Machine Learning Approach for Defect Prediction in Metal 3D Printing for Aerospace Applications

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DECLARATION

I hereby, declare that this manuscript, entitled "*Machine Learning Approach for Defect Prediction in Metal 3D Printing for Aerospace Applications*", is the result of my own work except for quotations and citations, which have been duly acknowledged.

I also declare that, to the best of my knowledge and belief, it has not been previously or concurrently submitted, in whole or in part, for any other degree or diploma at Nazarbayev University or any other national or intentional institution.

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ABSTRACT

In the aerospace industry, additive manufacturing (AM) has revolutionized the production of lightweight, high-strength components, such as engine parts and structural elements. The ability to create intricate geometries and reduce material waste is particularly beneficial for aerospace applications, where performance and weight savings are paramount. However, ensuring the quality and reliability of these components remains a challenge, particularly in mass production, related to material quality, expensive processes, and longer computational times than conventional manufacturing methods. The optimization process called machine learning (ML) can decrease the influence of those limitations and make AM applicable to mass market production.

This research proposes a solution in the form of a Decision Tree Classification Machine Learning Algorithm to predict the possibility of defect occurrence in additive manufacturing processes. The research aims to create a machine learning algorithm that provides a new pathway for printing defect-free parts without the expenses and time-consuming trial-and-error testing typically required in Powder Bed Fusion (PBF). Correspondingly, the defect susceptibility index was developed to eliminate defect formation before the part's manufacturing process, and the hierarchical order of importance of mechanistic variables on defect formation was determined. The obtained results demonstrate that a trained machine-learning algorithm can print defect-free parts without incurring expenses and time-consuming trials. This approach not only enhances the reliability of additive manufacturing in aerospace applications but also paves the way for its broader adoption in mass production. By integrating CFD analysis, machine learning, and experimental validation, this research provides a comprehensive solution to the challenges faced in additive manufacturing. The proposed methodology ensures the production of high-quality, defect-free components, making additive manufacturing a viable option for the aerospace industry and beyond.

Key words: *Additive Manufacturing, Metal printing, Machine Learning, defect formation, defect-free parts, aerospace applications.*

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LIST OF ABBREVIATIONS & SYMBOLS

AM – Additive Manufacturing

ML – Machine Learning

PBF – Powder Bed Fusion

DED – Directed Energy Deposition

L-PBF – Laser Powder Bed Fusion

RPM – Revolution Per Minute

LIST OF PUBLICATIONS

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CHAPTER 1 - INTRODUCTION

1.1 Research Background

Additive manufacturing and machine learning are two integral components of the fourth generation of industry, a framework that allows for the swift transformation from industrial progress towards advanced automation (Dilip et al., 2017). Both these technologies have garnered significant interest from researchers as distinct areas of study. Additive manufacturing (AM), or 3D printing, involves creating a component by adding layer after layer using various techniques. Additive manufacturing can fabricate complex metallic parts that conventional techniques cannot manufacture (DebRoy et al., 2021). The printed part is created from a digital 3D model or a computer-aided design (CAD) system.

Unlike traditional subtractive manufacturing methods, AM is a fundamentally different approach. One of the attractive techniques to print stainless steel alloy, which is widely used in different industries for commercial purposes, is the Laser Powder Bed Fusion (LPBF) (Li et al., 2021). The fabrication process starts with a laser beam that melts thin layers of metal powders, and these layers are subsequently solidified one after another to fabricate intricate components (Wei et al., 2021). However, when the melting and solidification processes are repeated, defects such as cracks often appear in the manufactured part (Dilip et al., 2017). Sometimes tiny particles in the form of balls form during the printing process and stick to the surface of the part. This is because of insufficient laser power, powder size, and process parameters (Gu et al., 2020). Nowadays, additive manufacturing is a step further in manufacturing engineering as it can produce complex shapes and reduce waste. Nevertheless, it has some limitations, especially in mass market production, associated with the quality of the printed material, the expensive manufacturing process, and the long computational time compared to conventional manufacturing methods. Therefore, there are both opportunities and obstacles associated with AM compared to traditional subtractive manufacturing technologies.

Generally, the printing process of a single part might take from several hours to several days, depending on the object's complexity and size. If a defect appears, the entire printing process and time spent will be wasted. Consequently, this leads to the idea that there is a need for an autonomous system capable of predicting defects on a printed part before manufacturing to minimize the wastage of material, time, and energy. As for now, there is no single approach that unifies all strategies to address defect formation. It means that the understanding of how process variables and alloy properties affect defect formation remains incomplete due to the ability to correlate them with the defect mechanism. The mechanisms of each variable have been individually examined. However, what is currently lacking is a comprehensive understanding of how these mechanistic variables collectively contribute to defect formation while printing.

The main goal of the research is to create a machine learning algorithm that will provide a new pathway for printing defect-free parts with no expenses and time-consuming trial and error testing in Powder Bed Fusion. To be precise, the research objective is to develop an autonomous machine learning algorithm that incorporates physics-based principles. This algorithm should be capable of predicting defects like crack formation and demonstrate that is feasible to prevent them before the printing of an object in the AM process. ML-based reliable pre-dictions will help to select appropriate process parameters and the right alloy for an application.

1.2 Problem Statement

Even if additive manufacturing is already used to produce the final products, the desired results are achieved through experimentation. Generally, conducting the experiments, and printing parts is an expensive process. The generation of a high volume of high-quality data is often cost-prohibitive. As a result, obtaining a simple product is achieved at the expense of wasting a large amount of time, energy, and material waste. This causes the entire printing process to restart and waste of used material (Antony, 2023). To eliminate such kinds of problems, this project aims to create a machine learning algorithm that can predict a defect formation before the printing of an object in the AM process.

1.3 Research Motivation

It is quite problematic to predict the exact appearance of defects before the printing process. Because the manufacturing process depends on the object's complexity and size, the printing process of a single part might take from several hours to several days. If a defect appears, the entire printing process and time spent will be wasted. Consequently, this leads to the idea that there is a need for an autonomous system capable of predicting defects on a printed part before manufacturing to minimize the wastage of material, time, and energy. The proposed machine learning algorithm for the defect prevention system will be able to predict anomaly formation before printing a part based on the inserted input data. The input data will be evaluated by the ML algorithm for possible errors. Since conducting the experiments, and printing parts is an expensive process, and the high volume of high-quality data is often cost-prohibitive, this system prevents material wastage and saves time by reducing the number of experiments required to obtain the desired result.

1.4 Aim and Objectives

The research aims to create a machine learning algorithm for predicting and mitigating defect formation in printed components, thereby eliminating the costly and time-consuming trial-and-error processes commonly associated with Powder Bed Fusion (PBF) technology.

The specific objectives of the research are to:

1. Investigate how machine learning can be used for defect prediction in metal 3d printing
2. Develop ML algorithm for defect prediction for Directed Energy Deposition (DED) printer
3. Collect and preprocess the data from the experimental results
4. Build a user interface setup to predict a defect formation in 3D metal printing

By achieving all of the above objectives, the research project makes a valuable contribution to metal alloy printing and implementing machine learning.

1.5 Research questions

The research questions for literature review are to:

- What are the challenges and benefits of ML and Metal AM?
- What are the connections between process parameters and defects?
- What process parameters and defects detected?
- How to create Machine Learning Algorithm for Metal AM?

1.6 Research Scope

The main scope of this thesis work will be within the frame of PBF technology especially DED printer and implementation of Machine Learning. Figure 1.1 .1 illustrates the scope of this research and out of scope.

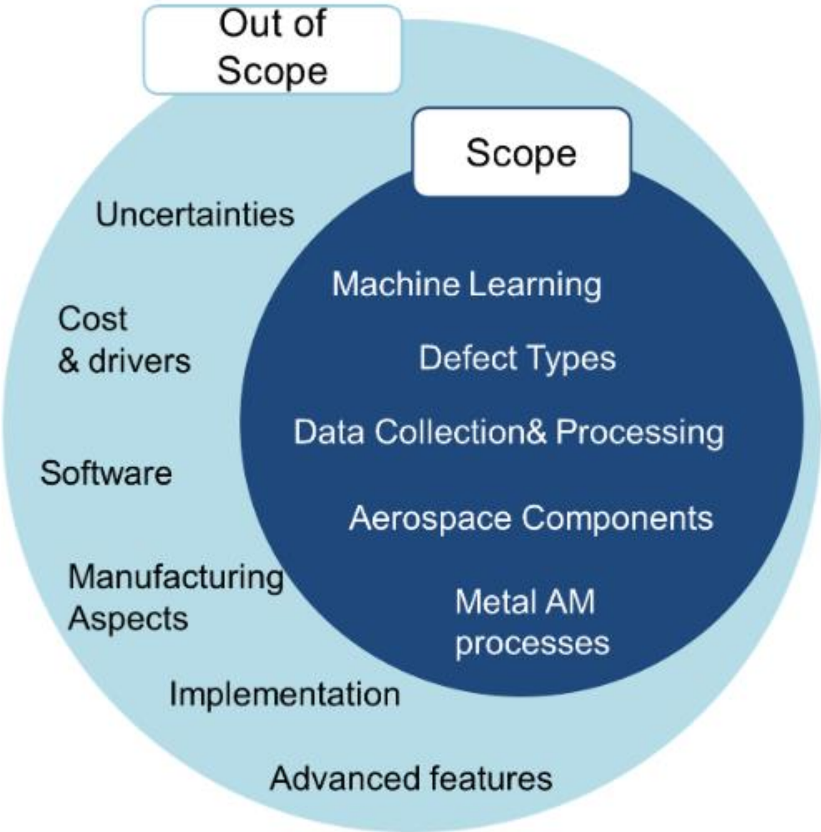

Figure 1.1 Research Scope

1.7 Thesis Structure

The thesis is structured into five main chapters, each contributing to a comprehensive understanding of the research.

Chapter 1 introduces the study by providing essential background information, establishing the research concept, and outlining the problem statement, aims, and objectives. Building on this foundation, Chapter 2 delves deeper into the research background, addressing key questions. This section explores metal additive manufacturing, the current state of 3D metal printing, the challenges involved, and the implementation of machine learning. It also reviews previous research studies, identifying their limitations.

Chapter 3 then shifts focus to the research methodology. It describes the process of developing a thorough understanding of the research context, selecting the appropriate additive manufacturing (AM) type, and conducting further reviews to pinpoint critical process parameters and potential defect types. Additionally, this chapter covers the creation of a 3D model, computational fluid dynamics (CFD) analysis, the training of a decision tree classification machine learning algorithm, and the development of an architecture for a user-friendly interface.

Chapter 4 presents key findings, including numerical results, CFD analysis, and experimental outcomes. It also highlights the integration of machine learning, data generation, and interface development.

Finally, Chapter 5 concludes the thesis by summarizing the research findings and offering suggestions for future directions.

CHAPTER 2 - LITERATURE REVIEW

2.1 Introduction

Currently, there is no single strategy that covers all approaches to solving the problem of defect formation. Consequently, the understanding of how process variables and alloy properties influence defect formation remains incomplete, primarily due to the difficulty of correlating them with the cracking mechanism. There are 12 variables that were obtained which influence the crack formation (Yadroitsev et al., 2010). Both alloy composition and process parameters influence all these mechanistic variables. Furthermore, the mechanisms of each variable have been individually examined. However, what is currently lacking is a comprehensive understanding of how these mechanistic variables collectively contribute to defect formation (Raissi et al., 2020). The research aims to demonstrate that machine learning can effectively reduce defects like crack formation while printing metal components.

