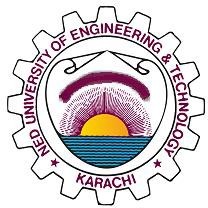
##### UNDERGRADUATE FINAL YEAR PROJECT REPORT

Department of Industrial and Manufacturing Engineering

NED University of Engineering and Technology



Enhancing the Surface Finish of Composite Products’ Mold through Machine Learning Technique

**Group Number: G20**

**Batch: 2020-2021**

**Group Member Names:**

Muhammad Daniyal Siddiqui

Hanzla Aqeel

Muhammad Usman Habib

Muhammad Arqam

IM-20051

IM-20063

IM-20068

IM-20319

Approved by

…………………………………………………………………………………………..

Dr. Muhammad Wasif

Associate Professor

Project Advisor

© NED University of Engineering & Technology. All Rights Reserved – 2024

Author’s Declaration

We declare that we are the sole authors of this project. It is the actual copy of the project that was accepted by our advisor(s) including any necessary revisions. We also grant NED University of Engineering and Technology permission to reproduce and distribute electronic or paper copies of this project.

|  |  |  |  |
| --- | --- | --- | --- |
| Signature & Date | Signature & Date | Signature & Date | Signature & Date |
|  |  |  |  |
| …………………. | ......……………... | ……………............ | ………………….. |
|  |  |  |  |
| Muhammad Daniyal Siddiqui | Hanzla Aqeel | Muhammad Usman Habib | Muhammad Arqam |
| IM-20051 | IM-20063 | IM-20068 | IM-20319 |
| [daniyalsiddique 606@gmail.com](mailto:daniyalsiddique606@gmail.com) | [hanzl.aq021 @gmail.com](mailto:hanzlaakeel83@gmail.com) | [usman376929 @gmail.com](mailto:usman376929@gmail.com) | [arqamsuleman 123@gmail.com](mailto:arqamsuleman@gmail.com) |

# **Statement of Contribution**

As a group of four diligent students, we collectively put our efforts together in the creation of this report. It was not possible without the contribution of each of the group member to complete this project. The contribution of each member in writing this report is as under:

**Muhammad Arqam:** The compilation of report and the Introductory chapter come under his contribution. He invested his efforts to maintain the structure of report.

**Muhammad Daniyal Siddiqui:** He invested his time in writing the chapter of Literature Review.

**Hanzla Aqeel:** He invested his efforts in writing the chapter of Literature Review as well as structuring of report.

**Muhammad Usman Habib:** He contributed his efforts in writing the chapter of Methodology as well as assisted in the compilation of report.

# **Executive Summary**

# **Acknowledgements**

We are thankful to Allah Almighty for providing us with an opportunity through Department of Industrial and Manufacturing Engineering at NED University of Engineering and Technology and gave us a chance to complete this chance under the supervision of our honorable Project Advisor Dr. Muhammad Wasif (Associate Professor, IMD) and Dr. Anis Fatima (Associate Professor, IMD). We are thankful to them for their sincere guidance and inspiration throughout the project. Their expertise and guidance enabled us to successfully complete this project within the given time. They constantly supported and encouraged us throughout this project.

**Table of Contents**

[Statement of Contribution iii](#_Toc171976568)

[Executive Summary iv](#_Toc171976569)

[Acknowledgements v](#_Toc171976570)

[1. Introduction 1](#_Toc171976571)

[1.1 Background 1](#_Toc171976572)

[1.1.1 Overview of Composite Material 1](#_Toc171976573)

[1.1.2 Importance and Applications of Composites 2](#_Toc171976574)

[1.1.3 Manufacturing of Composite Materials 3](#_Toc171976575)

[1.1.4 Role of Molds in Composite Manufacturing 5](#_Toc171976576)

[1.1.5 Challenges in Mold Surface Finish 6](#_Toc171976577)

[1.2 Problem Statement 6](#_Toc171976578)

[1.3 Objectives of the Project 7](#_Toc171976579)

[1.4 Significance of the Study 7](#_Toc171976580)

[1.5 Scope of the Project 8](#_Toc171976581)

[2. Literature Review 9](#_Toc171976582)

[2.1 Overview of Fused Deposition Modeling (FDM) 12](#_Toc171976583)

[2.2 Surface Finish Challenges in FDM 13](#_Toc171976584)

[2.3 Composite Materials and Their Manufacturing 14](#_Toc171976585)

[2.4 Machine Learning in Manufacturing 16](#_Toc171976586)

[2.5 Previous Work on Surface Finish Optimization 17](#_Toc171976587)

[2.6 Research Gap and Motivation 18](#_Toc171976588)

[3. Methodology 20](#_Toc171976589)

[3.1 Data Collection 20](#_Toc171976590)

[3.1.1 Source of Data 20](#_Toc171976591)

[3.1.2 Parameters Collected 20](#_Toc171976592)

[3.1.3 Description of the Dataset 21](#_Toc171976593)

[3.2 Data Preprocessing 21](#_Toc171976594)

[3.2.1 Data Cleaning 21](#_Toc171976595)

[3.2.2 Standardization 25](#_Toc171976596)

[3.2.3 Normalization 26](#_Toc171976597)

[3.2.4 Encoding Categorical Variables 26](#_Toc171976598)

[3.2.5 Exploratory Data Analysis (EDA) 27](#_Toc171976599)

[3.3 Machine Learning Models 27](#_Toc171976600)

[3.3.1 Random Forest Regressor 28](#_Toc171976601)

[3.3.2 K-Nearest Neighbors (KNN) Regressor 28](#_Toc171976602)

[3.3.3 XGBoost 28](#_Toc171976603)

[3.3.4 Neural Networks 29](#_Toc171976604)

[3.4 Model Training and Evaluation 29](#_Toc171976605)

[3.4.1 Training Process 29](#_Toc171976606)

[3.4.2 Evaluation Metrics 29](#_Toc171976607)

[3.4.3 Hyperparameter Tuning 30](#_Toc171976608)

[3.5 Optimization with Genetic Algorithm 30](#_Toc171976609)

[3.5.1 Introduction to Genetic Algorithm 30](#_Toc171976610)

[3.5.2 Implementation 30](#_Toc171976611)

[3.5.3 Genetic Algorithm Parameter Sets: 31](#_Toc171976612)

[4. Results and Discussion 32](#_Toc171976613)

[4.1 Model Performance Comparison 32](#_Toc171976614)

[4.1.1 Random Forest Results 32](#_Toc171976615)

[4.1.2 KNN Results 33](#_Toc171976616)

[4.1.3 XGBoost Results 33](#_Toc171976617)

