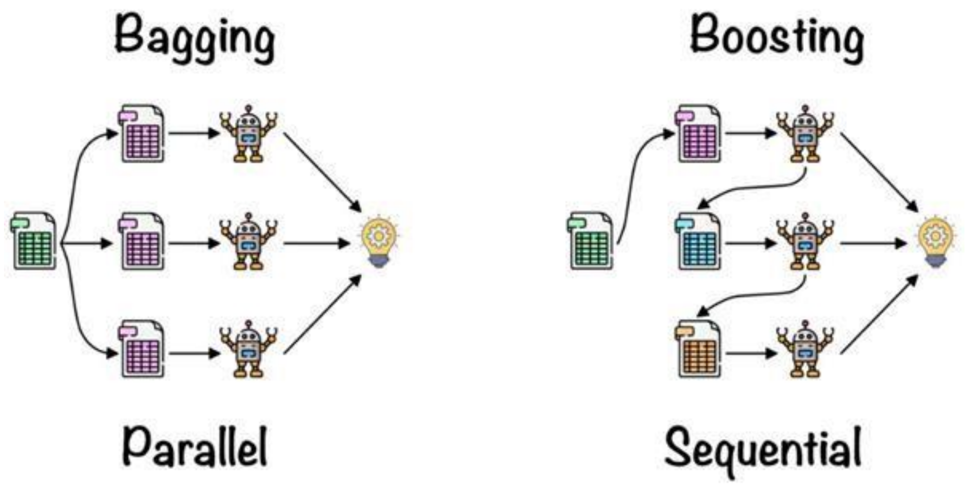


Figure 4: Bagging and Boosting (from link)

Figure 4 depicts a visual representation of the two types of enssembles. As mentioned earlier, Random Forest works on the Bagging principle. Now let's dive in and understand bagging in detail.

Bagging

Bagging, also known as ***Bootstrap Aggregation*** is the ensemble technique used by random forest. Bagging chooses a random sample from the data set. Hence each model is generated from the samples (Bootstrap Samples) provided by the Original Data with replacement known as ***row sampling***. This step of row sampling with replacement is called ***bootstrap***. Now each model is trained independently which generates results. The final output is based on majority voting after combining the results of all models. This step which involves combining all the results and generating output based on majority voting is known as ***aggregation***.

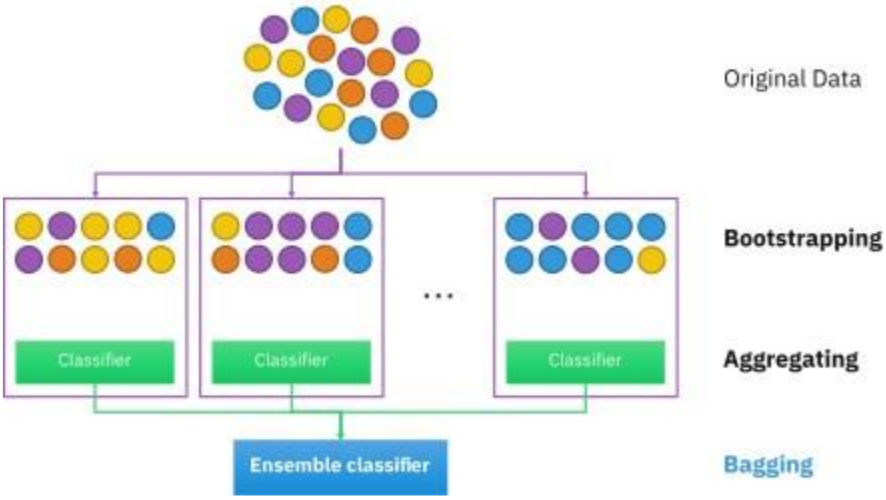
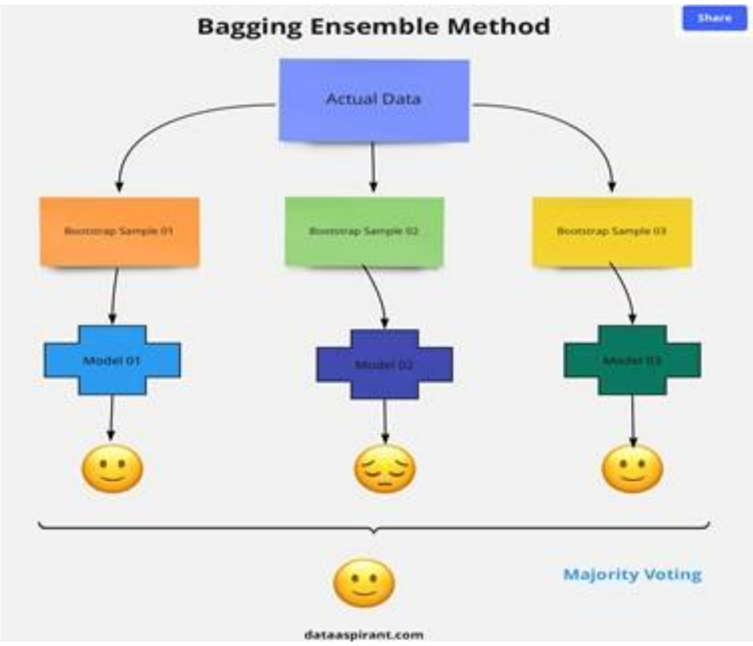


Figure 5: Ensemble Classifier (from link)

Now let's look at an example by breaking it down with the help of the (figures 5&6). Here the bootstrap sample is taken from actual data (Bootstrap sample 01, Bootstrap sample 02, and Bootstrap sample 03) with a replacement which means there is a high possibility that each sample won't contain unique data. Now the model (Model 01, Model 02, and Model 03) obtained from this bootstrap sample is trained independently. Each model generates results as shown. Now Happy emoji is having a majority when compared to sad emoji. Thus, based on majority voting final output is obtained as Happy emoji.