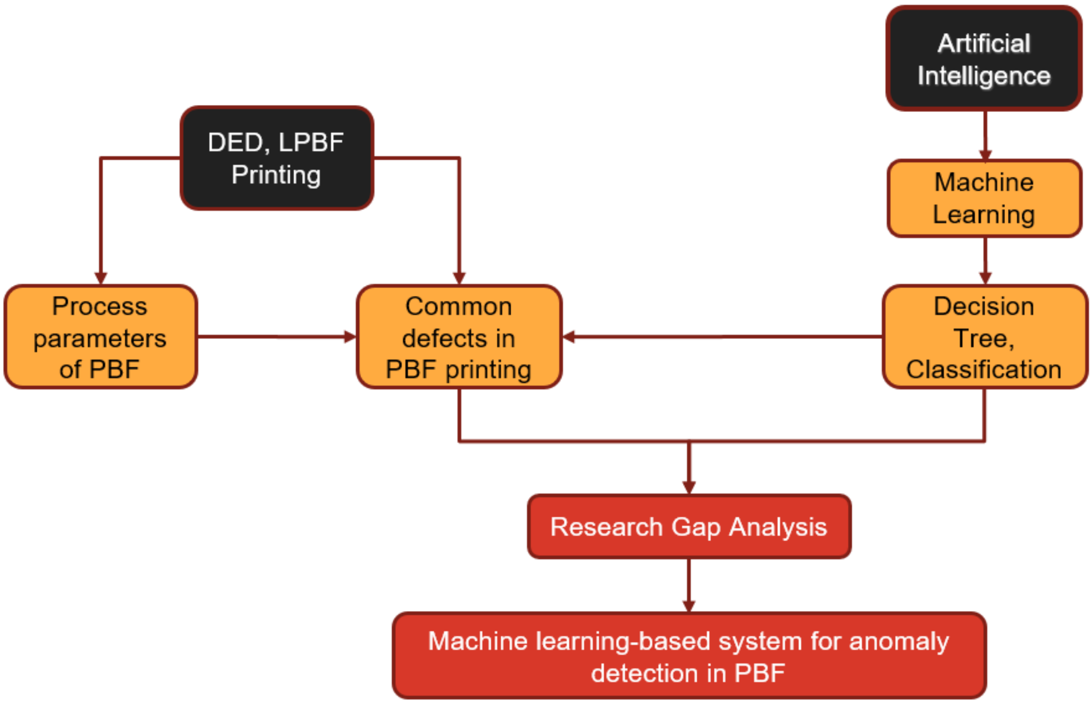

Figure 2.1 Literature Review Areas

The literature review follows a systematic narrowing approach, as illustrated in Figure 2.1. The review begins with a broad examination of additive manufacturing before focusing specifically on powder bed fusion technology in metal printing applications. The investigation then delves into three key aspects: material properties, processing parameters, and common defect formations. Following this, the review explores various types of Machine Learning and their implementation methods. The final segment examines current advances in applying machine learning techniques to metal Direct Energy Deposition (DED) 3D printing systems.

2.2 Additive manufacturing types

3D printers are categorized into seven common types which are listed below.

- Direct energy deposition (DED)
- Powder bed fusion (PBF)
- Binder jetting
- Stereolithography (SLA)
- Multi jet printing
- Laminated object manufacturing
- Fused filament fabrication (FFF)

Among these, three technologies - PBF, DED, and Binder Jetting - are primarily employed for manufacturing metal components. Within the PBF family, two variants have gained particular prominence in aerospace manufacturing: Laser Powder Bed Fusion (L-PBF) and Electron Beam Powder Bed Fusion (EB-PBF). These specialized PBF methods are specifically adapted for producing metal aerospace parts (Blakey-Milner et al., 2021).

2.2.1 Direct Energy Deposition

Direct energy deposition (DED) is primarily used to manufacture metal and metal alloy components, though it can occasionally be used for non-metallic materials. The process works by creating objects layer by layer: either powder or wire material (feedstock) is fed through a nozzle and melted using electron beams, laser beams, or an arc to form a melting pool. This technology's multi-axis capabilities make it particularly valuable in aerospace applications, where it's used to produce or repair complex parts like turbine blades, airfoils, engine chambers, and compressors. The final properties of DED-produced components vary depending on whether powder or wire feedstock is used, and are significantly influenced by factors such as cooling rates, post-heat treatment, and load direction - particularly in wire-fed laser systems (Blakey-Milner et al., 2021).

2.2.2 Powder Bed Fusion

Powder bed fusion (PBF) is a leading additive manufacturing technique for metal production, particularly favored in aerospace applications. While primarily used for metals, PBF can also work with other engineering materials like polymers and ceramics. The technology operates by progressively building components layer by layer, melting metal powder on the printer's bed (Blakey-Milner et al., 2017). A notable advantage of this process is that unused powder from each layer can serve both as support structure and be recycled for subsequent layers. PBF has gained significant traction in both industrial manufacturing and academic research due to its ability to produce high-resolution, quality components. The technology is especially well-suited for titanium alloys and excels at creating internal passages more effectively than direct energy deposition (DED) methods.

2.3 The Current State and Challenges in Metal 3D Printing

The additive manufacturing (AM), also known as 3D printing, involves creating a component by adding layer after layer using various techniques. Additive manufacturing is able to fabricate complex metallic parts that cannot be manufactured by conventional techniques (DebRoy et al., 2018). The printed part is created from a digital 3D model or a computer-aided design (CAD) system.

Unlike traditional subtractive manufacturing methods, AM is a fundamentally different approach. One of the attractive techniques to print aluminum alloy, which is widely used in different industries for commercial purposes, is the Laser Powder Bed Fusion (LPBF) (DebRoy et al., 2018). The fabrication process starts from a laser beam that melts thin layers of metal powders, and these layers are subsequently solidified one after another to fabricate intricate components (Wei et al., 2021). However, when the melting and solidification processes are repeated, defects such as cracks often appear in the manufactured part (Li et al., 2021). Sometimes tiny particles in the form of balls form during the printing process and stick to the surface of the part. This is because of insufficient laser power, powder size and process parameters (Gu et al., 2020). Nowadays, additive manufacturing is a step further in manufacturing engineering as it is able to produce complex shapes and reduce the waste. Nevertheless, it has some limitations, especially in mass market production, associated with the quality of the printed material, the expensive manufacturing process and the long computational time in comparison to conventional manufacturing methods. Therefore, there are both opportunities and obstacles associated with AM compared to traditional subtractive manufacturing technologies.

Generally, the printing process of a single part might take from several hours to several days, depending on the object complexity and the size. If a crack appears, the entire printing process and time spent will be wasted. Consequently, this leads to the idea that there is a need for an autonomous system capable of predicting cracks on a printed part before manufacturing to minimize wastage of material, time, and energy. As for now, there is no single approach that unifies all strategies to address the crack formation. It means that the understanding of how process variables and alloy properties effect on crack formation remains incomplete due to the ability to correlate them with the cracking mechanism. The mechanisms of each variable have been individually examined. However, what is currently lacking is a comprehensive understanding of how these mechanistic variables collectively contribute to crack formation.

The main goal of the research is to create a machine learning algorithm which will provide a new pathway for printing defect free parts with no expenses and time-consuming trials and error testing in Powder Bed Fusion. To be precise, the research objective is to develop an autonomous machine learning algorithm that incorporates physics-based principles. This algorithm should be capable to predict defects like crack formation and demonstrate that is feasible to prevent them before the printing of an object in the AM process. ML based reliable predictions will help to select appropriate process parameters and the right alloy for an application.

2.3.1 Current State of Metal Printing

Today, due to the potential to print complex geometries and the ability to overcome deficiencies of conventional manufacturing processes, the metal 3D printing is the fastest growing sector in Additive Manufacturing (Wohlers et al., 2018). However, there are some advancements and challenges associated with Metal 3D Printing (see Table 2.1). To print customized components the regular printed metallic materials that are utilized are stainless steel, aluminum, nickel and titanium alloys (Wei et al., 2021). According to Aversa and et. al. (2019) they are ideal materials for various applications in the aerospace and automotive fields. However, the additive manufacturing process for these alloys faces challenges which affects the processability due to their unique material properties such as low laser absorption, high thermal conductivity, and reduced powder flowability. While aluminum-silicon (Al-Si) alloys are commonly used in current additive manufacturing, recent efforts focus on developing and creating new alloy compositions specifically designed for laser-based powder bed AM processes.

The manufacturing process of metallic components begins from a three dimensional digital model of the customized component. After that, metal elements are layered together to create final geometry (DebRoy et al., 2018). Following approximately twenty-five years of dedicated research and discovery, only a restricted set of commercial alloys can currently undergo additive manufacturing. Regrettably, the collective market value of these additively manufactured products remains insignificantly small within the broader manufacturing economy (Wei et al., 2021). This problem mainly arises from their inherent vulnerability to common defects including porosity, cracking, balling and surface irregularities. The Figure 2.2 demonstrate the example of crack formation in additive manufacturing.

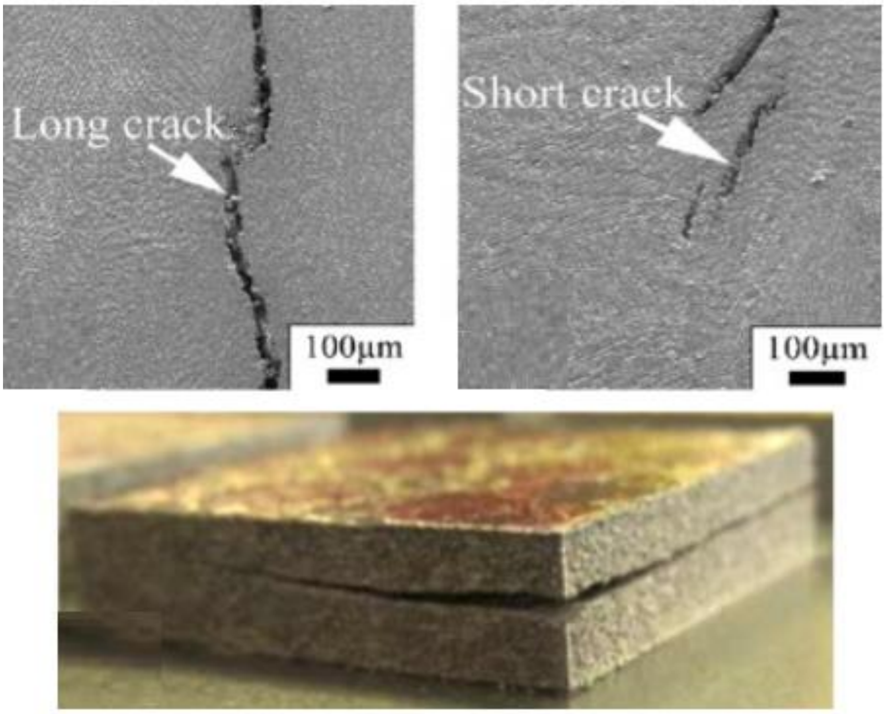

Figure 3.2 Delamination and crack formation while 3d printing (DebRoy et al., 2021)

Table 2.1 Advancements and Challenges in Metal 3D Printing

Advancements	Challenges	Author, year
Due to the potential to print complex geometries and the ability to overcome deficiencies of conventional manufacturing processes, the metal 3D printing is the fastest growing sector in Additive Manufacturing	The metallic alloys that are commonly used in current additive manufacturing are not specifically designed for specific Additive Manufacturing processes.	Wohlers et. al., 2018
To print customized components the regular printed metallic materials that are utilized are stainless steel, aluminum, nickel and titanium alloys	Regrettably, the collective market value of these additively manufactured products remains insignificantly small within the broader manufacturing economy	Wei et. al., 2021
stainless steel, aluminum, nickel and titanium alloys that are utilized in additive manufacturing are ideal materials for various applications in the aerospace and automotive fields	The additive manufacturing process for these alloys faces challenges which affects the processability due to their unique material properties such as low laser absorption, high thermal conductivity, and reduced powder flowability	Aversa and et. al. 2019

Those problems mainly arise from their inherent vulnerability to common defects including porosity, cracking, balling, and surface irregularities. As a result, defects affect to the final quality and reliability of the whole part. Also, parts with defects require additional post processing steps, which in turn increases the overall cost of production. Moreover, in the additive manufacturing since conducting the experiments, printing parts is an expensive process. Generation of the high volume of high-quality data is often cost prohibitive. Accordingly, achieving high-quality, defect-free additively manufactured parts remains a significant hurdle in the metal 3D printing industry (DebRoy et al., 2018).