[4.1.4 Neural Network Results 34](#_Toc171976618)

[4.2 Optimization Results 35](#_Toc171976619)

[4.2.1 Genetic Algorithm Optimization 35](#_Toc171976620)

[4.2.2 Comparison of Parameter Sets **Error! Bookmark not defined.**](#_Toc171976621)

[4.3 Experimental Validation 37](#_Toc171976622)

[4.3.1 Experiment Setup (CreatBot F160) 37](#_Toc171976623)

[4.3.2 Validation Results 37](#_Toc171976624)

[4.3.3 Comparison with Predicted Results 37](#_Toc171976625)

[5. Conclusion and Future Work 38](#_Toc171976626)

[5.1 Summary of Findings 38](#_Toc171976627)

[5.2 Contributions to the Field 38](#_Toc171976628)

[5.3 Limitations of the Study 38](#_Toc171976629)

[5.4 Recommendations for Future Research 38](#_Toc171976630)

**List of Figures**

[**Fig. ‎3.1** **Error! Bookmark not defined.**](#_Toc159283676)

[**Fig. ‎3.2** **Error! Bookmark not defined.**](#_Toc159283677)

**List of Tables**

[Table 1 List of resources reviewed **Error! Bookmark not defined.**](#_Toc159185402)

CHAPTER 01

# Introduction

## Background

### Overview of Composite Material

Composite materials have revolutionized various industries due to their unique properties and versatility. These materials are formed by combining two or more constituent materials with significantly different physical or chemical properties. When combined, they produce a material with characteristics different from the individual components, often superior in terms of strength, weight, or other properties.

The two main components of a composite are:

1. The matrix: This is the continuous phase that holds the reinforcement together.

2. The reinforcement: This provides the main source of strength and stiffness.

Common types of composites include:

* Fiber-reinforced composites (e.g., carbon fiber reinforced polymers)
* Particulate composites (e.g., concrete)
* Laminar composites (e.g., plywood)
* Hybrid composites (combining different types of reinforcements)

### Importance and Applications of Composites

The importance of composite materials in modern engineering and manufacturing cannot be overstated. Their unique combination of properties makes them ideal for a wide range of applications across various industries:

* Aerospace: Composites are extensively used in aircraft and spacecraft construction due to their high strength-to-weight ratio. Examples include the Boeing 787 Dreamliner, which is composed of approximately 50% composite materials.
* Automotive: The automotive industry utilizes composites to reduce vehicle weight, improve fuel efficiency, and enhance performance. Carbon fiber reinforced polymers are increasingly used in high-performance cars and racing vehicles.
* Construction: Fiber-reinforced polymers are used for reinforcing concrete structures, while composite panels are employed in modern architectural designs.
* Marine: Boat hulls and marine structures benefit from the corrosion resistance and light weight of composite materials.
* Sports Equipment: From tennis rackets to bicycle frames, composites have revolutionized sports equipment design, offering improved performance and durability.
* Wind Energy: Wind turbine blades are typically made from glass fiber reinforced polymers, allowing for larger and more efficient turbines.
* Medical: Composite materials are used in prosthetics, dental implants, and various medical devices due to their biocompatibility and customizable properties.

### Manufacturing of Composite Materials

The manufacturing of composite materials involves combining the matrix and reinforcement in a controlled manner to achieve desired properties. The choice of manufacturing technique depends on factors such as the type of composite, desired shape and properties, production volume, and cost considerations.

#### Modern Manufacturing Techniques

##### Automated Fiber Placement (AFP)

AFP is an advanced manufacturing technique that allows for precise placement of composite fibers. It involves using a robotic arm to lay down narrow strips of composite material (tows) onto a mold or mandrel. Key features of AFP include:

* High precision and repeatability
* Ability to create complex geometries
* Reduced material waste compared to manual methods
* Increased production speed for large parts

AFP is widely used in the aerospace industry for manufacturing large, complex structures such as fuselage sections and wing skins.

##### Resin Transfer Molding (RTM)

RTM is a closed mold process that offers several advantages over traditional open mold techniques:

* Dry reinforcement is placed in a closed mold
* Resin is injected under pressure, thoroughly wetting the fibers
* Both sides of the part have a smooth finish
* Consistent part quality and reduced void content
* Reduced emissions compared to open mold processes

RTM is used in automotive, aerospace, and marine industries for producing high-quality, complex-shaped parts.

##### Additive Manufacturing for Composites

The integration of additive manufacturing (3D printing) with composite materials is an emerging field with significant potential:

* Continuous Fiber 3D Printing: Allows for the embedding of continuous fibers within a thermoplastic matrix during the printing process.
* Large-Scale Additive Manufacturing: Enables the production of large composite structures without the need for molds.
* Multi-Material Printing: Offers the ability to vary material composition within a single part, optimizing properties for specific load cases.

These advanced techniques are pushing the boundaries of what's possible in composite manufacturing, enabling more complex geometries, improved material properties, and increased production efficiency.

#### Traditional Manufacturing Technique

* Hand Lay-up: This is one of the oldest and simplest techniques. Reinforcement fibers are manually placed in a mold and resin is applied by hand. This method is labor-intensive but allows for complex shapes and is suitable for low-volume production.
* Spray-up: Similar to hand lay-up, but uses a spray gun to apply chopped fibers and resin simultaneously. This method is faster than hand lay-up but may result in less consistent fiber distribution.
* Compression Molding: This involves placing pre-impregnated reinforcement (prepreg) or a mixture of resin and fibers into a heated mold cavity. The mold is then closed and pressure is applied, forcing the material to conform to the mold shape.
* Filament Winding: Used primarily for hollow, cylindrical components. Fibers are wound around a rotating mandrel in a controlled pattern and then impregnated with resin.
* Pultrusion: A continuous process used to produce long, straight profiles. Fibers are pulled through a resin bath and then through a heated die that shapes and cures the composite.

### Role of Molds in Composite Manufacturing

Molds play a crucial role in shaping composite materials and determining the surface quality of the final product. The importance of molds in composite manufacturing cannot be overstated:

* Shape Definition: Molds define the geometry of the composite part, including complex curves and detailed features.
* Surface Quality: The surface finish of the mold directly impacts the surface quality of the composite part. A smooth mold surface results in a smooth composite surface.
* Dimensional Accuracy: Molds ensure that composite parts are produced to the required dimensions and tolerances.
* Resin Distribution: In processes like RTM, the mold design influences resin flow and distribution, affecting the overall quality of the part.
* Curing Environment: Molds can be heated or cooled to control the curing process of thermoset resins.
* Production Efficiency: Well-designed molds can improve production speed and reduce material waste.
* Cost Implications: While high-quality molds can be expensive to produce, they can significantly reduce per-part costs in high-volume production.