Steps involved in random forest algorithm:

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on ***Majority Voting or Averaging*** for Classification and regression respectively. Refer to figure 7.

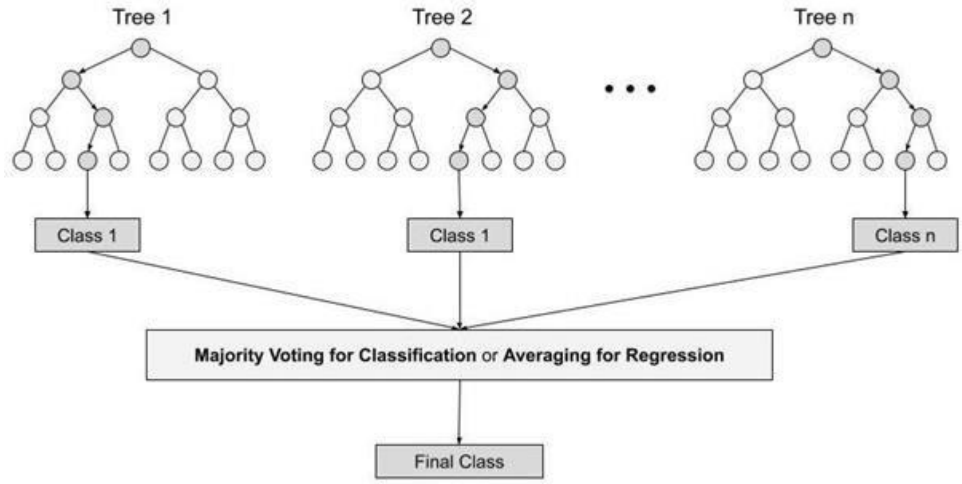


Figure 7: Steps involved in Random Forest Algorithms (from link)

For example: consider the fruit basket as the data as shown in the figure below. Now n number of samples are taken from the fruit basket and an individual decision tree is constructed for each sample. Each decision tree will generate an output as shown in the figure. The final output is considered based on majority voting. In the below figure you can see that the majority decision tree gives output as an apple when compared to a banana, so the final output is taken as an apple.

Random forest adds additional randomness to the model, while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features (refer to figure 8 below).

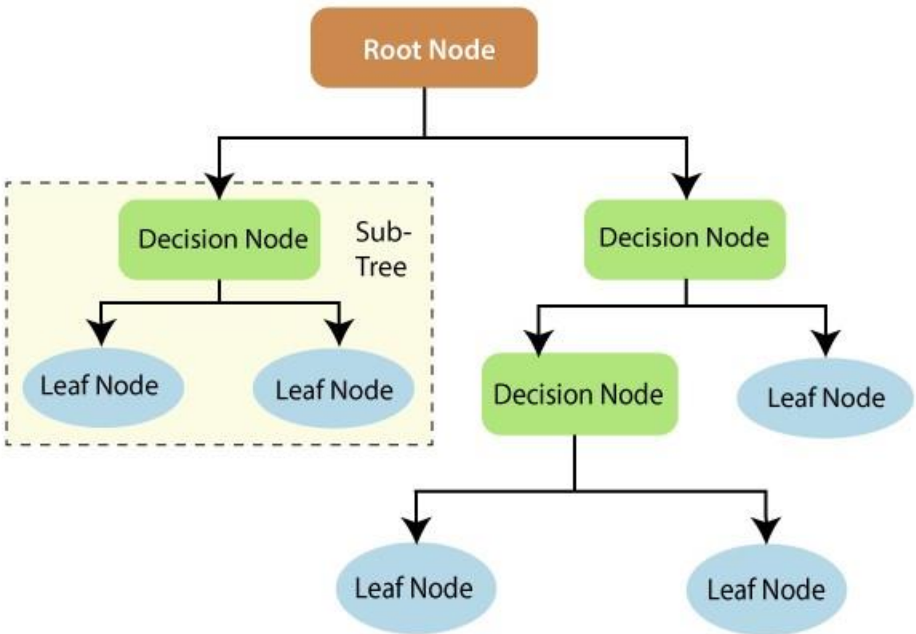


Figure 8: Random Forest and Decision Trees (from link)

Real life analogy: Ram wants to decide where to go during one-year vacation, so he asks the people who know him best for suggestions. The first friend he seeks out asks him about the likes and dislikes of his past travels. Ram starts asking more and more of his friends to advise him. Finally, Ram chooses the places that where recommend the most to him, which is the typical random forest algorithm approach.

Feature Importance: how much the tree nodes that use that feature reduce impurity across all trees in the forest. It computes this score automatically for each feature after training and scales the results so the sum of all importance is equal to one. This is important because a general rule in machine learning is that the more features you have the more likely your model will suffer from overfitting and vice versa.