2.3.2 Conventional Approaches and Their Limitations

Today, due to the potential to print complex geometries and the ability to overcome deficiencies of conventional manufacturing processes, metal 3D printing is the fastest-growing sector in Additive Manufacturing. To print customized components, the regular printed metallic materials that are utilized are stainless steel, aluminum, nickel, and titanium alloys. According to Aversa et al. (2019), these materials are ideal for various applications in the aerospace and automotive fields. However, the additive manufacturing process for these alloys faces challenges that affect the processability due to their unique material properties such as low laser absorption, high thermal conductivity, and reduced powder flowability.

In a recent study, Ghadhban and Hasan (2022) investigated the differences in hardness and surface roughness between cobalt-chromium alloy specimens produced by conventional casting and selective laser melting (SLM) techniques. Their findings indicated that SLM-fabricated specimens exhibited significantly higher hardness values and smoother surfaces compared to those produced by conventional casting, suggesting that SLM is a viable alternative for producing Co-Cr dental alloys. Also, Qian et al. (2024) examined the effects of processing parameters on defects, microstructure, and mechanical properties of Ti-6Al-4V titanium alloy fabricated using laser powder bed fusion. They found that insufficient energy density led to a lack of fusion defects, while excessive energy density caused cracking, highlighting the importance of optimizing processing parameters to minimize defects and enhance material performance.

Additionally, Andreu et al. (2024) shared valuable insights into the challenges of DED printers in their study on processing challenges and delamination prevention in titanium-steel DED 3D printing. Cracks commonly occur in titanium alloys due to their brittle nature, making material selection crucial. Moreover, preheating the substrate up to ~800K significantly enhances the formation of titanium aluminide.

The role of digital twin systems in metal additive manufacturing has also gained significant attention in recent research. Jyeniskhan et al. (2023) developed a machine-learning-based digital twin for additive manufacturing, particularly in FDM printing, showcasing the integration of AI-driven predictive modeling. Jin et al. (2024) conducted a comprehensive review on big data, machine learning, and digital twin-assisted additive manufacturing, highlighting the data integrity challenges and the relationship between datasets and predictive models. However, their study lacked practical implementation details. Malik et al. (2024) presented an advanced study on digital twin-driven optimization of laser powder bed fusion processes, with a focus on lack-of-fusion defects in AISI 316L steel, demonstrating the practical applications of digital twins in metal 3D printing. Furthermore, Kantaros et al. (2021) explored the integration of computational models and sensors within digital twin frameworks to improve accuracy in metal 3D printing, discussing current trends and limitations in this field. Currently, the defects that occurs while printing metallic parts are minimized by implementing conventional approaches to optimize the process with plenty of trials and errors. For example, in their study, the Hong et.al. (2016) investigated how the process parameters affect the surface roughness of an additively manufactured Cobalt-Chromium alloy. In order to overcome the defects, especially crack formation, Dilip et. al. (2017) also considered the influence of changing the processing parameters and microstructures of elements especially on titanium alloy.

The table 2.2 highlights the conventional approaches and their limitations. The idea of the studies was to change one of the process variables and modify the characteristics of the alloy by different treatments and grain refinements to solve defects such as cracking. However, conventional techniques are not ideal for additive manufacturing as it requires to conduct extensive experiments to explore a large number of process parameters and feedstock costs. In general, due to the complexity of the additive manufacturing process, trial and error experiments often fail to achieve optimal defect elimination conditions (Gradl et al., 2020). To effectively predict and eliminate defects, a thorough understanding of how alloy characteristics and process parameters influence the occurrence of defects is necessary. In this situation, if all the data is available, machine learning can play a crucial role in controlling the defect formation in additive manufacturing (Goh et al., 2021).

Table 2.2 Conventional Approaches and Their Limitations

Approaches	Main findings	Limitations	Author, year
Trial and error experiments (Changing the process parameters of the process)	Investigated how the process parameters like laser power, scanning speed affect the surface roughness of an additively manufactured Cobalt-Chromium alloy	The defects that occur while printing metallic parts are minimized only with plenty of trials and errors. It is difficult to optimize the process parameters independently	Hong et.al. 2016
Adjusting the process parameters and microstructures of element	Considered the influence of changing the processing parameters and microstructures of elements especially on titanium alloy. The idea of the study was to change one of the process variables and modify the characteristics of the alloy by different treatments and grain refinements to solve defects such as cracking.	The extensive experiments were conducted to achieve the desired results. The results were not satisfied	Dilip et. al. 2017
Material selection	A decision matrix was created for material selection. The matrix is normalized using a ratio model and a unified rule. Also, the loss function and expected losses for each material alloy were computed using three-way decision theory and relational analysis.	There is a limited material data available. During Additive Manufacturing process different alloys behaves differently and balancing the cost and mechanical properties is quite problematic	Qin, Y. *et al*. 2023

2.3.3 Machine Learning in Additive Manufacturing

Even if additive manufacturing is already used to produce the final products, the desired results are achieved through a lot of experimentation. Generally, conducting the experiments, printing parts is an expensive process. Generation of the high volume of high-quality data is often cost prohibitive. As a result, obtaining a simple product is achieved at the expense of wasting a large amount of time, energy, and material waste. This causes the entire printing process to restart and waste of used material. The Table 2.3 demonstrates different approaches that were used by researches to eliminate such kind of problems. To eliminate the problems associated with defect formation, the implementation of physics-informed machine learning algorithm will allow to predict a defect, especially crack and surface imperfection formations before the printing of an object in the additive manufacturing process. Below, there are current studies and approaches of eliminating the defect formation while printing:

Table 3.3 Current studies and approaches of optimizing the process

Approaches	Main findings	Author, year
Machine Learning (Convolution neural networks (CNN))	While convolutional neural networks can detect defects using visual information, it is unable to predict and mitigate those problems	Zhang et al., 2019
Experimental trials	A combination of low energy density with insufficient scanning speed and laser power can result in the laser powder be fusion process of aluminum alloy parts can lead to process instability, which in turn occurrence of surface defects	Zhang et al., 2019
Machine Learning (CNN)	A deep learning convolutional neural network can identify and track the formation of the defect formation for metal alloys, especially for nickel alloy. However, it also cannot predict and reduce the problem	Williams et al., 2018
Image data-based Machine Learning	Gaussian process regression model has been used to predict surface defects, but no practical results have been demonstrated for defect reduction	Akhil et al., 2020

Mechanistic models	Insufficient power can lead to defects because the substrate does not melt, which is explained by the mesoscale heat source model for aluminum alloy parts	Liu et al., 2020

Table 2.3 demonstrates several examples of mechanistic models, experimental trials and machine learning approaches that tried to change the process parameters to mitigate the surface defects occurrence. It should be noted from Table 2.4 and Table 2.5 that the different approaches were mainly focused only on detecting the defects while printing the metallic parts. Correspondingly, none of them are not focused on overcoming before the printing or predicting detecting, which leads to the idea of continuing research efforts on overcoming and predicting defect occurrence on 3D printed aluminum alloy parts before the printing process.

Table 2.4 Comparison of different machine learning algorithms

Methods	Advantages	Disadvantages	Author, year
Decision tree	It can solve both classification and regression problems. The learning process is relatively simple. Requires minimal data preparation. Importantly, it can handle non-linear relationships without relying on complex mathematical equations.	If there are inaccuracies during the training process, it can lead to significant errors.	A. R. Kapil. 2022 H. Jeong et al., 2022 H. Patel and P. Prajapati. 2018
Naive Bayes Algorithm	It is capable with both classification and training. Does not require a large dataset. Highly versatile.	Limited applicability in real world situations. Zero frequency problem may occur.	Zhang et al., 2019
Logistic regression	This approach offers a simple learning process and setup. It excels when working with data in	This method will not work well when dealing with correlated variables.	B. Akkaya and N.

	which different results or differences are easily separated in a linear fashion. It has the ability to identify relationships between variables and their impact on the final results.	Moreover, it is not suitable for classifying data into multiple classes.	Çolakoglu., 2019
Support Vector Machine	This method quickly gathers new information and is built on a solid theoretical foundation. It is important to note that it can effectively apply the trained data to new cases.	When working with large data sets, this method may not be the most efficient due to its computational complexity.	J. Cervantes et al., 2022

Table 2.5 Implication of Machine Learning approaches for different defects in metal printing

Defect type	Main themes and Gaps	Author, year
Balling	During Laser Powder Bed Fusion (L-PBF) process, to differentiate and clarify the balling from the printed part, the logistic regression was used. This means that the model cannot predict the problem, it can just monitor and differentiate the defect.	Repossini, G. Et al, 2017
Surface roughness	The neural network was used to detect the defects associated with the surface of the printed part of Ti-6Al-4V in L-PBF process. The results were satisfactory but the model still is not able to predict and reduce the surface defects.	Khorasani, A. Et al, 2020
Crack formation	A deep neural network was successfully used to track the crack formation in nickel alloy. However, it also cannot predict and reduce the defects	Kumar, R. Et al, 2005

2.3.4 Motivation of Implementing Machine Learning

Even if additive manufacturing is already used to produce the final products, the desired results are achieved through a lot of experimentation. Generally, conducting the experiments, printing parts is an expensive process. Generation of the high volume of high-quality data is often cost prohibitive. As a result, obtaining a simple product is achieved at the expense of wasting a large amount of time, energy, and material waste. This causes the entire printing process to restart and waste of used material. To eliminate such kinds of problems, the implementation of machine learning algorithm will allow to predict a defect, especially crack and surface imperfection formations before the printing of an object in the additive manufacturing process. Using the available sets of raw data and data from a well-tested mechanistic model it is possible to derive a cracking susceptibility index that can forecast when cracks may form in a 3d printed part.

Table 2.6 Motivation of Implementing Machine Learning

Key findings	Author, year
The understanding of how process variables and alloy properties influence crack formation remains incomplete, primarily due to the difficulty of correlating them with the cracking mechanism. There are 12 variables that were obtained which influence the crack formation. Both alloy composition and process parameters influence all these mechanistic variables.	Yadroitsev et. al., 2010
The mechanisms of each variable have been individually examined. However, what is currently lacking is a comprehensive understanding of how these mechanistic variables collectively contribute to crack formation	Raissi et. al., 2020
If a two-factor design of experiments is used to represent data for 12 variables, 4096 experiments would be required, as calculated by raising 2 to the power of 12. Assuming one experiment is conducted daily, this would mean conducting experiments every day for the next 11 years. Consequently, there is a need to limit the number of variables.	Antony, 2023
The most variables that contribute to defects occurrence can be derived from physics's best model of additive manufacturing. There exist four factors: the temperature gradient, cooling rate, solidification rate, and relaxation time. Thanks to these variables, only 16 experiments are needed to identify the cracking process.	Martin et. al., 2017

2.4 Application in Aerospace Engineering

3D-printed stainless steel is revolutionizing aerospace engineering by enabling the creation of complex geometries, reducing weight, and streamlining manufacturing processes.