### Challenges in Mold Surface Finish

Achieving and maintaining a high-quality surface finish on molds is critical but challenging:

* Material Limitations: Some mold materials may not inherently provide the desired surface smoothness.
* Wear and Tear: Molds degrade over time due to repeated use, potentially affecting surface quality.
* Complex Geometries: Intricate shapes and deep cavities can be difficult to finish uniformly.
* Temperature Effects: Thermal cycling during production can cause surface defects or dimensional changes in the mold.
* Chemical Interactions: Some resins or release agents may interact with the mold surface, causing degradation over time.
* Cost-Quality Trade-off: Achieving extremely high-quality surfaces often involves expensive materials and time-consuming finishing processes.
* Consistency: Maintaining consistent surface quality across large mold surfaces and between different molds can be challenging.

## Problem Statement

The problem statement outlines the specific issue that our project aims to address. In our case, it might read:

"Despite the advancements in Fused Deposition Modeling (FDM) technology, achieving high-quality surface finish on 3D printed molds for composite manufacturing remains a significant challenge. The complex relationships between printing parameters and surface quality are not fully understood, leading to suboptimal mold surfaces that can negatively impact the quality of produced composite parts. There is a need for a systematic, data-driven approach to optimize FDM printing parameters specifically for mold production in composite manufacturing."

## Objectives of the Project

This section lists the specific goals you aim to achieve through our research. Our objectives might include:

* To develop a comprehensive dataset of FDM printing parameters and their effects on surface roughness, specifically for mold production.
* To compare and evaluate various machine learning models for predicting surface roughness based on FDM printing parameters.
* To implement a genetic algorithm optimization approach to determine optimal printing parameters for minimizing surface roughness.
* To validate the predictive models and optimized parameters through experimental testing on a CreatBot F160 3D printer.
* To provide practical, tiered sets of optimized printing parameters suitable for different levels of FDM printer capabilities.

## Significance of the Study

This section explains why our research is important and how it contributes to the field. You might highlight:

* The potential to significantly improve the quality of composite parts by enhancing mold surface finish.
* The novel integration of machine learning and optimization techniques in the context of FDM mold production.
* The practical implications for industry, potentially reducing post-processing needs and improving efficiency in composite manufacturing.
* The contribution to the broader field of smart manufacturing, demonstrating the potential of data-driven approaches in additive manufacturing.

## Scope of the Project

This section defines the boundaries of our research, clarifying what is included and what is not. Our scope might include:

* Focus on FDM technology using ABS and PLA materials.
* Consideration of key printing parameters including layer thickness, print speed, temperature, infill pattern, and others identified in the literature review.
* Development and comparison of machine learning models including Random Forest, KNN, XGBoost, and Neural Networks.
* Optimization using genetic algorithms.
* Experimental validation using a CreatBot F160 printer.
* Emphasis on surface roughness as the primary quality metric.

CHAPTER 02

# Literature Review

|  |  |  |  |
| --- | --- | --- | --- |
| Author | Mold Material | Process | Topics discussed |
| J. Nagendra, M.K. Srinath, S. Sujeeth, K.S. Naresh, M.S. Ganesha Prasad | Nylon aramid | FDM | Rapid prototyping, Additive manufacturing, ABS, Product lifecycle management |
| Priyadarsini Morampudi a, V.S.N. Venkata Ramana b, K. Aruna Prabha a, S. Swetha a, A.N. Brahmeswara Rao a | ABS | FDM | Rapid prototyping, additive manufacturing, product lifecycle management, ABS, surface finish |
| Ramesh Chand, Vishal S. Sharma, Rajeev Trehan, Munish Kumar Gupta, and Murat Sarikaya | Photopolymer (PLA) | MJP | 3d printing, additive manufacturing, dimensional accuracy, multi-jet printing, rapid prototyping, surface roughness |
| Anjali Yadav, Bhukya Poorna Prakash, Karanam Sai Dileep, Sureddi Arjuna Rao, G.B. Veeresh Kumar | PLA and ABS | FDM | Layer-by-Layer Manufacturing FDM Poor, Surface Finish, Vapor Smoothing Process |
| AHM Haidiezul, AF Aiman2 and B Bakar3 | ABS | FDM | Surface finish and coating, additive manufacturing, slicing, Stair case effect |
| Fulvio Lavecchia, Maria Grazia Guerra Luigi Maria Galantucci | PLA | FDM | Additive manufacturing, Fused deposition model, Roughness, Surface finish, PLA, Chemical vapor treatment |
| Esther Molero, Juan Jesús Fernández, Oscar Rodríguez-Alabanda, Guillermo Guerrero-Vaca \* and Pablo E. Romero | PLA | FDM | fused deposition modeling, FDM, data mining, machine learning, PLA, surface roughness; WEKA, decision trees, neural networks, ANN, frame glasses |
| M. Mani a, A.G. Karthikeyan a, K. Kalaiselvan a, P. Muthusamy, P. Muruganandhan | PLA | FDM | PLA, 3-D Printer Orthogonal Array, Fused Deposition Modeling |
| J. Nagendra, M. S. Ganesha Prasad | PLA | FDM | Fused deposition modelling, Nylon–aramid composite, Process optimization by Taguchi technique |
| <https://xometry.eu/en/surface-finishes-for-3d-printing/> | Alumide® / PA 12 filled with aluminium, ABS, EPX 82 | SLS, FDM, SLS, DMLS | provides surface roughness measurements for SLS, MJF, FDM, DMLS, Carbon DLS, and Polyjet 3D prints |
| M. Manoj Prabhakar a, A.K. Saravanan b, A. Haiter Lenin c, I. Jerin leno d, K. Mayandi a, P. Sethu Ramalingam b | ABS, PLA, PET, TPU | FDM | 3D printing, Methods Parameters, Polymers |
| Yingguang Li, Nanya Li, James Gao | FR Composite, Invar, Steel and Aluminum | Forming, microwave curing, vacuum pressure | Polymer composites manufacturing, Anisotropic composite tooling design, Vacuum-pressure microwave curing, Aerospace composite materials |
| Irshadullah, Muhammad Wasif, Anis Fatima, Muhammad Tufail | PETG | FDM | 3D printer, 3D Scanner, Composite Mold, Shrinkage, Dimensional Accuracy |
| Omar A. Mohamed, Syed H. Masood,  Jahar L. Bhowmik | ABS, PC | FDM | Fused deposition modeling (FDM), Experimental design, Additive manufacturing, Process parameters, Mechanical properties, Part quality |
| Irshad Ullah, Muhammad Wasif, Muhammad Tufail1 | ABS, PLA, PETG | FDM | Additive manufacturing (AM), Composite tooling, 3D printing, Shrinkage compensation, 3D scanning, 3D printed molds |
| Maraboina Raju, Munish Kumar Gupta, Neeraj Bhanot3, Vishal S. Sharma | ABS | FDM | Evolutionary algorithm, Mechanical properties, Optimization, Surface roughness, Rapid prototyping |
| Thomas Zeke Sudbury, Robert Springfield, Vlastimil Kunc, Chad Duty | CF-ABS | FDM | Additive manufacturing, Composite materials, 3-D printing, Manufacturing techniques, Molds |
| Ankita Jaisingh Sheoran  , Harish Kumar | ABS, PLA | FDM | Additive Manufacturing, Mechanical properties, Fused Deposition modeling, Optimization Process parameters, Design of Experiments |
| Ahmed Arabi Hassen, Robert Springfield2, John Lindahl1, Brian Post, Lonnie Love1, Chad Duty, Uday Vaidya, R. Byron Pipes, Vlastimil Kunc1 | CF-ABS | Vacuum Assisted Resin Transfer Molding (VARTM) | Additive Manufacturing, Mold fabrication, BAMM, VARTM, CTE |
| Dean Grierson, Allan E. W. Rennie, Stephen D Quayle | Aluminum, PLA | FDM, PBF | machine learning, reinforcement learning, design and monitoring for additive manufacturing |
| Prairit Sharma, Harshal Vaid, Ritam Vajpeyi, Pritish Shubham, Krishna Mohan Agarwal a, Dinesh Bhatia b | ABS, PLA | FDM | Additive manufacturing, Fused deposition modelling, Machine learning, Artificial intelligence, 3D printing |
| Mohammad Shirmohammadi, Saeid Jafarzadeh Goushchi, Peyman Mashhadi Keshtiban | PLA | FDM | 3D printing, Surface roughness, Artificial neural network, Particle swarm optimization algorithm, Response surface method |