Difference between Decision Trees and Random Forests:

While RF is a collection of decision trees but there are some differences

- For example, to predict whether a Ram will click on an online advertisement, you might collect the ads the Ram clicked on in the past and some features that describe his decision. If you put the features and labels into a decision tree, it will generate some rules that help predict whether the advertisement will be clicked or not. With the help of the RF algorithm randomly selects observations and features to build several decision trees and then averages the results.
- "deep" decision trees might suffer from overfitting. Most of the time, random forest prevents this by creating random subsets of the features and building smaller trees using those subsets. Afterwards, it combines the subtrees. It's doesn’t work every time and it also makes the computation slower, depending on how many trees the random forest builds.

Important Hyperparameters:

Hyperparameters in random forest are either used to increase the predictive power of the model or to make the model faster.

1. **Increasing the predictive power** there is the n**_estimators** hyperparameter, which is just the number of trees the algorithm builds before taking the maximum voting or taking the averages of predictions. In general, a higher number of trees increases the performance and makes the predictions more stable, but it also slows down the computation. Another important hyperparameter is **max_features,** which is the maximum number of features random forest considers to split a node. The last important hyperparameter is **min_sample_leaf.** This determines the minimum number of leafs required to split an internal node.

2. **Increasing the model's speed**

The **n_jobs** hyperparameter tells the engine how many processors it is allowed to use. If it has a value of one, it can only use one processor. A value of “-1” means that there is no limit. The **random_state** hyperparameter makes the model’s output replicable. The model will always produce the same results when it has a definite value of random_state and if it has been given the same hyperparameters and the same training data.

Lastly, there is the **oob_score** (also called oob sampling), which is a random forest cross-validation method. In this sampling, about one-third of the data is not used to train the model and can be used to evaluate its performance. These samples are called the out-of-bag samples. It's very similar to the leave-one-out-cross-validation method, but almost no additional computational burden goes along with it.

Implementation of RF:

Advantages:

1. RF algorithm is less prone to overfitting than Decision Tree and other algorithms
2. RF algorithm outputs the importance of features which is a very useful **Disadvantages**:

1. RF algorithm may change considerably by a small change in the data.
2. RF algorithm computations may go far more complex compared to other algorithms

2.2 Applications of ML in Additive Manufacturing

Use of ML Algorithms in the field of 3D printing covers various aspects that have a direct impact on the quality of the final 3D printed parts. The aspects include design for 3D printing, part process parameter optimization, in-situ monitoring for quality control, part evaluation. There are some other aspects related to the efficiency of the design and manufacturing process which will be explained in this section as you read further.

2.2.1 Designing 3D models and importance of ML

There are many research papers that show this ML technique has helped inexperienced designers by providing ideas and design features. For example, in a study [9], ML algorithm used in AM helped less-experienced designers who were new to 3D printing to determine suitable AM design features for the remote-controlled car components without any trial and errors. In another study [10], ML algorithms again helped the inexperienced designers with the ML technique that enables feature recommendations to existing CAD models, thus helping designers speed up the whole process and with lesser and lesser trials.

ML algorithms have also been used for manufacturing analysis in 3D printing. In a study, [11], it helped designers recognize the possible faults early and eliminate them. Multiscale Clustering method and heat kernel signature were used to detect manufacturing constraints in the CAD model and eliminate them. In a study, [12] to determine ideal print orientation to avoid putting support structures on user-preferred features, a double-layered Extreme Learning Machine (DLELM). In this DL-ELM, the first layer was the ELM classification to evaluate the relative score between the various part orientations, and the second layer was the ELM regression to construct a global score for all printing directions. It was found to be able to identify the best printing directions with minimum visual artifacts due to support removal.

Additive Manufacturing has also encouraged the development of new designs such as biometric structures, according to a research [13]. Various research about many such ML technologies are mentioned in Table 1 shown below.

Table 1: Various research into different AM processes

AM Processes	Purposes	Input Parameters	ML Methods	References

FDM	Surface Roughness	Layer thickness, build angle	RBF ANN Imperialist Competitive Algorithm (ICA)	[19]
FDM	Dynamic Modulus of Elasticity	Layer thickness, air gap, raster angle, build orientation, road width, fiber spacing	ANN	[20]
FDM	Scaffold wire width	Platform movement speed, extrusion speed, nozzle diameter, fiber spacing	ANN and GA	[21]
FDM	Geometric Accuracy	Part angle, distance between parallel faces	ANN	[22]
FDM	Tensile Strength	Thickness, temperature, raster pattern	ANN	[23]
FDM	Optimize Compressive Strength	Layer thickness, orientation, raster angle, raster width, airgap	Resilient Backpropagation (RBP) ANN	[24]
FDM	Wear	Layer thickness, orientation, raster angle, raster width, air gap	MGGP, SVR, ANN	[25]
FDM	Surface Roughness	Layer thickness, extruder temperature, feed rate to flow rate	Ensemble algorithm	[26]
SLS	Tensile strength	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	ANN	[27]
SLS	Shrinkage ratio	Laser power, scan speed, hatch spacing, layer thickness, powder temperature	ANN, GA	[28]
SLM	Porosity	Part position and orientation, recycled powder content	ANN	-
SLA	Printability	Print speed	Ensemble method, Siamese network	[29]
SLA	Local Deviation	-	Bayesian Network	[30]

2.2.2 Process Parameter Optimization

Process parameter development and optimization are implemented to additively manufacture new materials or parts. Design of the experiment approach involves trial and error. Effects of these parameters have been investigated in research works in [14][15]. The physical based simulation can reveal the underlying mechanism for the formation of specific features during processing, like, keyhole, melt-pool geometry and other microstructures and help us save time and money. In macrostructures, there is always some trial and error. There is readily available data for the production of ML tools, so there is no need for manual parameter optimization. These tools make up a plurality of the research on ML for AM [16] and are largely a running point in optimizing key parameters for a particular quality indicator or set of indicators. Moreover, some researchers even applied ML to construct process maps, which served as an excellent visualization tool to identify the process windows [17].