This technology has found applications in various critical com-ponents of aerospace systems. For rocket engines, 3D printing allows the production of intricate fuel injectors and combustion chambers with improved cooling channels, enhancing overall engine performance (Gu et al., 2020). Aerospace companies increasingly use 3D-printed stainless steel for structural parts such as brackets and hinges, significantly reducing weight while maintaining structural integrity (Nickels et al., 2015). The technology also facilitates the efficient manufacturing of complex, light-weight heat exchangers, crucial for thermal management in aerospace systems (Wong et al., 2007). In jet propulsion, additively manufactured stainless steel parts are being explored for use in turbine components, potentially improving fuel efficiency and engine performance (Guo & Leu, 2013). This versatility in application demonstrates the transformative potential of 3D-printed stainless steel in aerospace engineering, offering opportunities for cost reduction, performance enhancement, and design innovation. As the technology continues to mature, it is expected to play an increasingly significant role in shaping the future of aerospace manufacturing and design.

2.5 Research Gap Analysis

According to the Table 2.6, there are many studies in the literature on 3D printing, machine learning implementation, and machine learning for additive manufacturing. However, most of the research efforts are focused on plastic materials. Moreover, they are limited in the number of data variables to understand the defect formation process. Therefore, there is a small portion of studies that demonstrate the impact of multiple process variables on defect formation, especially how they simultaneously affect the defect formation. In addition, there are different conventional approaches and methods to achieve a defect free part used by researches but they are almost the same and utilizes a lot of expensive equipment. The main limitation in the literature review is excessive use of sensors, software and equipment. Additionally, the researches are mainly focused on detecting the defect, they are not focused on predicting and overcoming the defect formation before printing. This research work concentrated on implementing Machine Learning algorithm to predict defect formation for DED printers.

CHAPTER 3 – METHODOLOGY

The methodology of this research project is divided into six distinct phases, as illustrated in Figure 3.1. The initial phase focuses on conducting a literature review, which is carried out separately for additive manufacturing (AM), machine learning (ML), and ML applications specific to metal AM. This step aims to develop a comprehensive understanding of the research context. Following this, the next step involves selecting the appropriate AM type and conducting further reviews to identify critical process parameters and potential defect types. The second phase of the methodology is to create a 3D model for testing and simulation processes using SolidWorks software.

Third phase of this study is to perform CFD analysis and calculate the 4 mechanistic variables using a 3D, transient, heat transfer and material flow model for different, independent experimental data.

The fourth step is using generated data from simulation to train the Machine Learning algorithm especially training of Decision Tree Classification Machine Learning Algorithm. Afterward, the developed architecture and model were validated using data from the machine learning (ML) process. Subsequently, the experimental data generated during this validation phase were reused to train the ML algorithm, enhancing the accuracy of the results.

Finally, in the concluding stage, a user-friendly interface will be created, and the research project will be archived.

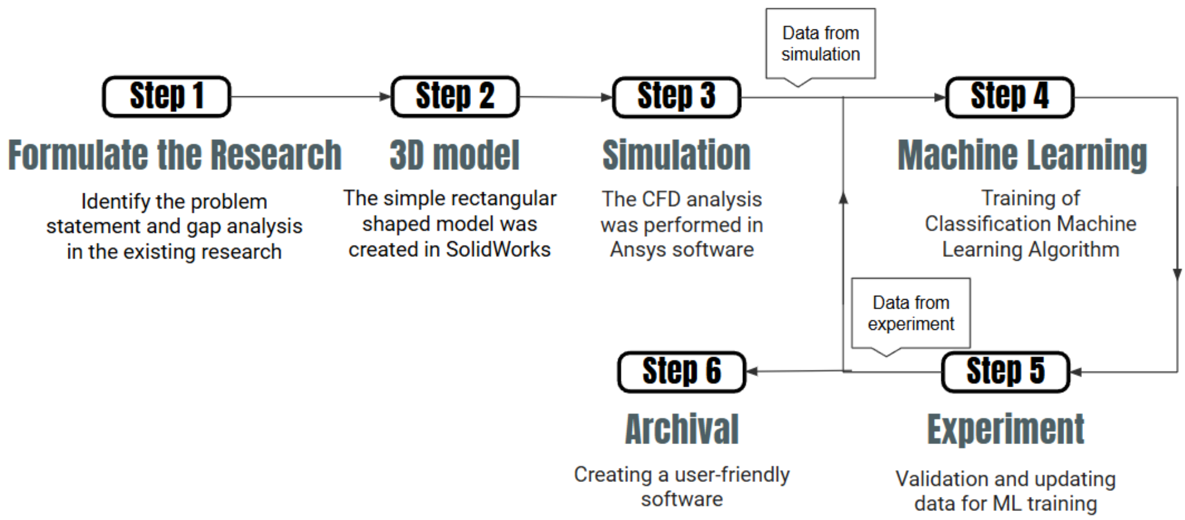

Figure 4.1 Research Methodology

The required resources for this thesis work:

Table 7.1 Required resources

Name	The amount
Meltio M450 DED 3D printer	1
Desktop computer	1
Material for 3D Printing	Powders SS316 and Inconel 718
Substrate (not identified - types)	2-5
Software accesses (Ansys, Solidworks)	3-6 month (preferable)

3.2 Computational Modeling and Simulation

In the initial phase, SolidWorks 2024 software was employed to generate a precise three-dimensional rectangular solid model. The geometric parameters were meticulously defined with dimensions of 80.0 millimeters in length, 25.0 millimeters in width, and 8.0 millimeters in height. This CAD model was subsequently exported in .STEP format to ensure optimal compatibility with the ANSYS simulation environment.

The second phase involved comprehensive CFD analysis utilizing ANSYS Workbench, specifically focusing on Direct Energy Deposition (DED) simulation. The geometry preparation stage encompassed the import of the previously generated CAD model into ANSYS Design Modeler, followed by the generation of an appropriate substrate domain for thermal analysis. Particular attention was paid to verifying the geometric interfaces between the component and substrate to ensure accurate simulation results.

The mesh generation process constituted a critical component of the analysis workflow. This stage involved the implementation of a systematic discretization strategy and the generation of a computational grid suitable for the specific requirements of the DED simulation. The mesh generation process necessitated careful consideration of multiple parameters, including element type selection, determination of appropriate element numbers, identification of mesh refinement regions, and evaluation of critical mesh quality metrics such as skewness and element quality parameters.

For the detailed simulation implementation, a comprehensive G-code weld path strategy was developed for the rectangular geometry. The primary scanning pattern incorporated a raster configuration with parallel tracks, utilizing a track spacing of 0.6 mm between adjacent passes and a layer height increment of 0.1 mm per layer. The scanning speed was set at 300 mm/min. The path programming sequence included an initial contour path following the rectangular perimeter, followed by an infill pattern utilizing bi-directional scanning with 90-degree rotation between successive layers. A dwell time of 0.2 seconds was implemented at turning points to ensure process stability.

The process parameters were meticulously defined within ANSYS, incorporating laser parameters (starting from 200 W power, 0.4 mm spot diameter, Gaussian power distribution, 0.35 absorption coefficient), material properties for SS316 and Inconel 718 (powder feed rate: 2.5 g/min, particle size: 36.6 μm, and environmental conditions (ambient temperature: 298 K, convective heat transfer coefficient: 10 $W/(m^2 \cdot K)$, Argon shielding gas at 8 L/min). All of these variables were manipulated to generate the data for training Machine Learning Algorithm.

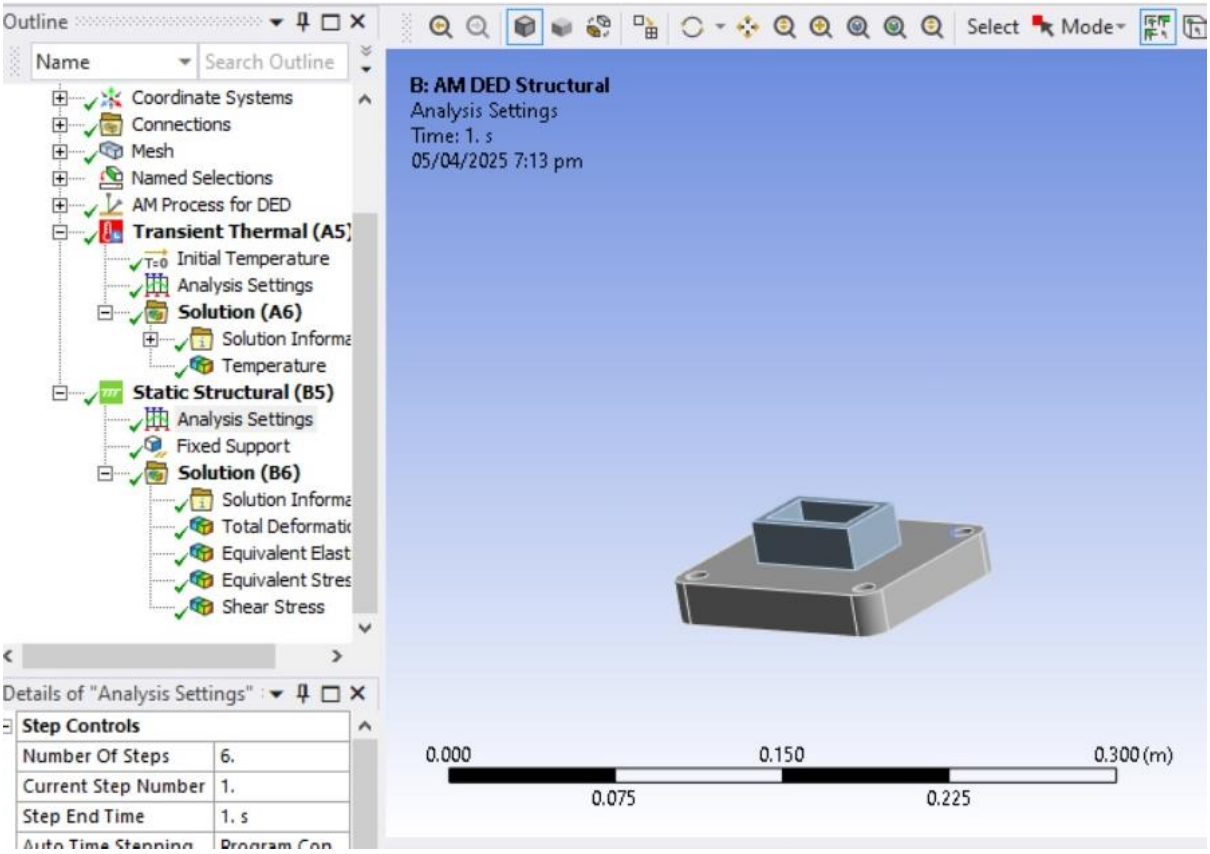

Figure 5.2 The CFD analysis in Ansys Software for data generation

The Figure 3.2 demonstrate the transient heat flow and static structural analysis that were analyzed during the simulation. The four mechanistic variables cooling rate (K/s), Temperature Gradient (K/mm^2), Solidification Stress (MPa) and Relaxation time (s) were calculated using a 3D, transient, heat transfer and material flow model for different, independent experimental data.