## Overview of Fused Deposition Modeling (FDM)

Fused Deposition Modeling (FDM), also known as Fused Filament Fabrication (FFF), is an additive manufacturing process that has gained significant popularity in recent years due to its versatility, cost-effectiveness, and accessibility.

FDM works on the principle of material extrusion:

* Material Feed: A thermoplastic filament is fed from a spool into a heated nozzle.
* Melting: The filament is heated to a semi-liquid state.
* Extrusion: The molten material is extruded through the nozzle.
* Layer Deposition: The extruded material is deposited in thin layers on a build platform.
* Layer Bonding: Each new layer bonds to the previous layer as it cools and solidifies.
* Build Completion: The process repeats until the entire 3D object is formed.

Common materials used in FDM include:

* ABS (Acrylonitrile Butadiene Styrene)
* PLA (Polylactic Acid)
* PETG (Polyethylene Terephthalate Glycol)
* Nylon
* TPU (Thermoplastic Polyurethane)

FDM has found applications in various fields, including:

* Rapid prototyping
* Custom manufacturing
* Aerospace and automotive parts
* Medical models and devices
* Educational tools

Key advantages of FDM include its ability to create complex geometries, relatively low material and machine costs, and the wide range of available materials. However, it also faces challenges, particularly in achieving high-quality surface finishes, which is a critical aspect of our project.

## Surface Finish Challenges in FDM

Surface finish quality is one of the primary limitations of FDM technology. Several factors contribute to surface finish issues in FDM-printed parts:

* Layer Lines: The layer-by-layer nature of FDM results in visible layer lines, often referred to as the "staircase effect."
* Stringing: Small strings of plastic may form between separate parts of the print, affecting surface smoothness.
* Warping: Uneven cooling can cause parts to warp, distorting the surface geometry.
* Overhangs and Bridges: Unsupported sections can sag or droop, impacting surface quality.
* Layer Shifting: Mechanical issues can cause layers to misalign, creating visible defects.
* Infill Pattern Visibility: In some cases, the internal structure (infill) can be visible through the outer layers.
* Nozzle Diameter: The size of the nozzle affects the minimum feature size and surface detail that can be achieved.

Research by Wang et al. (2019) demonstrated that layer thickness has a significant impact on surface roughness, with thinner layers generally resulting in smoother surfaces but at the cost of increased print time.

Kuo and Mao (2016) investigated the effects of infill patterns on surface quality, finding that certain patterns can minimize surface defects while maintaining structural integrity.

These surface finish challenges are particularly relevant when using FDM for mold production, as the surface quality of the mold directly impacts the surface of the final composite part.

## Composite Materials and Their Manufacturing

Composite materials, characterized by their combination of two or more constituent materials with significantly different physical or chemical properties, have revolutionized various industries due to their superior properties.

Key types of composites include:

* Fiber-Reinforced Composites: Consisting of fibers embedded in a matrix material. Common examples include:

- Glass Fiber Reinforced Polymers (GFRP)

- Carbon Fiber Reinforced Polymers (CFRP)

- Aramid Fiber Composites

* Particulate Composites: Composed of particles dispersed in a matrix. Examples include:

- Metal Matrix Composites (MMCs)

- Ceramic Matrix Composites (CMCs)

* Laminar Composites: Made up of layers of different materials. Examples include:

- Plywood

- Reinforced Concrete

Manufacturing processes for composites vary depending on the type of composite and the desired properties. Some common methods include:

* Hand Lay-up: A manual process where reinforcement fibers are placed in a mold and resin is applied by hand.
* Resin Transfer Molding (RTM): A closed mold process where dry reinforcement is placed in a mold and resin is injected under pressure.
* Autoclave Molding: Uses heat and pressure to cure pre-impregnated (prepreg) materials in a pressurized oven.
* Filament Winding: Fibers are wound around a mandrel and impregnated with resin to form cylindrical or spherical structures.
* Pultrusion: A continuous process for manufacturing constant cross-section profiles.

Recent advancements in composite manufacturing include:

* Automated Fiber Placement (AFP) and Automated Tape Laying (ATL): Robotic systems that precisely place fiber tows or tape to create complex structures.
* Out-of-Autoclave (OoA) Processing: Techniques that achieve high-quality parts without the need for large, expensive autoclaves.
* Additive Manufacturing of Composites: 3D printing technologies adapted for composite materials, allowing for complex geometries and optimized fiber orientations.