Let's take a particular AM process and also take into account the materials required. We would need a process-structure properties (PSP) relationship database that help us in the proper selection of the parameters based on the information in the database. But the high dimensionality of the PSP relationship makes it complicated to establish a working mathematical formula of the process. So instead, ML algorithms have been used to determine the PSP relationships for many such ML techniques. For example, in [18], Gan attempted using SOM to identify the PSP relationship of the directed energy deposition process for Inconel 718. We can use high-dimensional dataset obtained from simulation and validated with experimental results with the help of visualized SOM to obtain multiple objective optimizations of the process parameters.

In the material extrusion-based AM process, the focus of research is macro-scale mechanical properties. In FDM, the process parameters that were extensively investigated include layer thickness, print temperature, raster angle and build orientation. In this process, the most prevailing ML approach is MLP (Multi-Layer Perceptron). A properly trained MLP shows superiority in capturing the non-linear relationship of the system for data fitting and estimation capabilities. Hence, it was vastly employed to predict tensile properties, compressive strength, wear rate, recovery properties of PLA and PC-ABS materials.

Thus, the process parameters of any AM processes are the key part and the core of the entire machine. This is why the process is investigated and tests are run for optimization and categorization purposes in ML and for general information.

Since different ML techniques have been used in the AM processes, comparision of ML methods (Table 1) is beneficial for further developments. Also, in most of the AM processes, ANN is widely used. It is a very complex, but also the most efficient algorithm, which is why it is so common. Studies have shown that algorithms based on neural networks (NNs) have higher classification accuracy compared to other algorithms. Although ANN is the most common, it is not always the go to algorithms in AM models. Other algorithms to determine surface roughness such as Random Forest Network (RFN) [31], support vector regression (SVR) [32], Genetic Algorithm (GA) [33], ensemble algorithms [34], siamese network [35] have also been used.

2.2.4 FDM – The most commonly used AM

FDM Characteristics: The available build size of a desktop 3D printer is commonly (200 x 200 x 200) in millimeter, while for industrial machines this can be as big as (1000 x 1000 x 1000) millimeter.

The typical layer height used in FDM varies from 50 to 400 microns and can be determined upon placing an order. A smaller layer height brings out smoother parts and captures curved geometries more precisely, while a larger height brings out parts faster and at a low cost. Usually, a layer of 200 microns is used.

Process Parameters:

FDM is a complex process that exhibits much difficulty in determining optimal parameters due to the presence of a large number of conflicting parameters that will influence the part quality and material properties. The part quality and mechanical properties of the fabricated parts can be attributed to the proper selection of process parameters [34] [35].

One of the most crucial process parameters is the model's orientation, as it affects the model's internal structure, strength, accuracy, and surface quality. Orientation can be said as the angular difference between the plane determining the direction of the object division into layers and selected, the basic plane of the manufactured object. It is also a relevant parameter in the economic aspects of 3D manufacturing. Figure 9 shows all the process variables that need to be studied and optimized in FDM process. Several statistical optimization techniques have been successfully used for the optimization of process conditions of FDM technology.

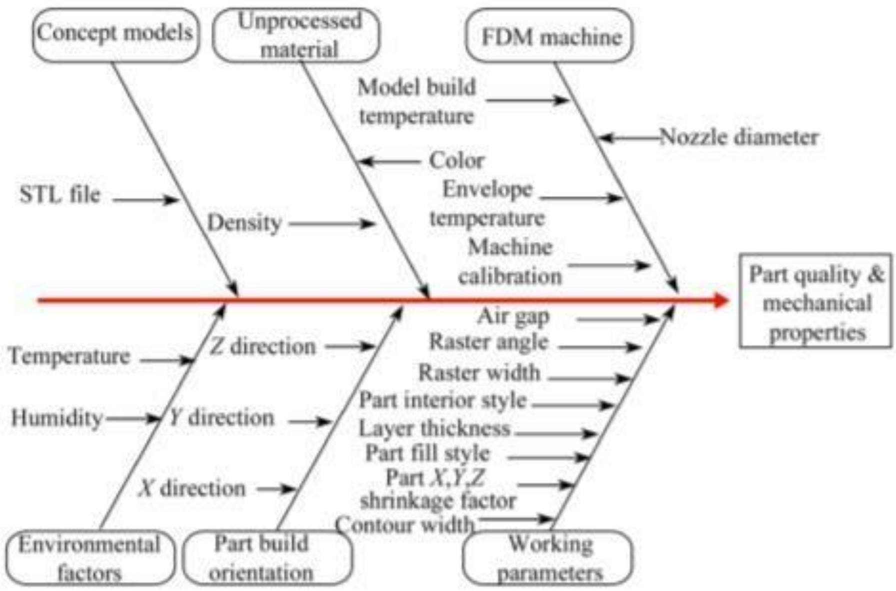


Figure 9: Process Variables in FDM (from link) Some

of the other main parameters are described as follows:

- Layer thickness. The slice height of the layer, or the thickness of the layer, when varied would have the same effect as varying the bead width (the thickness of the bead that nozzle deposits) of the ABS plastic.
- Raster angle refers to the angle of the raster pattern with respect to the X axis on the bottom part layer. Specifying the raster angle is very important in parts that have small curves. The typical allowed raster angles are from 0 to 90.
- Air Gap, another critical process parameter, is the space between the beads of FDM material. It affects the quality of the printed parts. The default is usually zero, but it can be modified to leave a little bit of gap so that the parts print faster, guaranteeing that the structure would be a little loose-packed. It can also be modified to leave a negative gap, meaning that the two beads would be occupying the same space, which will lead to a denser structure, which requires longer build time.