3.3 Machine Learning Algorithm and Defect Prediction

The dataset generated from CFD simulations and GANs was used to train a machine learning algorithm, specifically the Decision Tree Classification algorithm DecisionTreeClassifier via Python on a computer with an Intel® Core™ i9-9900K CPU @ 3.60GHz × 16 and an NVIDIA Corporation TU104 [GeForce R4X 2080] GPU. The 80% of training data and 20% data was used for validation while training Machine Learning algorithm (see Figure 3.3). A user-friendly interface was developed to allow users to input process parameters and predict whether a defect would occur. The decision-making process in the ML model starts with assessing solidification stress and laser power, followed by an evaluation of other mechanical variables and process parameters based on their hierarchical influence on defect formation. The final output determines the probability of defect formation based on these mechanistic estimates. The materials utilized in both the experiments and CFD analysis were 316 stainless steel and Inconel 718, which are fundamental materials in aerospace engineering. ‘

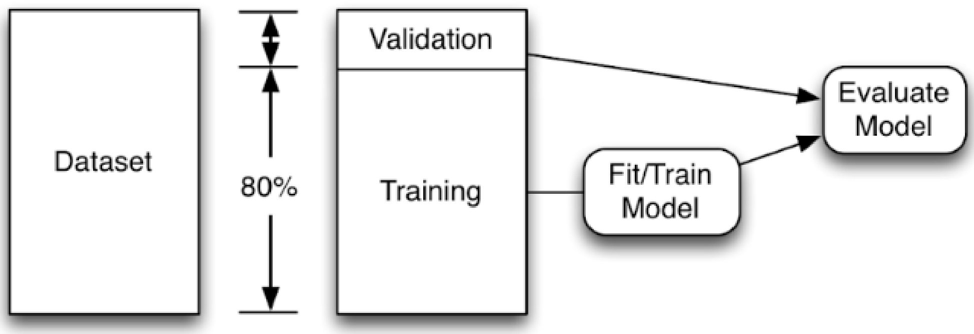

Figure 6.3 Machine Learning cross validation

The model was validated against independent experimental datasets, and four key mechanistic variables were calculated to understand their influence on defect formation. To enhance data efficiency, generative adversarial networks (GANs) were employed to synthesize additional data, reducing the need for extensive physical experiments. The synthetic data was evaluated for feasibility before being incorporated into the training dataset.

3.4 Experimental Validation and Materials

The trained ML model was validated experimentally using the Meltio M450 DED printer. During the validation phase, the experimental data collected was fed back into the ML model to improve prediction accuracy.

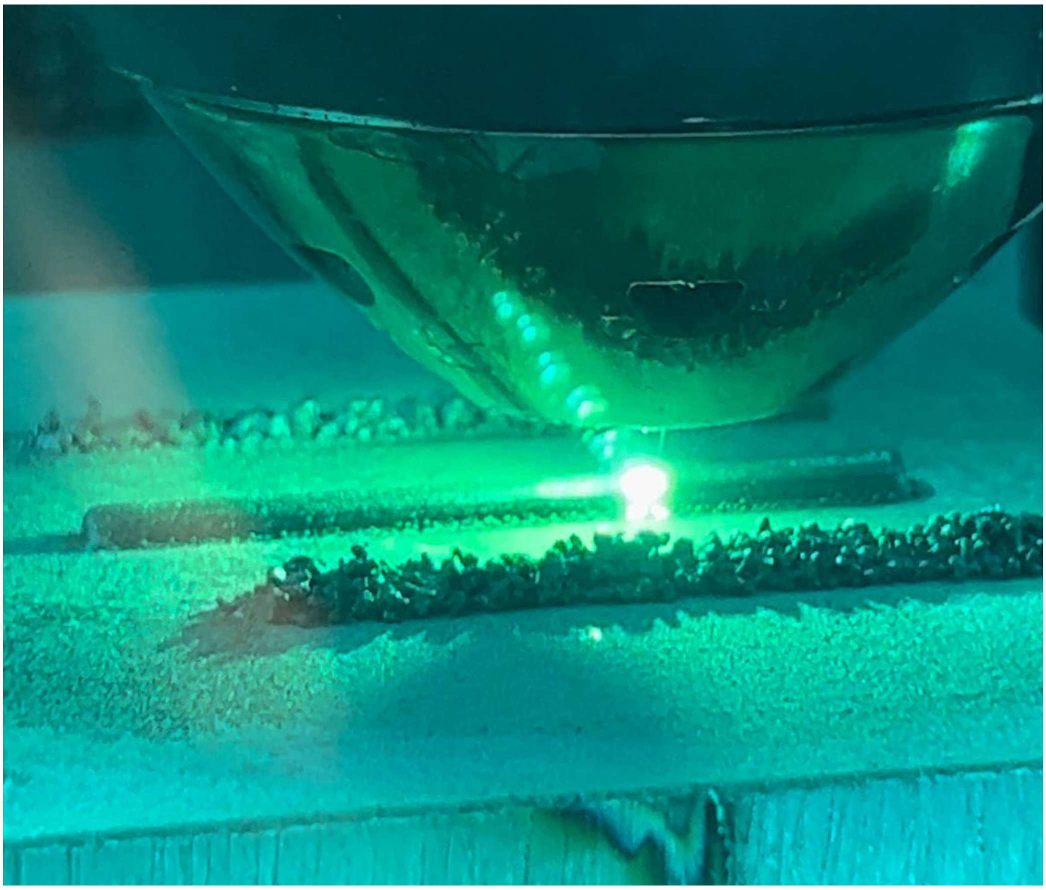

Figure 7.4 Meltio M450 DED printer during the validation phase

The Figure 3.4 showcases a Directed Energy Deposition (DED) additive manufacturing process. A high-powered laser is focused onto a substrate while metallic powder is simultaneously deposited into the melt pool. The laser energy melts the material, allowing layer-by-layer fabrication of metal components. The process is commonly used for repairing parts, hybrid manufacturing, and fabricating complex structures with high precision.

For these reasons, the validation step was conducted with a simple box model, ensuring compatibility with the printer's limitations. A workspace with five applied layers was selected to facilitate a structured approach to defect analysis. The materials used for both experimental and computational studies were 316 stainless steel and Inconel 718, which are widely utilized in aerospace engineering. The developed methodology integrates physics-based modeling, synthetic data generation, ML training, and experimental validation, providing a robust framework for defect prediction in AM processes. The materials were utilized in Powder Bed Fusion with a laser heat source Meltio M450 Directed Energy Deposition (DED) which is demonstrated in Figure 3.5.

Figure 8.5 Meltio M450 3D printer

CHAPTER 4 - EXPERIMENTAL AND SIMULATION RESULTS

The Machine learning requires data on the impact of variables. Many variables can affect the quality of 3D-printed parts. For example, laser power, beam radius, scanning speed, layer thickness, etc. Overall, 12 such variables affect the quality of the part. If a two-factor design of experiments is used to represent data for 12 variables, 4096 experiments would be required. However, it is time-consuming to cover all of them manually. Nevertheless, in fact, only 4 variables in the data set represent the physics of defect formation to implement machine learning. They were successfully identified previously by Martin et al. (2017). Although the number of variables has decreased, the number of experiments is still large. Therefore, to eliminate such kind of problem machine learning is used to correlate variables with the possibility of the occurrence of defects. This illustrates how these factors contribute to defect formation in 3d printing with no expenses and time-consuming trial and error testing. Machine Learning reliable predictions with less data will help to select appropriate process parameters and the right alloy for an application within a short period.

One of the main steps is to generate the data. The data for training Machine learning was generated using a 3D transient, heat transfer, and material flow model using Ansys software for various independent experimental data as shown in Figure 4.1.

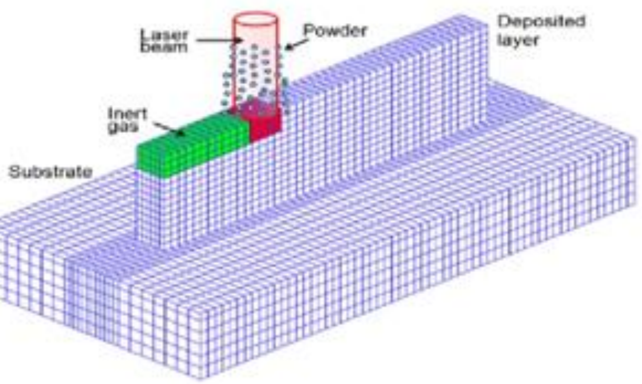

Figure 9.1 Computational Fluid Dynamics (CFD) Model

4.1 Data Collection and Simulation Analysis

The data, consisting of over 1500 cases, was systematically collected from Ansys Software Simulation to analyze both defective and non-defective parts. The comprehensive dataset encompassed various parameters and conditions under which the simulations were performed, providing valuable insights into part quality and manufacturing process reliability. These simulations helped identify critical factors contributing to defect formation and enabled a better understanding of optimal manufacturing conditions. The analysis included detailed mechanical properties, stress distributions, and deformation patterns, allowing for precise differentiation between parts that exhibited defects and those that maintained structural integrity. This extensive collection of simulation results serves as a robust foundation for developing predictive models and implementing quality control measures in the manufacturing process. Using the available sets of raw data and data from a well-tested mechanistic model it is possible to derive a defect susceptibility index that can forecast when defects and surface defects may form in a 3d printed part. The goal is to create a relationship between these variables and defect occurrence. Table 1 presents a comparison between CFD simulations and experimental results, showing a general agreement. However, in certain cases, defects still appeared in experimental trials despite Ansys predicting a defect-free part. This discrepancy highlights the limitations of physics-based modeling alone and underscores the need for experimental validation. Figure 4.2 illustrates an Inconel 718 specimen with unexpected defect formation, demonstrating these variations. To address this issue, experimental data were incorporated into the machine learning algorithm to improve accuracy in defect prediction. The initial physics-based model provided a preliminary understanding, while subsequent integration of experimental data refined the model's predictions.

Table 8.1 Comparison of CFD and Experimental Results

	Simulation				Experimental				
Alloy	**Pool Aspect ratio**	**Surface tension force (N)**	**Solidification time**	**Surface anomalies**	**Laser Power (W)**	**Speed (mm/s)**	**Hatch Spacing (μm)**	**Layer thickness (mm)**	**Surface anomalies**
	2.85	0.0016	0.0528	0	125	110	150	0.1	0
SS316	2.73	0.00135	0.031	0	125	140	150	0.1	0
	3.10	0.00134	0.0255	0	125	290	150	0.1	1
	3.55	0.00134	0.0129	1	125	320	150	0.1	1

As shown in Table 4.1, the results of the CFD simulations and experimental data exhibit a general agreement. However, validation reveals that in certain cases, the simulation results deviated from the actual experimental outcomes. This discrepancy indicates that when the process parameters derived from the simulation were implemented in the actual printing process, defects still occurred, even though the Ansys software predicted a defect-free part. Consequently, the experimental results deviated from the simulation predictions, with defects appearing despite theoretically optimal conditions (see Figure 4.2).

Figure 10.2 Inconel 718 specimen with unexpected defect formation

4.2 Integration of Experimental Data for Model Enhancement

To improve defect prediction accuracy, the experimental data were incorporated into the Machine Learning algorithm to retrain the model, thereby improving its accuracy in predicting defect formation. The initial pre-training step, which utilized data generated by the physics-based model, can be considered analogous to developing a lower-accuracy model. The subsequent step of refining the pre-trained model through parameter updating involved integrating higher-accuracy data with the experimental results to enhance the model's predictive capabilities.

The decision-making process begins with an assessment of the solidification stress and laser power, if the data passes certain conditions, the process moves on to the assessment of other mechanical variables based on the hierarchical order of influence of mechanistic variables in defect formation. Based on these estimates, a determination is made about the probability of defect formation.