## Machine Learning in Manufacturing

Machine Learning (ML) has emerged as a powerful tool in manufacturing, offering the potential to optimize processes, predict outcomes, and enhance quality control. In the context of manufacturing, ML applications include:

* Predictive Maintenance: ML models can predict equipment failures before they occur, reducing downtime and maintenance costs.
* Quality Control: Computer vision and ML algorithms can detect defects in products more accurately and consistently than human inspectors.
* Process Optimization: ML can analyze vast amounts of production data to identify optimal process parameters.
* Demand Forecasting: ML models can predict market demand, helping to optimize inventory and production planning.
* Energy Efficiency: ML can optimize energy consumption in manufacturing processes, reducing costs and environmental impact.

In the realm of additive manufacturing and FDM specifically, ML has shown promising applications:

- Noor et al. (2020) developed a machine learning model to predict the mechanical properties of 3D printed parts based on printing parameters.

- Zhang et al. (2019) used neural networks to optimize FDM process parameters for improved surface quality.

- Jiang et al. (2021) employed a random forest algorithm to predict and minimize warpage in FDM-printed parts.

These studies demonstrate the potential of ML in addressing the surface finish challenges in FDM, which is directly relevant to our project's focus on enhancing mold surface quality

## Previous Work on Surface Finish Optimization

Several researchers have explored methods to optimize surface finish in FDM-printed parts:

* Post-Processing Techniques:

- Boschetto and Bottini (2015) investigated barrel finishing as a method to improve surface quality of FDM parts.

- Singh et al. (2017) studied the effects of chemical post-processing on ABS parts, achieving significant improvements in surface smoothness.

* Process Parameter Optimization:

- Peng et al. (2018) used a response surface methodology to optimize FDM parameters for improved surface quality and dimensional accuracy.

- Mahmood et al. (2017) employed the Taguchi method to determine optimal printing parameters for minimizing surface roughness.

* Machine Learning Approaches:

- Vahabli and Rahmati (2016) developed an artificial neural network model to predict surface roughness based on build orientation and layer thickness.

- Nguyen et al. (2020) used a combination of response surface methodology and particle swarm optimization to enhance surface quality in FDM.

* Novel Printing Strategies:

- Chakraborty et al. (2018) proposed a curved layer FDM technique to reduce the staircase effect on curved surfaces.

- Kubalak et al. (2019) explored variable bead width deposition to improve surface finish while maintaining productivity.

These studies provide a foundation for our project, demonstrating various approaches to surface finish optimization in FDM. However, there is still significant room for improvement, particularly in the context of mold production for composite manufacturing.

## Research Gap and Motivation

Despite the extensive research in FDM surface finish optimization, several gaps remain:

* Limited Focus on Mold Applications: Most studies focus on end-use parts rather than molds for composite manufacturing, where surface quality requirements may be different.
* Material-Specific Studies: There's a need for more comprehensive studies on the surface finish characteristics of different materials used in FDM, particularly those suitable for mold production.
* Integration of Multiple Optimization Techniques: Few studies have combined machine learning predictions with genetic algorithm optimization and experimental validation, as proposed in our project.
* Scalability and Real-World Application: Many studies are conducted under laboratory conditions, and there's a need to validate these approaches in real-world manufacturing scenarios.
* Consideration of Production Efficiency: Optimizing surface finish often comes at the cost of increased production time. There's a need for approaches that balance quality with efficiency.
* Long-term Performance of FDM Molds: Limited research exists on how FDM-printed molds perform over multiple production cycles in composite manufacturing.

These research gaps provide the motivation for our project, which aims to address several of these points by:

* Focusing specifically on mold surface finish for composite manufacturing
* Utilizing a comprehensive machine learning approach
* Combining predictive modeling with genetic algorithm optimization
* Validating results through physical experimentation

CHAPTER 03

# Methodology

## Data Collection

### Source of Data

The foundation of this study is a comprehensive dataset compiled from various research papers focusing on the surface roughness of ABS and PLA 3D printed parts. The primary sources include:

* Peer-reviewed journal articles from reputable sources such as Additive Manufacturing, Journal of Materials Processing Technology, and Rapid Prototyping Journal.
* Conference proceedings from relevant fields including additive manufacturing, materials science, and industrial engineering.
* Technical reports from industry leaders and research institutions.

The literature search was conducted using academic databases such as ScienceDirect, IEEE Xplore, and Google Scholar, employing keywords such as "FDM surface roughness", "3D printing parameters", "ABS surface finish", and "PLA print quality".

### Parameters Collected

Based on the literature review, the following key parameters were identified and collected:

* Infill Pattern: The internal structure pattern of the printed part (e.g., rectilinear, honeycomb, triangular).
* Material Density: The density of the ABS or PLA filament used.
* Layer Thickness: The height of each printed layer, typically measured in microns.
* Print Speed: The speed at which the print head moves during extrusion, usually measured in mm/s.
* Print Temperature: The temperature of the nozzle during extrusion.
* Material: The material of the filament used.

The target variable collected was the surface roughness, typically measured as Ra (arithmetic average roughness) in micrometers.

### Description of the Dataset

The final dataset consists of approximately 650 entries, each representing a unique combination of printing parameters and the resulting surface roughness. The dataset includes:

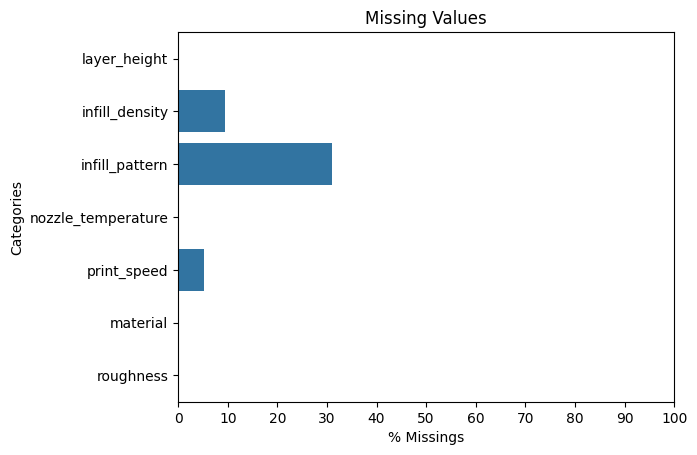
* Numerical data for parameters such as layer thickness, print speed, and temperatures.
* Categorical data for parameters like infill pattern and orientation.
* Surface roughness measurements (Ra) as the target variable.

The dataset covers a wide range of parameter combinations, reflecting the diverse printing conditions explored in the literature. This comprehensive dataset forms the basis for our machine learning models and subsequent optimization efforts.