- Raster width is the width of the material bead used for rasters. Larger value of raster width will build a part with a stronger interior. Smaller value will require less production time and material. The value of raster width varies based on nozzle tip size.

There are other parameters such as envelope temperature, model temperature, nozzle diameter, build speed, fan speed (cooling purpose) etc. These do not define the quality much, but are still important.

FDM Filament Material - One of the key strengths of FDM is wide range of available materials. these can range from commodity thermoplastic {such as PLA (Polylactic Acid or Polylactide) and ABS (Acrylonitrile Butadiene Styrene)} to Engineering material {such as PA (Nylon or Polyamide), PETG (Polyethylene Terephthalate) and TPU (Thermoplastic Polyurethane)} and high- performance thermoplastic {such as PEEK (Polyether Ether Ketone) and PEI (Polyetherimide)} etc.

Thermoplastics materials Pyramid available in FDM. As thumb rule, the higher the pyramid of a material is the better its mechanical properties will be. The material type used will affect the mechanical properties and accuracy of the printed part.

Surface Roughness and FDM:

Roughness plays an important role in determining how a real object will interact with its environment. Surface roughness is often a good predictor of the performance of a mechanical component.

In a study, [36], Anitha investigated the effects of some critical FDM process parameters on the surface roughness of the ABS prototype. Three process parameters, including layer thickness, road width, and speed of deposition, were considered. This study revealed that the most crucial influence on the surface roughness was the layer thickness compared to road width and speed. It was also revealed that there was an inverse relationship between layer thickness and surface roughness.

In another study, [37], Nancharaiah studied the influences of process parameters such as layer thickness, raster angle, road width, and air gap on the surface finish of FDM processed ABS part through Taguchi method and ANOVA technique. It was seen that surface roughness could be improved by using a lower value of layer thickness and air gap because it reduced the voids between layers.

Wang, in research [38], used a statistical optimization method to investigate the effects of control parameters such as layer thickness, support style, deposition style, and deposition orientations on the surface roughness by integrating the Taguchi method with the gray relational analysis. The surface roughness improved by 62.27% by using the optimum factor settings. This study revealed that optimal parameter combinations of surface roughness were obtained with fewer experimentations using the Taguchi method than complete factorial design, which yielded similar results.

Advantages of FDM:

- Most cost-effective way of producing custom thermoplastic parts and prototypes.
- The lead times of FDM are short (as fast as next-day-delivery), due to high availability of the technology.
- A wide range of thermoplastic materials is available, suitable for both prototyping and noncommercial functional applications.

Disadvantages of FDM:

- It has the lowest dimensional accuracy and resolution differentiates to other 3D printing technologies, so it is not suitable for parts with complicated details.
- Its parts are likely to have visible layer lines, so post-processing is required for a smooth finish.
- The layer adhesion mechanism makes FDM parts inherently anisotropic.

2.2.6 Planning and Challenges faced

Experimental practices have shown to provide reliable data, but, however, they aren't so costeffective compared to numerical simulations, which are cost-effective, but not very reliable. In this contrast, ML overcomes such limits for research in the AM domain. Many investigations, researches and studies have shown and confirmed the fact that, basically, ML rules all. It has led to faster computations compared to pure physics-based simulations in the field of 3D printing. And as the ML technology continue to advance, it will, in time, no doubt will take over the AM printing, so much, that it will come to be an important factor when it comes to AM machines. However, for the time being, below are the list of some of the possible challenges faced in this field from a study in [39]:

- Data preprocessing is a crucial prerequisite in some ML based systems. Erasing dirty data and utilizing correct data is an essential step, but there are some difficult tasks like the images obtained from scanning electron microscope contain grain and porosity information. Accurate extraction of the crack distribution in these images is a challenging issue which depends on the profound knowledge of the user on fracture mechanics and image processing.
- In the layer-by-layer fabrication technology, quality control of every layer is important, so, multiple types of sensors (thermal, electrical etc.) have been utilized. Applying ML for analyzing the information obtained from these sensors remains an important research direction for quality control of the printed layer.
- Due to the complexity of the physical transformations, metal-based 3D printing is characterized by the lack of repeatability. Improvement in repeatability of fabrication of 3D printed parts would increase the accuracy of the printed anomalies. In contrast, access to both x-ray and thermal data of several AM products is a necessity.
- Feature selection with the aim of selecting most useful features, and feature combination can bring considerable benefits. In context, operation of algorithms on a good set of features is a challenging issue of significance.
- Modeling and processing of thermal images of 3D printing is also a challenging issue. Data collection and generation is massive. There should be applications developed to save this big data and make them valuable. Huge datasets decrease the accuracy of the obtained results.

Considering the above challenges, it is clear that further research works are to be developed to focus on application of ML in 3D printing technology. Among the various challenges mentioned above, one thing is clear, and that is that, the data sharing culture among the materials community is sparse, and it needs to be improved. On this note, this marks the end of the literature review chapter.