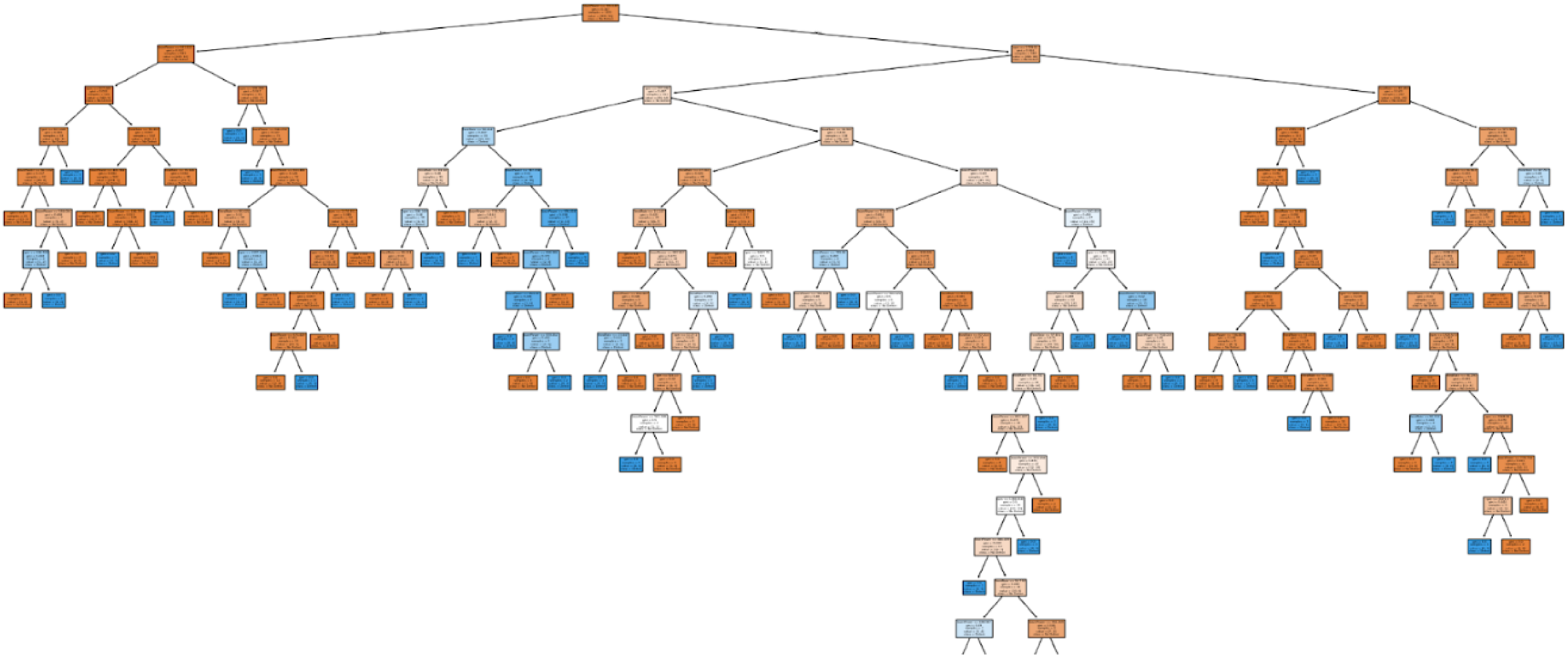

Figure 11.3 The black box of the Machine Learning Decision Tree Classifier

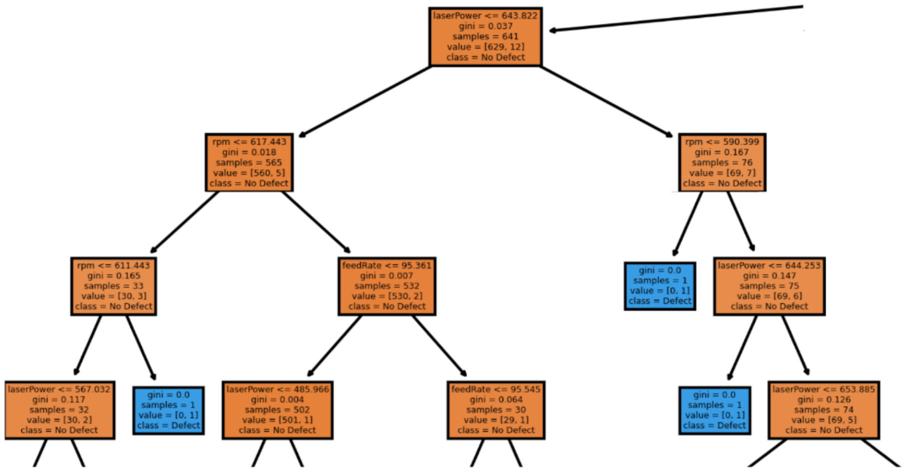

Figure 12.4 The small portion of the black box of the Machine Learning Decision Tree Classifier

Figure 4.4 represents the small part of how the tree makes decisions depending on the values that were entered. Typically, these internal components remain hidden from the user. A more user-friendly interface is depicted in Figure 4.5, where users can input process parameter values and receive predictions regarding defect presence.

```
=== Defect Prediction ===
Enter RPM: 800
Enter Laser Power (W): 700
Enter Feed Rate (mm/s): 13
=== Prediction Result ===
+-----------------------------+----------+
|          Parameter          |  Value   |
+-----------------------------+----------+
|            RPM              |  800.0   |
|        Laser Power (W)      |  700.0   |
|        Feed Rate (mm/s)     |  13.0    |
|  Predicted Defect Presence  |  0       |
+-----------------------------+----------+

Given the above parameters, the defect is : NOT PRESENT
```

```
=== Defect Prediction ===
Enter RPM: 700
Enter Laser Power (W): 800
Enter Feed Rate (mm/s): 13
=== Prediction Result ===
+-----------------------------+----------+
|          Parameter          |  Value   |
+-----------------------------+----------+
|            RPM              |  700.0   |
|        Laser Power (W)      |  800.0   |
|        Feed Rate (mm/s)     |  13.0    |
|  Predicted Defect Presence  |  1       |
+-----------------------------+----------+

Given the above parameters, the defect is : PRESENT
```

Figure 13.5 A visual representation of a user-friendly setup

Although decision trees lack a straightforward mathematical formula like linear regression, they can still be utilized to determine the most influential features in defect formation. This analysis is conducted through feature importance evaluation. The results indicate that the optimal laser power value is the most significant factor, accounting for approximately 45% of the total influence on defect formation. A user-friendly interface (Figure 4) was developed to allow users to input process parameters and predict defect occurrence.

4.3 Model Optimization and Computational Efficiency

Throughout the training process, the model fine-tunes its internal parameters to enhance its prediction accuracy. This is achieved by minimizing a loss function, which quantifies the disparity between the model's predicted output and the actual output. Training loss refers to the value of the loss function calculated on the training dataset at each training epoch. The key idea behind training GANs is that the generator tries to produce data that is indistinguishable from real data, while the discriminator tries to get better at distinguishing between real and fake data. Over iterations, both models improve resulting in a generator that produces increasingly convincing data.

Table 9.2 RMSE of the Proposed Model for 100 data

Model	RMSE		
GANs	Training	Validation	Test
	2.5051	2.2644	0.083

Table 10.3 RMSE of the Proposed Model for 1000 data

Model	RMSE		
GANs	Training	Validation	Test
	0.2843	0.4352	0.026

Further training with the remaining data samples greatly enhanced the accuracy and reliability of the ML model. The prediction's error metric was measured using Root Mean Square Error (RMSE). Regarding time-saving, there is definitely an obvious reduction in computation time and data generation time. This means that we save significant time on data generation and performing defect prediction before printing by implementing the machine learning approach. The average time required to generate data for a DED metal 3D printer for a simple beam of the corresponding dimensions is given in Table 4.4.

Table 11.4 The comparison of time taken to generate the one set of data

Software	Ansys DED	ML Approach
Time (sec)	2583	4.93×10-3

The ML model underwent extensive training to minimize prediction errors. RMSE values for different dataset sizes (Tables 4.2 and 4.3) demonstrated improved accuracy with increased training data. Compared to conventional Ansys simulations, the Machine Learning approach significantly reduced computation time, as shown in Table 4.4. The ML model processed defect prediction in milliseconds, whereas Ansys simulations for a simple beam model took over 2,500 seconds. It should be noted that the model is a simple beam with dimensions of 4 cm × 2 cm × 2 cm. Simulations of more intricate and complex shapes may require significantly more time, potentially taking up to several days in existing software like Ansys. Whereas, the computational time of the Machine Learning algorithm will take several ms.