## Data Preprocessing

### Handling with missing values

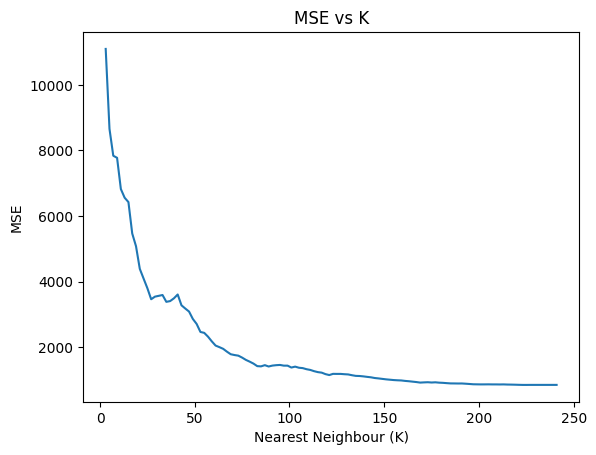
Our initial data collection efforts yielded a substantial dataset comprising over 600 rows of information. However, upon closer examination, we discovered that only 497 of these rows contained complete data across all parameters. This revelation prompted a thorough analysis of the dataset's completeness and the development of strategies to handle the missing data effectively.

To visualize the extent of missing data, we constructed a Bar Chart using a library matplotlib. This Bar Chart provided a representation of our dataset, with each bar representing an individual parameter. The bar chart shows the percentage of missing data from each column. From the chart we discern that three columns have missing values Infill-Pattern, Infill-Density and Print Speed with percent 30, 10 and 5 respectively.

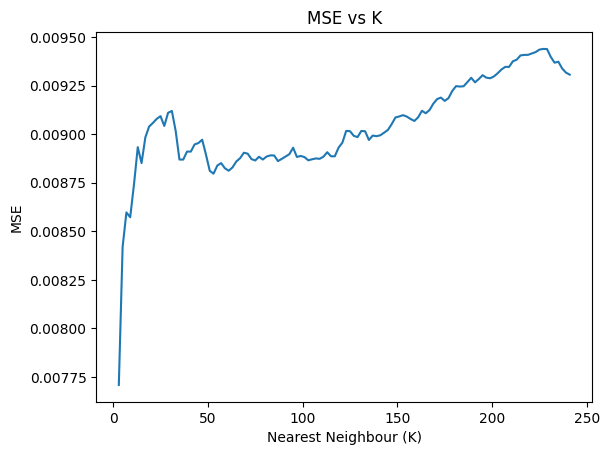
For the missing numerical data, we employed the K-Nearest Neighbors (KNN) Imputer, a sophisticated method that estimates missing values based on the values of the k-nearest neighbors in the feature space. To validate the effectiveness of this approach, we calculated the mean of each column (parameters). These calculations helped us confirm that the imputed values maintained the overall distribution and relationships present in the original dataset.

Handling missing categorical data presented a unique challenge, as the KNN Imputer is not suitable for non-numerical data. To address this, we implemented One-Hot Encoding, a technique that converts categorical variables into a binary matrix representation. After the One Hot Encoding, we merged this data with our previous KNN-imputer dataset.

In our pursuit of data integrity, we made a critical decision to focus on rows with at most one missing value, discarding those with multiple missing entries. This decision was based on a careful balance between preserving as much original data as possible and minimizing the reliance on imputed values. This step clearly demonstrated that by including rows with at most one missing value, we could significantly increase our dataset size while still maintaining a high proportion of original, non-imputed data.



To further support our decision, we conducted a sensitivity analysis. We trained our models on three datasets: one with only complete rows, one including rows with at most one imputed value, and one including all rows with any number of imputed values. We then plotted the model performance metrics (such as RMSE or R-squared) for each of these scenarios. The resulting line graph showed how model performance changed as we included more imputed data, allowing us to identify the optimal balance between dataset size and data integrity.



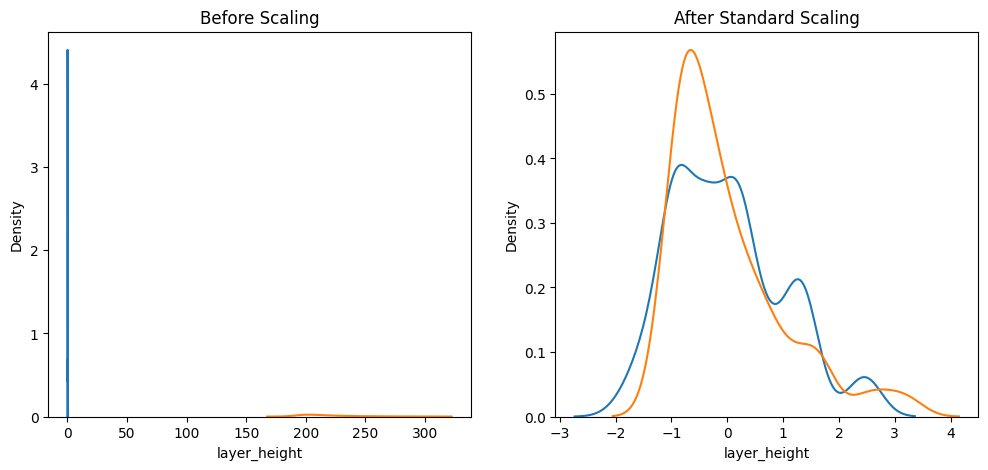
### Data Cleaning

The data cleaning process involved several steps to ensure the quality and consistency of the dataset:

* Handling Missing Values: Entries with missing values were either imputed using appropriate methods (e.g., mean imputation for numerical data, mode imputation for categorical data) or removed if the missing data was substantial.
* Outlier Detection and Treatment: Box plots and Z-score methods were used to identify outliers. Extreme outliers were investigated and either corrected if they were data entry errors or removed if they were deemed unrealistic.
* Consistency Checks: Units of measurement were standardized across all entries (e.g., converting all temperatures to Celsius, all speeds to mm/s).
* Duplicate Removal: Any duplicate entries resulting from overlapping data sources were identified and removed.