Chapter 3

OBJECTIVE & METHODOLOGY

3.1 Objective

Our main objective is:

- To perform 3D printing of samples by varying 5 input parameters and measure their surface roughness and tensile properties
- To formulate mathematical model between input and output process parameters of FDM process using three ML algorithms
- To compare the performance of ML algorithms based on their prediction results and error analysis.

3.2 Methodology & Work Plan

Our approach towards the aforementioned objective for the three ML algorithms is thoroughly explained in a series of steps given below. Note that

1. Sample 3D Printing with different process parameters

We will be using FDM (Fused Deposition Modelling) Machine in this case. It is far by the most common according to the research papers we have looked through. The professor in charge also recommends this AM Machine for our experiments. We will be printing different samples with varying process parameters, mainly print speed, layer thickness, orientation, raster width, airgap, nozzle diameter, fiber spacing, etc., and many more to mention.

2. Sample Testing and Data collection

We will now use the printed samples to test on them for purposes like finding compressive strength, wear volume, surface roughness, etc. And collect the values to form datasets for our ML Algorithms, because, after all, data-driven models need data to work on and FDM is a data-driven model. We will be using three ML Algorithms, namely, LGBM, XG Boost and RF as the core of our BTP projects up ahead.

3. Use the data as input for AI algorithms

AI Algorithms need huge chunks of datasets before they can do predictive analysis for the model. Datasets of CSV, TSV or other training dataset formats that contain raw data containing parameter information is fed to the ML Algorithms. Some readily available dataset obtained from previous experiments could also be used as input data.

4. AI will predict the surface roughness (output) and provide mathematical model

In this study, we will use ML Algorithms to predict surface roughness in the 3D printing process. This output will then be used to supplement the AM process in FDM. It can also be used to provide mathematical model for the printed part and some of its properties.

5. For given input Finding MSE(mean square error), RMSE(root mean square error), in classification correlation accuracy and R(square) score basically difference of square of predicted value or trained data and its square and taking average of all.

Input data are given as:

Exp no.	x1	x2	x3	x4	x5	output(y)
1	0.178	15	30	0.4564	0.004	12.48
2	0.254	0	60	0.4064	0.008	15.83
3	0.254	30	0	0.4064	0.008	10.78
4	0.127	0	0	0.5064	0	13.89
5	0.127	30	60	0.5064	0	11.83
6	0.178	15	0	0.4564	0.004	11.95
7	0.178	15	60	0.4564	0.004	11.87
8	0.178	0	30	0.4564	0.004	14.98
9	0.178	30	30	0.4564	**0.004**	12.28
10	0.254	30	60	0.4064	0	16.98
11	0.127	30	0	0.5064	0.008	11.13
12	0.178	15	30	0.4064	0.004	11.01
13	0.127	0	60	0.5064	0.008	13.58
14	0.127	30	60	0.4064	0.008	7.444
15	0.254	30	60	0.5064	0.008	10.78
16	0.127	0	60	0.4064	0	14.28
17	0.254	0	60	0.5064	0	16.29
18	0.127	0	0	0.4064	0.008	15.21
19	0.254	0	0	0.5064	0.008	16.18
20	0.127	30	0	0.4064	0	10.16
21	0.178	15	30	0.4564	0.004	11.31

22	0.254	30	0	0.5064	0	10.44
23	0.178	15	30	0.4564	0.004	12.88
24	0.127	15	30	0.4564	0.004	12.49
25	0.254	15	30	0.4564	0.004	12.34
26	0.178	15	30	0.4564	0.004	11.72
27	0.178	15	30	0.4064	0.004	11.56
28	0.178	15	30	0.5064	0.004	11.25
29	0.178	15	30	0.4564	0	12.26
30	0.178	15	30	0.4564	0.008	11.09
31	0.178	15	30	0.4564	0.004	12.67
32	0.254	0	0	0.4064	0	12.41

Chapter 4

CONCLUSION

3D printing or AM technology has been widely used by researchers, scientists, or normal people in the everyday world. It is a big part of industry 4.0; however, the printed model does not come out as perfect as you expect it to be. In the real world, there are many defects that lead to many trials and errors and affect the quality of the product. The coming of ML algorithms in 3D technology has been a big timesaver and reduced the trials and errors, therefore being a big boost and an integral part of AM technology.

The use of ML in AM covers a broad spectrum of applications, ranging from design for 3D printing, process optimization to in situ quality control and defect monitoring. ML algorithms have shown to be an essential tool to perform data-driven numerical simulations, real-time anomaly detection, design recommendation, material analysis for further use. It has vastly outperformed conventional optimization methods (physics-based and whatnot), especially when dealing with high-dimensional chunks of data. There are many ML algorithms even to name; each one of them has proven to be highly useful in dealing with a particular parameter in the AM process. This report summarizes the various input and output parameters of ML algorithms in 3D printing. The research studies into many such algorithms in AM process have been cited in this BTP report.

FDM is the most common AM process, being widely utilized and low of cost, it can be termed as the citizen's machine, as there exist many AM processes that are more accurate to scientific perfection whenever required, but that's not to mean FDM is not exceptionally good at what it prints. ML algorithms like RF, XGBoost, and LGBM can be used in FDM to predict surface roughness, which is our work plan as mentioned in section 3 above. These three tree-based algorithms have shown to be effective in the AM processes, and this ongoing research is a report about the same. These are supervised learning ML models that use training data to understand the manufacturing aspects and aid us in the process. The utilization and the analysis of these ML models in FDM will be carried out in the following semesters.