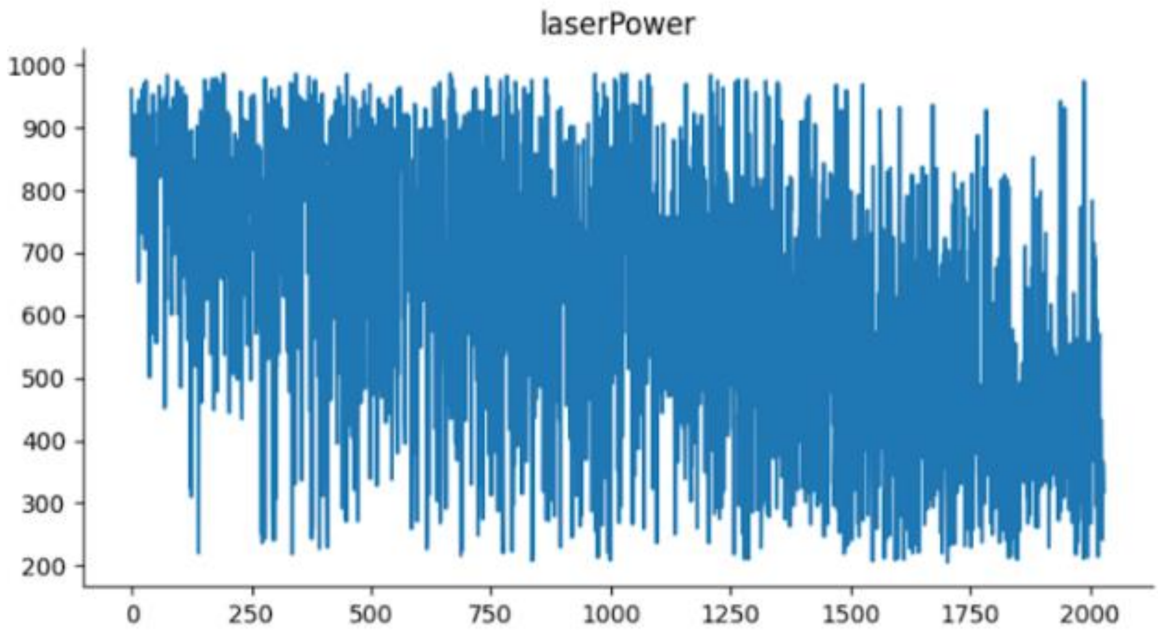

Figure 14.6 The 2000 synthetic data that was generated for Laser Power

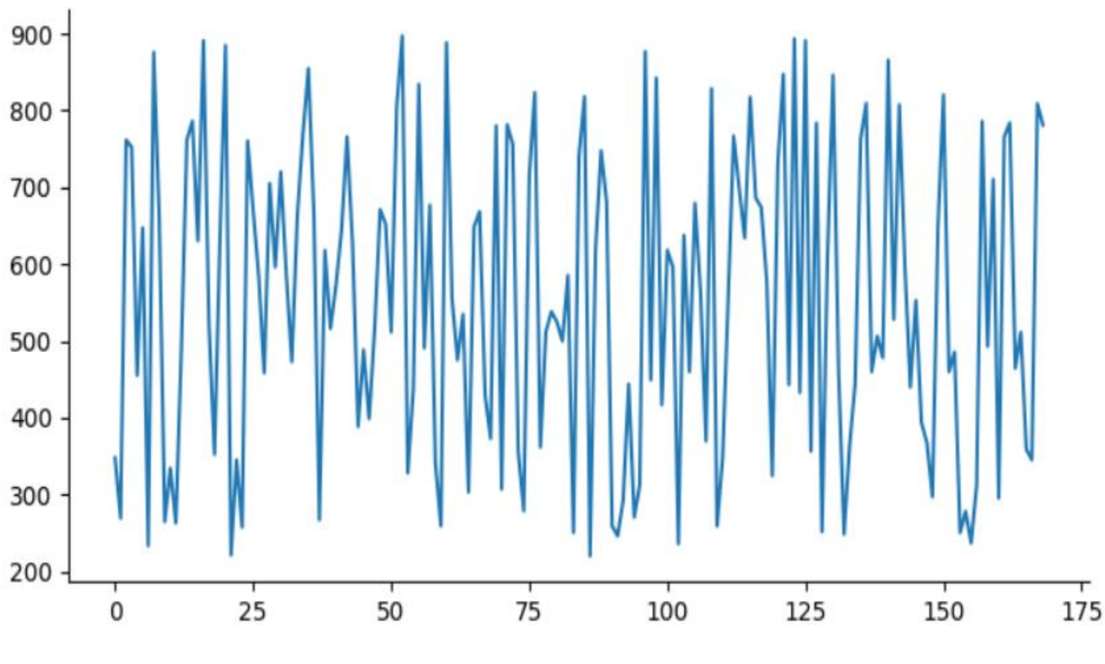

Figure 15.7 The 170 synthetic data that was generated for Laser Power

From Figure 4.6 and Figure 4.7 we can see that the data did not exceed the max and min boundaries of real data values. This figure depicts only 170 data points that were synthesized by the GANs model. Nevertheless, the model may become overfitted to the training data, implying that it has learned to memorize rather than generalize to new, unseen data. To prevent overfitting, it is essential to assess the model's performance on a separate dataset known as the validation dataset, which includes input data and corresponding labels that were not used during training. The validation loss represents the value of the loss function calculated on the validation dataset at each training epoch. Monitoring the validation loss helps evaluate the model's performance on unseen data and identify overfitting. If the validation loss increases while the training loss continues to decrease, it may indicate that the model is overfitting to the training data and is not generalizing well to new data. In this case, the early stopping was implemented in the code to halt the training process after a specific number of epochs when the validation loss value is not increasing while the training loss continues to decrease. This approach ensures that the results are sufficiently accurate without additional computations. By doing so, we effectively save training time and computational resources, as the model is prevented from overfitting and unnecessary further processing is avoided.

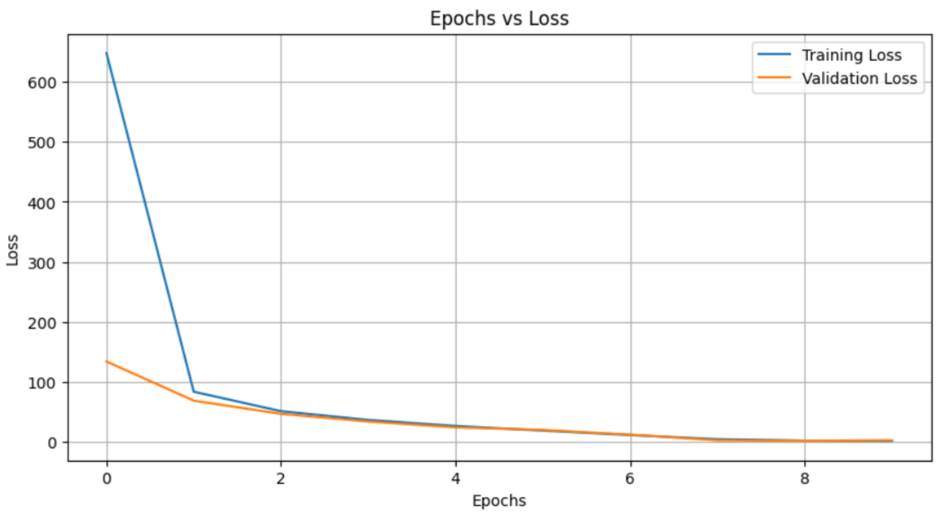

Figure 16.8 The effect of epoch on an error

Figure 4.8 demonstrates the examples of well-predicted structures by machine learning that can be achieved. Thanks to this we can understand that there is no need to do extra computation by increasing the epochs numbers. For this reason, the early stop was also introduced.

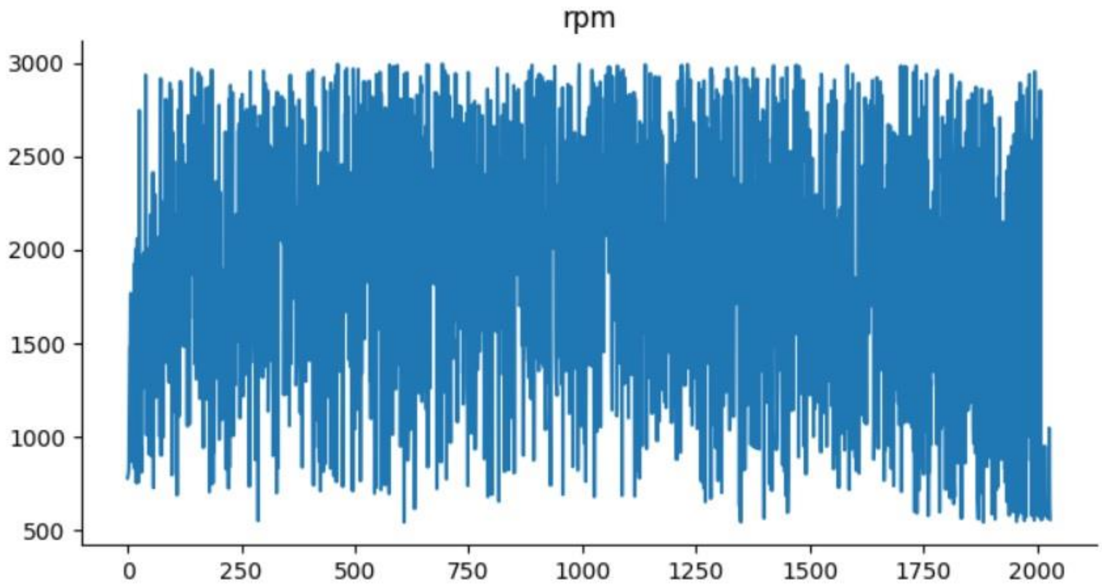

Figure 17.9 The 2000 synthetic data that was generated for RPM

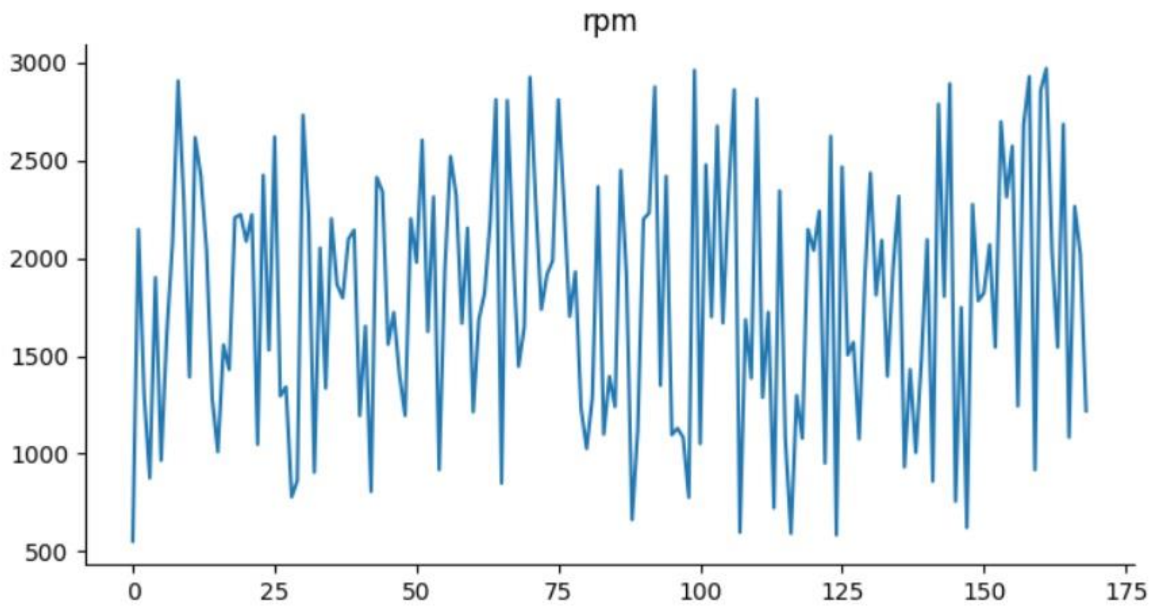

Figure 18.10 The 170 synthetic data that was generated for RPM

From Figure 4.9 and Figure 4.10 we can see that the data did not exceed boundaries of real data values. This figure depicts only 170 and 2000 synthetic data points that were synthesized by the GANs model. As a result, thanks to GANs model it was possible to generate more than 3000 synthetic data in a short period of time to train the Machine Learning algorithm for defect detection (see Figure 4.11). Utilizing GANs model substantially decreased the computational time for generating the data for training.

	laserPower	rpm	feedRate
0	960.049574	779.799049	22.649767
1	856.467961	788.664729	17.768866
2	860.167802	805.754568	13.085609
3	854.421695	834.037862	55.870392
4	881.671067	1151.172309	23.685287
...	...	...	...
2024	272.964882	603.932148	78.059225
2025	241.345377	578.965362	82.232711
2026	366.000509	1047.101809	98.549375
2027	354.051026	639.937032	93.377481
2028	317.658785	559.096465	98.108300

Figure 19.11 The 2000 synthetic data generated by GANs model

4.4 Experimental Validation and Real-World Applications

The experimental validation phase utilized a Meltio M450 DED printer to test the model's predictions. Successfully printed 316 stainless steel samples were compared with defective parts, as shown in Figure 4.11. These results reinforced the importance of integrating real-world data with simulation-based predictions to achieve reliable defect detection. Despite theoretically optimal conditions, defects can still emerge due to process variations, reinforcing the need for experimental validation in AM. The developed framework, which integrates physics-based simulations, ML-based predictions, and real-world validation, provides a robust approach for defect detection in metal additive manufacturing.

Figures 4.12 and 4.13 illustrates the results of a successful 3D-printed SS316 model.

Figure 20.12 Successfully printed SS316 part

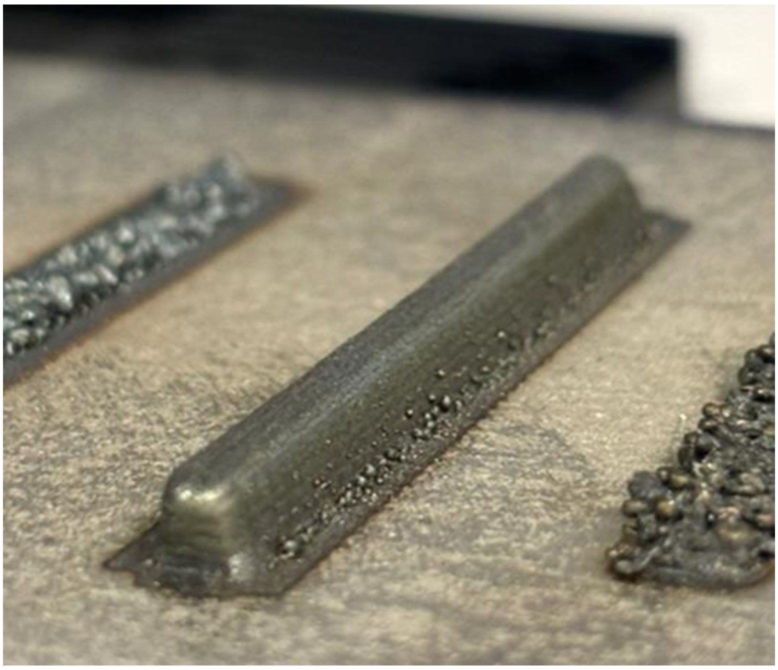

Figure 21.13 Successfully printed SS316 part (side view)

The importance of experimental validation cannot be overstated, particularly when theoretical models or simulations are involved. While theoretically optimal conditions may suggest that processes such as printing should occur without issue, real-world scenarios often reveal otherwise. In some cases, according to the Table 4.1, defects can still appear, demonstrating the limitations and gaps in purely theoretical predictions. Therefore, experimental data becomes crucial not only for validating and refining these models but also for enhancing the accuracy of machine learning algorithms used in predictive tasks. By using experimental data to retrain and adapt these algorithms, we improve their ability to accurately predict and adapt to real-world variations and complexities, ultimately leading to more robust and reliable performance.