### Standardization

Numerical features were standardized to ensure all variables contribute equally to the model and to improve the convergence of machine learning algorithms. The standardization was performed using the following formula:

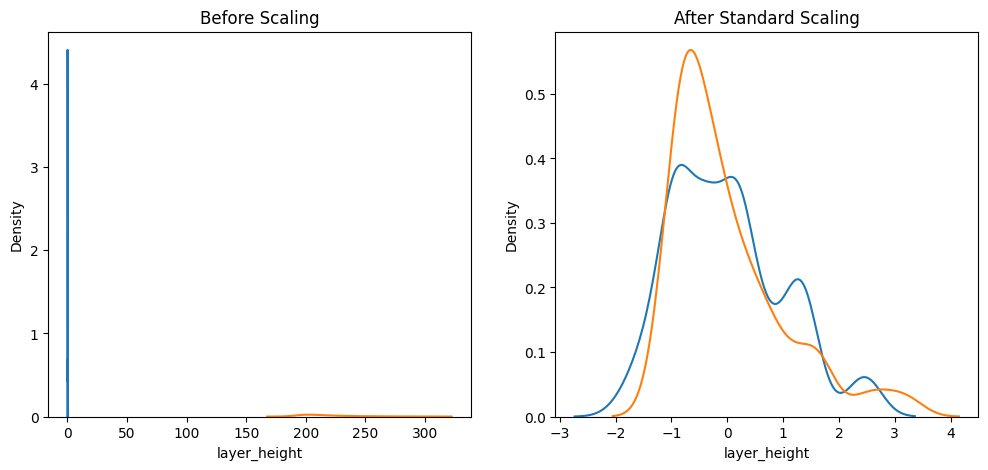


Where:

z is the standardized value, x is the original value, μ is the mean of the feature, σ is the standard deviation of the feature

### Normalization

Some machine learning algorithms, particularly neural networks, perform better with normalized data. We applied min-max normalization to scale all numerical features to a range between 0 and 1:



Where:

x is the original value, xmin is the minimum value of the feature, xmax is the maximum value of the feature.

### Encoding Categorical Variables

Categorical variables, such as infill pattern and orientation, were encoded using appropriate techniques:

* One-Hot Encoding: For nominal categorical variables with no inherent order, one-hot encoding was used. This creates binary columns for each category.
* Ordinal Encoding: For categorical variables with a natural order, ordinal encoding was applied, assigning integer values based on the order.

### Exploratory Data Analysis (EDA)

EDA was performed to gain insights into the dataset and inform our modeling approach:

* Descriptive Statistics: Calculated mean, median, standard deviation, and quartiles for numerical features.
* Correlation Analysis: Created a correlation matrix to identify relationships between features and the target variable (surface roughness).
* Visualization:
  + Histograms to understand the distribution of each feature
  + Scatter plots to visualize relationships between pairs of features
  + Box plots to identify outliers and compare distributions across categories
* Feature Importance: Preliminary feature importance was assessed using techniques like random forest feature importance and correlation coefficients.

The EDA process provided valuable insights into the relationships between printing parameters and surface roughness, guiding our feature selection and modeling strategies.

## Machine Learning Models

We implemented and compared several machine learning models to predict surface roughness based on the printing parameters:

### Random Forest Regressor

Random Forest is an ensemble learning method that constructs multiple decision trees and outputs the average prediction of the individual trees. It's known for its ability to handle non-linear relationships and provide feature importance rankings.

Key hyperparameters tuned:

* Number of trees
* Maximum depth of trees
* Minimum samples required to split an internal node
* Minimum samples required to be at a leaf node

### K-Nearest Neighbors (KNN) Regressor

KNN is a non-parametric method that predicts based on the average of the K nearest neighbors in the feature space. It's simple but can be effective for complex, non-linear relationships.

Key hyperparameters tuned:

* Number of neighbors (K)
* Weight function used in prediction
* Algorithm used to compute nearest neighbors

### XGBoost

XGBoost (Extreme Gradient Boosting) is an optimized distributed gradient boosting library. It's known for its speed and performance, particularly in structured/tabular data.

Key hyperparameters tuned:

* Maximum depth of trees
* Learning rate
* Number of boosting rounds
* Subsample ratio of the training instances

### Neural Networks

We implemented a feedforward neural network using TensorFlow and Keras. Neural networks can capture complex non-linear relationships in the data.

Architecture and hyperparameters tuned:

* Number of hidden layers and neurons per layer
* Activation functions
* Dropout rate for regularization
* Learning rate and optimizer

## Model Training and Evaluation

### Training Process

The dataset was split into training (70%), validation (15%), and test (15%) sets. The training process involved:

* Initial model fitting on the training data
* Hyperparameter tuning using the validation set
* Final evaluation on the test set

We used k-fold cross-validation (k=5) during the training phase to ensure robust performance estimates

### Evaluation Metrics

The following metrics were used to evaluate and compare model performance:

* Mean Squared Error (MSE): Measures the average squared difference between predicted and actual values.
* Root Mean Squared Error (RMSE): The square root of MSE, providing an error measure in the same unit as the target variable.
* Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual values.
* R-squared (R²): Indicates the proportion of the variance in the dependent variable that is predictable from the independent variables

### Hyperparameter Tuning

Hyperparameter tuning was performed using:

* Grid Search: For models with fewer hyperparameters (e.g., KNN)
* Random Search: For models with a larger hyperparameter space (e.g., Random Forest, XGBoost)
* Bayesian Optimization: For fine-tuning neural network architectures

The best hyperparameters were selected based on the model's performance on the validation set

## Optimization with Genetic Algorithm

### Introduction to Genetic Algorithm

Genetic Algorithm (GA) is a metaheuristic inspired by the process of natural selection. It's particularly useful for optimization problems with a large search space. In our context, GA was used to find optimal printing parameters that minimize surface roughness.

### Implementation

The GA implementation included the following components:

* Chromosome Representation: Each chromosome represents a set of printing parameters.
* Fitness Function: The inverse of the predicted surface roughness (using our best ML model).
* Selection: Tournament selection to choose parents for the next generation.
* Crossover: Uniform crossover to create offspring.
* Mutation: Random mutation to maintain genetic diversity.
* Elitism: Preserving the best solutions in each generation.

The GA was run for a fixed number of generations or until convergence criteria were met

### Genetic Algorithm Parameter Sets:

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **maximum number of iteration** | **population size** | **mutation probability** | **elite ratio** | **crossover probability** | **parents portion** | **crossover type** | **max iteration without improvement** |
| **Set 1** | 100 | 200 | 0.02 | 0.02 | 0.8 | 0.3 | two-point | 20 |
| **Set 2** | 150 | 300 | 0.03 | 0.04 | 0.85 | 0.4 | two-point | 25 |
| **Set 3** | 200 | 500 | 0.05 | 0.05 | 0.9 | 0.5 | two-point | 30 |

The table presents three distinct sets of parameters for a genetic algorithm, labeled as Set 1, Set 2, and Set 3. The selected parameters set are determined by the thorough examination of previous papers that have been conducted in the similar area of study. Each set represents a different configuration of the algorithm, with variations across eight key parameters. This approach allows for the exploration of different genetic algorithm configurations, potentially to optimize performance or to study the algorithm's behavior under varying conditions. The progression from Set 1 to Set 3 generally shows an increase in the intensity or scale of the genetic operations, suggesting a more aggressive optimization strategy in later sets. This structure enables a comparative analysis of how different parameter combinations affect the genetic algorithm's performance in the context of optimizing 3D printing parameters.