CHAPTER 5:

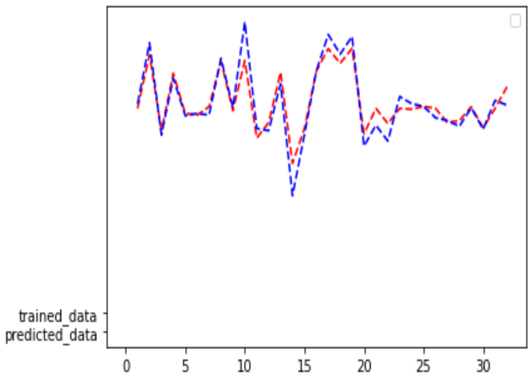
Results

12/11

The value of (output(y)) is given:

[12.17023054 15.42474 10.89914667 14.0054 12.05594 11.84943643
12.12832024 14.70604286 12.02283333 15.05776167 10.5121
11.35929333 14.07304 8.79262333 11.58156 14.10064 15.3915
14.61958 15.5517 10.67742833 12.17023054 11.645 12.17023054
12.21235714 12.42504329 12.17023054 11.35929333 11.62101879
12.31110984 10.92357006 12.17023054 13.6291]

R2_score = 0.829032831092849
Mean squareerror = 0.664013691600152
Root mean square error = 0.8148703526329523



CODE:

References

[1] Mohan Kumar V, Lokesha, “An Experimental Investigation of Influence of Process Parameters on Cutting Tool Chatter”

[2] Christopher Kantzos, Joseph Pauza, Ross Cunningham, Sneha P. Narra, Jach Beuth, Anthony Rollett, “An Investigation of process Parameter Modifications on Additively Manufactured Inconel 718 parts”

[3] Inovar Communications, “METAL AM – The magazine for the additive manufacturing industry.”

[4] Abdelkablr Bacha, Jamal Benhra, “Fault Diagnosis in the Field of Additive Manufacturing (3D Printing) Using Bayesian Networks.

[5] Grace X. Gu, Chun-The Chen, Markus J. Buehler “De novo composite design based on machine learning algorithm

[6] Luke Scime, Jack Beuth, “Anomaly Detection and classification in a laser power bed additive manufacturing process using a trained computer vision algorithm.

[7] Ikenna A. Okaro, Sarini Jayasinghe, Chris Sutcliffe, Kate Black, Paolo Paoletti, Peter L.Green, “Automatic Fault detection for laser powder-bed fusion using semi-supervised machine learning”

[9] Yao, Siling; Moon, Seung Ki; Bi, Guijan, “A hybrid machine learning approach for additive manufacturing design feature recommendation”

[10] Shajahan Bin Maidin, Ian Campbell, Eujin Pei, “Development of a design feature database to support design for additive manufacturing”

[11] Yang Shi, Yicha Zhang Steven Baek, Wout De Backer, Ramy Harik, “Manufacturability analysis for additive manufacturing using a novel feature recognition technique”

[12] Xiaoting Zhang, Xinyi Le, Athina Panotopoulou, Emily whiting, Charlie C.L. Wang, “perceptual models of preference in 3D printing Direction.

[14] R.N. Chikkangoudar, T.G. Sachidananda, Niranjan pattar, “Influencd of 3D printing parameter on the dimensional stability of polypropylene/clay printed parts using laser scanning technique”

[15] SETHU RAMALINGAM PIRAMANAYAGAM, K. MAYANDI, V. BALASUBRAMANIAM, K. CHANDRASEKAR, “EFFECT OF 3D PRINTING PROCESS PARAMETERS ON THE IMPACT STRENGTH OF ONYX – GLASS FIBER REINFORCED COMPOSITED”

[16] SAYAK PAUL HYPERPARAMETER OPTIMIZATION IN MACHINE LEARNING MODELS

[17] Kenta AOYAGI, HAO WANG, HIDEKI SUDO, AKIHIKO CHIBA, “SIMPLE METHOD TO CONSTRUCT PROCESS MAPS FOR ADDITIVE MANUFACTURING USIGN A SUPPORT VECTOR MACHINE”

[18] ZHENGTAO GAN, HENGYANG LI, SARAH J. WOLFF, JENNIFER L. BENNETT, GREYOGY HYATT, GREGORY J. WANGER, JIAN CAO, WING KAM LIU, “DATA-DRIVEN MICROSTRUCTURE AND MICROHARDNESS DESING IN ADDITIVE MANUFACTURING USING A SELF-ORGINIZING MAP”

[19] Ebrahim Vahabli, Sadegh Rahmati, “Application of an RBF neutal network for FEM parts/ surface roughness prediction for enhancing surface quality”

[20] Omar Ahmed Mohamed S.H Masood, Jahar Bhowmik, “Investigation of dynamic elastic deformation of parts processed by fused deposition modeling additive manufacturing”

[21] Zhenglong Jiang, Yuanyuan liu, Qingxi Hu, “Optimization of Process Parameters for Bilogical 3D printing forming based on BP Neural Network and Genetic Algorithm”

[22] A. Noriega, D. Blanco, B.J. Alvarez, A. Garcia, “Dimensional accuracy improvement of FDM square cross-section parts using artificial neural networks and an optimization algorithm”

[23] Omer Bayraktar, Gultekin Uzun, Ramazan Cakiroglu, Abdulmecit Guldas, “Experimental study on the 3D printed plastic parts and predicting the mechanical properties using artificial neural networks”

[24] Anoop K. Sood Raj K. Ohdar, Siba S. Mahapatra, “Experimental investigation and empirical modelling of FDM process for compressive strength improvement”