CHAPTER 5 – CONCLUSION

5.1 Conclusions

The research study provides significant advancements and valuable contributions in metal alloy 3d printing and Machine Learning. The findings are one of the first steps toward future research on integrating machine learning systems into metal additive manufacturing processes. The research opens a new path for selecting suitable process parameters with the right metal alloys for aerospace applications with no expensive and time-consuming trial and error-testing. The project is based on scientific principles, which in turn means that it does not require expensive equipment.

There are various 3D printing techniques and a wide range of machine learning algorithms. This research focuses on the implementation of the DecisionTreeClassifier algorithm for anomaly detection. The developed defect detection method is discussed in detail in this study. The primary objective of this research is to minimize material waste and reduce trial-and-error testing before printing, while maintaining minimal expenditures. According to the obtained results, compared to conventional Ansys simulations that took roughly one hour to generate one data set, the Machine Learning approach significantly reduced computation time to milliseconds. This leads to the idea that implementation of Machine Learning is efficient in time savings. Moreover, a key novelty of this work is its closed-loop system, which in turn achieves up to 99% accuracy. This high precision is attained because the model is trained using not only simulation data but also validation data obtained from experimental trials. The experimental results were utilized to retrain the machine learning algorithm, further enhancing the accuracy of the final output. Although the model was validated using the Meltio M450 DED printer, the algorithm can be applied to any Powder Bed Fusion printer with minor modifications to the Machine Learning architecture.

The successful implementation of a machine learning algorithm for defect prediction highlights the potential of computational methods in quality assurance for additive manufacturing. However, improving its generalizability requires larger datasets with diverse geometric configurations and structured model training from actual experimental results. This research advances metal alloy additive manufacturing by integrating machine learning, offering a novel approach to process optimization and alloy selection for aerospace applications while reducing reliance on costly trial-and-error methods. Despite its benefits, limitations remain, particularly in dataset dimensionality, which affects predictive accuracy. Future efforts should focus on expanding datasets, refining models with advanced architectures and hybrid approaches, conducting more validation studies, and developing standardized deployment strategies. These advancements could enhance predictive capabilities, enable real-time process optimization, and extend benefits beyond aerospace to other precision-driven industries.

The generated algorithm shows that it is possible to implement machine learning for defect prediction. One limitation of this method is the size of the dataset; larger datasets obtained from experimental data tend to yield more accurate results. For future applications, it is recommended to collect a new, unique dataset for different geometries and train the model in the same manner.

5.2 Key Research Contribution to Knowledge

The field of metal additive manufacturing is attracting significant interest in both research and various industrial applications. Currently, due to the affordability and efficiency of metal powders, Powder Bed Fusion (PBF) and Directed Energy Deposition (DED) 3D metal printers are widely used. Consequently, advancements in PBF and DED printers drive increased production and adoption across different industrial sectors.

However, current challenges associated with this technology include defect formation during printing, time-consuming trial-and-error testing, and excessive waste of time, money, and materials. This research presents a novel approach where artificial intelligence and machine learning are implemented to address these challenges. By integrating machine learning for early defect detection, material waste, computational time, and costly error-prone testing are significantly reduced, thereby streamlining data generation.

Overall, this project enhances the 3D metal printing process and can be applied to any industrial field, depending on the materials used.

5.3 Future Research Directions

The future research involves enhancing Computational Fluid Dynamics (CFD) analysis by extracting comprehensive datasets from advanced simulations and analyzing fluid behavior and thermal characteristics. This will be complemented by an experimental validation protocol, including additional experimental trials, rigorous validation studies to verify simulation results, and systematic documentation of empirical observations and measurements. Simultaneously, machine learning model development will integrate experimental and simulation datasets, implement initial algorithm training, and optimize model parameters based on collected data. Furthermore, a comparative algorithm analysis will deploy alternative machine learning algorithms, conduct accuracy assessments, and refine the system based on performance metrics to ensure robust and precise outcomes.

In the next phase of this research, a digital twin will be integrated into the Directed Energy Deposition (DED) process to enable real-time defect detection and adaptive parameter control. By leveraging machine learning, the system will continuously analyze sensor data, identifying defects as they occur and tracing them back to specific process parameters. This information will then be used to dynamically adjust the relevant parameters—such as laser power, scanning speed, and powder flow rate without interrupting the printing process. The goal is to create a closed-loop feedback system where the digital twin not only predicts potential defects but also ensures that the machine learning model optimizes process conditions in real time. This approach aims to enhance print quality, minimize defects, and increase the efficiency of additive manufacturing by eliminating the need for manual intervention or process halts. Through experimental validation, the effectiveness of this adaptive system will be assessed, demonstrating its potential to advance intelligent additive manufacturing by merging digital twin technology with AI-driven process optimization.

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Appendix A

The main Machine Learning script of Decision Tree Classifier

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
from sklearn.tree import DecisionTreeClassifier
from colorama import Fore, Style, init  # For colored console output

# Initialize colorama
init(autoreset=True)

# Print current working directory
print(Fore.CYAN + "Current Directory:", os.getcwd())

# Load dataset from GitHub CSV file
csv_url = "https://raw.githubusercontent.com/YGabdulla/Data/main/auto1000.csv"

try:
    data = pd.read_csv(csv_url)
    print(Fore.GREEN + "File loaded successfully!")
except Exception as e:
    print(Fore.RED + f"Error loading file: {e}")
    exit()

# Train Decision Tree Classifier Model
X = data[['rpm', 'laserPower', 'feedRate']]
y = data['defect']

model = DecisionTreeClassifier()
model.fit(X, y)
```

```
# Function to predict crack presence
def predict_crack():
    print(Fore.YELLOW + "\n=== Defect Prediction ===")
    try:
        rpm = float(input(Fore.BLACK + "Enter RPM: "))
        laser_power = float(input(Fore.BLACK + "Enter Laser Power (W): "))
        feed_rate = float(input(Fore.BLACK + "Enter Feed Rate (mm/s): "))

        # Create input data with feature names matching those used in training
        input_data = pd.DataFrame([[rpm, laser_power, feed_rate]], columns=['rpm',
'laserPower', 'feedRate'])

        # Predict crack presence
        prediction = model.predict(input_data)[0]

        # Display the result in a table format
        print(Fore.GREEN + "\n=== Prediction Result ===")
        print(Fore.WHITE + "+----------------------------+--------+")
        print(Fore.WHITE + "|         Parameter          | Value  |")
        print(Fore.WHITE + "+----------------------------+--------+")
        print(Fore.WHITE + f"|            RPM             | {rpm:<7.1f}|")
        print(Fore.WHITE + f"|       Laser Power (W)      | {laser_power:<7.1f}|")
        print(Fore.WHITE + f"|      Feed Rate (mm/s)      | {feed_rate:<7.1f}|")
        print(Fore.WHITE + f"|    Predicted Defect Presence| {prediction:<7d}|")
        print(Fore.WHITE + "+----------------------------+--------+")

        # Display the prediction
        presence_text = "PRESENT" if prediction == 1 else "NOT PRESENT"
        print(Fore.BLUE + f"\nGiven the above parameters, the defect is: {presence_text}")
    except ValueError:
        print(Fore.RED + "Invalid input. Please enter numeric values.")
```

```
# Run prediction function
predict_crack()
```

While decision trees do not have a simple mathematical formula like linear regression, we can still find out which feature has the most influence on defect formation. To analyze it we see feature importance analysis.

```
importances = model.feature_importances_
feature_names = ['rpm', 'laserPower', 'feedRate']

for feature, importance in zip(feature_names, importances):
    print(f"{feature}: {importance:.4f}")
```

Appendix B

The Machine Learning script of Generative Adversarial Networks (GAN) for generation Synthetic Data

```
try:
    from google.colab import drive
    %tensorflow_version 2.x
    drive.mount('/content/drive', force_remount=True)
    COLAB = True
    print("Note: using Google CoLab")
except:
    print("Note: not using Google CoLab")
    COLAB = False

# HIDE OUTPUT
CMD = "wget https://raw.githubusercontent.com/Diyago/"\
  "GAN-for-tabular-data/master/requirements.txt"

!{CMD}
!pip install -r requirements.txt
!pip install tabgan

!pip3 install mxnet-mkl==1.6.0 numpy==1.23.1

# HIDE OUTPUT
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
import pandas as pd
import io
import os
import requests
```

```
import numpy as np
from sklearn import metrics
False
df = pd.read_csv("https://raw.githubusercontent.com/YGabdulla/Data/main/auto-mpg.csv")


COLS_USED = ['laserPower', 'rpm', 'feedRate', 'defect']
COLS_TRAIN = ['laserPower', 'rpm', 'feedRate']

df = df[COLS_USED]

# Split into training and test sets
df_x_train, df_x_test, df_y_train, df_y_test = train_test_split(
    df.drop("defect", axis=1),
    df["defect"],
    test_size=0.20,
    #shuffle=False,
    random_state=42,
)

# Create dataframe versions for tabular GAN
df_x_test, df_y_test = df_x_test.reset_index(drop=True), \
  df_y_test.reset_index(drop=True)
df_y_train = pd.DataFrame(df_y_train)
df_y_test = pd.DataFrame(df_y_test)

# Pandas to Numpy
x_train = df_x_train.values
x_test = df_x_test.values
y_train = df_y_train.values
y_test = df_y_test.values
```

```
# Build the neural network
model = Sequential()
# Hidden 1
model.add(Dense(50, input_dim=x_train.shape[1], activation='relu'))
model.add(Dense(25, activation='relu')) # Hidden 2
model.add(Dense(12, activation='relu')) # Hidden 2
model.add(Dense(1)) # Output
model.compile(loss='mean_squared_error', optimizer='adam')

monitor = EarlyStopping(monitor='val_loss', min_delta=1e-3,
        patience=5, verbose=1, mode='auto',
        restore_best_weights=True)
model.fit(x_train,y_train,validation_data=(x_test,y_test),
        callbacks=[monitor], verbose=2,epochs=1000)
```

We now evaluate the trained neural network to see the RMSE. We will use this trained neural network to compare the accuracy between the original data and the GAN-generated data.

```
pred = model.predict(x_test)
score = np.sqrt(metrics.mean_squared_error(pred,y_test))
print("Final score (RMSE): {}".format(score))
```

Next, we will train the GAN to generate fake data from the original MPG data.

```
from tabgan.sampler import GANGenerator
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split

gen_x, gen_y = GANGenerator(gen_x_times=1.1, cat_cols=None,
           bot_filter_quantile=0.001, top_filter_quantile=0.999, \
```

```
    is_post_process=True,
  adversarial_model_params={
     "metrics": "rmse", "max_depth": 2, "max_bin": 100,
     "learning_rate": 0.02, "random_state": \
      42, "n_estimators": 500,
  }, pregeneration_frac=2, only_generated_data=False,\
  gen_params = {"batch_size": 500, "patience": 25, \
 "epochs" : 500,}).generate_data_pipe(df_x_train, df_y_train,\
 df_x_test, deep_copy=True, only_adversarial=False, \
 use_adversarial=True)
```

Next we generate the synthetic data

```
gen_x
```

Finally, we present the synthetic data to the previously trained neural network to see how accurately we can predict the synthetic targets. As we can see, you lose some RMSE accuracy by going to synthetic data.

```
# Predict
pred = model.predict(gen_x.values)
score = np.sqrt(metrics.mean_squared_error(pred,gen_y.values))
print("Final score (RMSE): {}".format(score))
```