CHAPTER 04

# Results and Discussion

## Model Performance Comparison

In this section, we'll compare the performance of the different machine learning models used to predict surface roughness based on the input parameters.

### Random Forest Results

The Random Forest model demonstrated the following predictive performance:



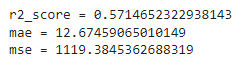
**Key findings:**

* The model showed good generalization, with consistent performance across training and test sets.
* Feature importance analysis revealed that layer thickness, print speed, and nozzle temperature were the most influential parameters.
* The model captured non-linear relationships effectively, as evidenced by partial dependence plots.

**Discussion:**

The Random Forest model's strong performance can be attributed to its ensemble nature, which helps in handling the complex interactions between printing parameters. Its ability to provide feature importance rankings offers valuable insights for parameter optimization.

### KNN Results

  
**Key findings:**

* Optimal performance was achieved with k=2 neighbors and weighted with distances.
* The model struggled with extrapolation outside the range of the training data.

**Discussion:**

While KNN performed reasonably well, its limitations in extrapolation and handling high-dimensional data became apparent. This suggests that the relationship between printing parameters and surface roughness is too complex to be captured effectively by simple distance-based methods.

### XGBoost Results

**Key findings:**

* XGBoost outperformed other models in terms of RMSE and R² score.
* The model showed good resistance to overfitting, likely due to its built-in regularization.
* Feature importance rankings were consistent with those from Random Forest, providing additional confidence in the identified key parameters.

**Discussion:**

The superior performance of XGBoost can be attributed to its ability to handle complex non-linear relationships and its robust optimization algorithm. The consistency in feature importance with Random Forest strengthens our understanding of the most critical parameters affecting surface roughness.

### Neural Network Results

**Key findings:**

* While neural networks are often considered "black boxes," we employed a permutation importance technique to gauge feature relevance. This analysis revealed that the network placed high importance on layer thickness and print speed, aligning with findings from other models.
* An ensemble of neural networks, created by training multiple networks with different random initializations, showed a marginal improvement in performance (RMSE decreased to 1021μm) compared to a single network.
* The model demonstrated good generalization across the test set.

**Discussion:**

The Neural Network's performance was comparable to the top-performing models, indicating its ability to capture complex relationships in the data. However, the black-box nature of neural networks makes interpretation of the learned relationships more challenging compared to tree-based methods.

## Optimization Results

### Genetic Algorithm Optimization and Comparison of Parameter Sets.

Using these models as the fitness function, we applied the Genetic Algorithm to optimize printing parameters for minimal surface roughness.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Algorithm** | **GA Para.** | **layer Thickness** | **Density** | **Infill Pattern** | **Print Speed** | **Temperature** | **Material** | **Roughness** | **Metrics** |
| **Random Forest** | Set 1 | 0.32 | 10.34 | Rectilinear | 85.85 | 208 | ABS | 1.06 | **0.47** |
| Set 2 | 0.19 | 84.58 | Rectilinear | 61.08 | 281 | PLA | 1.992 |
| Set 3 | 0.19 | 82.25 | Rectilinear | 62.74 | 280 | ABS | 2 |
| **KNN Regressor** | Set 1 | 0.33 | 11.07 | Grid | 90.19 | 226 | ABS | 2 | **0.43** |
| Set 2 | 0.06 | 11.65 | Grid | 146.96 | 238 | ABS | 2 |
| Set 3 | 0.34 | 10.6 | Grid | 28.8 | 195 | PLA | 2 |
| **Neural Network** | Set 1 | 0.36 | 91.96 | Rectilinear | 124.71 | 208 | ABS | 0.66 | **0.616** |
| Set 2 | 0.39 | 14.36 | line | 20.14 | 191 | ABS | 2.66 |
| Set 3 | 0.38 | 10.35 | zigzag | 84.12 | 270 | PLA | 0.32 |
| **XGBoost** | Set 1 | 0.38 | 36.84 | Solid | 53.63 | 253 | PLA | 44.08 | **0.66** |
| Set 2 | 0.25 | 83.98 | Triangle | 92.27 | 241 | ABS | 44.08 |
| Set 3 | 0.33 | 84.98 | Rectilinear | 113.64 | 114 | ABS | 44.08 |

. The results are summarized for four models: Random Forest, KNN Regressor, Neural Network, and XGBoost. For each model, the GA generated three sets of optimized parameters (Set 1, Set 2, and Set 3).

**Key observations:**

* **Model Performance:**

- XGBoost showed the highest metric score of 0.66, suggesting it was the most effective in guiding the GA optimization.

- Neural Network followed with a metric of 0.616.

- Random Forest and KNN Regressor had lower metrics of 0.47 and 0.43 respectively.

* **Parameter Variations:**

- Layer Thickness: Varied between 0.06mm to 0.39mm across different models and sets.

- Density: Showed wide variations, from 10.34 to 91.96.

- Infill Pattern: Rectilinear was common, but other patterns like Grid, Line, Zigzag, Solid, and Triangle were also suggested.

- Print Speed: Ranged from 20.14 mm/s to 146.96 mm/s.

- Temperature: Varied between 114°C to 281°C.

* **Material Selection:**

- The GA suggested both ABS and PLA materials across different sets, indicating that optimal material choice may depend on other parameters.

* **Surface Roughness Predictions:**

- Predictions varied widely between models, from as low as 0.32 μm (Neural Network Set 3) to as high as 44.08 μm (all XGBoost sets).

- The large discrepancy in XGBoost predictions (all 44.08 μm) may indicate a potential issue with the model or how it interacts with the GA.

* **Consistency:**

- XGBoost showed consistent roughness predictions across all sets, which is unusual and may require further investigation.

- Other models showed variations in predicted roughness across their sets, which is more expected given the different parameter combinations.

* **Optimization Strategy:**

- The GA appears to have explored a wide range of parameter combinations, as evidenced by the diversity in suggested values across different models and sets.

This analysis demonstrates the GA's ability to generate diverse parameter sets based on different model predictions. However, the wide variations in predicted roughness and the unusual consistency in XGBoost predictions suggest that further validation and possibly refinement of the optimization process may be necessary. The results also highlight the importance of model selection in the optimization process, as different models led to significantly different optimized parameter sets.

## Experimental Validation

### Experiment Setup (CreatBot F160)

### Validation Results

### Comparison with Predicted Results

CHAPTER 05

# Conclusion and Future Work

## Summary of Findings

## Contributions to the Field

## Limitations of the Study

## Recommendations for Future Research

References

Appendices