[25] Anoop kumar sood, asif Equbal, vijay toppo, r.k. ohdar, s.s. Mahapatra, an investigation on sliding wear of FDM built parts”

[26] Zhixiong li, Ziyang zhang, dazhong wu, “prediction of surface roughness in extrusion based additive manufacturing with machine learning”

[27] Xinbo qi, guofeng chen yong li, xuan cheng, changpeng li, “Applying Neural-Network-Based machine learning to additive manufacturing: Current Applications, Challenges, and Future perspectives”

[28] Wang Rong-Ji LiXin-hua, Wu Qing-ding, Wang Lingling, “Optimizing process parameters for selective laser sintering based on neural network and genetic algorithm”

[29] Haiyang He, Yang Yang, Yayue Pan, “Machine Learning for continuous liquid interface production: printing speed modelling”

[30] Arman Sabbaghi, Qiang Huang Tirthakar Dasgupta, “Bayesian Model Building for small samples of disparate data for capturing In- Plane deviation in additive manufacturing”

[31] ZHIZIONG LI, ZIYANG ZHANG, DAZHONG WU, “PREDICTION OF SURFACE ROUGHNESS IN EXTRUSION-BASED ADDITIVE MANUFACTURING WITH MACHINE LEARNING”

[33] GEORGE-CHRISTOPHER VOSNIAKOS, T. MAROULIS, DIMITRIOS, I. PANTELIS, “A METHOD FOR OPTIMIZING PROCESS PARAMETERS IN LAYER-BASED RAPID PROTOTYPING”

[34, 35] Haiyeng He, Yang Yang, “Machine learning for continuous interface production: printing speed modelling.”

[36] Anita R., Arunachalam, “Critical Parameters Influencing the Quality of Prototypes in Fused Deposition Modelling. Journal of Materials Processing Technology”

[37, 39] Sara Nasiri, Mohammad Reza Khosravani, "Machine learning in predicting mechanical behavior of additively manufactured parts"

[38] C.wang, ta-wei lin, shr-shiung hu, "pOtimizing the rapid prototyping process by integrating the Taguchi method with the Gray relational analysis"

[40] Syed H. Masood, "Intelligent rapid prototyping with fused deposition modelling"

[41] Dr. T. S. Srivatsan, "Material and manufacturing process"

[42] Ala'aldin Alafaghani, Ala Qattawi, Muhammad Ali Ablat, "Design Consideration for Additive Manufacturing: Fused Deposition Modelling"

[43] T. Nancharaiah *d. Ranga Raju, V. Ramah, Ra Raju, "An experimental investigation on surface quality and dimensional accuracy of FDM components"

[44] Abdelkabir Bacha, Ahmed Haroun Sabry, "Fault diagnosis in the field of additive manufacturing (3D printing) using bayesian networks.

[45] C K Basavaraj and M Vishwas, "Studies on Effect of Fused Deposition Modelling Process Parameters on Ultimate Tensile Strength and Dimensional Accuracy of Nylon".

[46] Wieslaw Kuczko, Radoslaw Wichiniarek, "INFLUENCE OF PROCESS PARAMETERS ON DIMENSIONAL ACCURACY OF PARTS MANUFACTURED USING FUSED DEPOSITION MODELLING TECHNOLOGY"

[47] Tata Nancharaiarah, D ranga raju, "An experimental investigatoin on surface quality and dimensional accuracy of FDM components"

[48] Beibet Zyharylkassyn, Asma Perveen, "Effect of process parameters and materials on the dimensional accuracy of FDM parts".

[49] Mohammad Farhan Khan, Aftaab Alam, "Real-time defect detection in 3D printing using machine learning"

[50] Ugandhar Delli, Shing Chang, "Automated Process Monitoring in 3D Printing Using Supervised Machine Learning"

[51] Muammel M. Hanon, Quanjin Ma, "Accuracy investigation of 3D printed PLA with various process parameters and different colors"

[52] C. Wang, X. P. Tan, "Machine learning in additive manufacturing: State-of-the-art and perspectives"

[53] Dean Grierson, Allan E. W. Rennie, "Machine Learning for additive Manufacturing"

[54] Grace X. Gu, Chun The-Chen, "De novo composite design based on Machine Learning Algorithm"

[55] Luke Scime, Jack Beuth, "Anomaly detection and classification in a laser powder bed additive manufacturing process using a trained computer vision algorithm"

[56] Ikenna A. Okaro, Sarini Jayasinghe, "Automatic fault detection for laser powder-bed fusion using semi-supervised machine learning"

[57] A hybrid machine learning approach for additive manufacturing design feature recommendation

[58] Shajahan Bin Maidin, Ian Campbell, "development of a design feature database to support design for additive manufacturing"

[59] Menderes Kam, Ahmet Ipeczi, "Investigation of the effect of FDM process parameters on mechanical properties of 3D printed PA12 samples using Taguchi method"

[60] M. Kamaal, M. Anas, "Effect of FDM process parameters on mechanical properties of 3Dprinted carbon fibre–PLA composite"

[61] YuanBin Wang, Pai Zheng, "Smart additive manufacturing: Current artificial intelligenceenabled methods and future perspectives"

[62] Leila Jannesari Ladani , "Applications of artificial intelligence and machine learning in metal additive manufacturing"

[63] Xinbo Qi, Guofeng Chen, "Applying Neural-Network-Based Machine Learning to Additive Manufacturing: Current Applications, Challenges, and Future Perspectives"

THANK YOU