# Fatigue Life Prediction of Additively Manufactured Part Using Machine Learning Algorithms for Varying Deposition Attributes

Project report submitted in partial fulfilment of the requirements for the degree of

**BACHELOR OF TECHNOLOGY**

*in*

**Mechanical Engineering**

*by*


**Antara Parui**

**(Roll No. 210103019)**

**Hrishi Inani**

**(Roll No. 210103120)**


*Under the supervision of*

**Prof. Swarup Bag**

*to*


**DEPARTMENT OF MECHANICAL ENGINEERING**

**INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI**

**GUWAHATI – 781039, INDIA**


*[July-November 2023]*

# CERTIFICATE

This is to certify that the work contained in this project report entitled **"Fatigue Life Prediction of Additively Manufactured Part Using Machine Learning Algorithms for Varying Deposition Attributes"** submitted by **Antara Parui (210103019)** and **Hrishi Inani (210103120)** to the Indian Institute of Technology Guwahati towards the partial requirement of **Bachelor of Technology** in **Mechanical Engineering** is a bona fide work carried out by them under my supervision and that it has not been submitted elsewhere for the award of any degree.

**(Prof. Swarup Bag)**

**Mechanical Engineering**

**IIT GUWAHATI**

**Nov 2023**

# DECLARATION

We declare that this written submission represents our ideas in our own words, and where others' ideas or words have been included, we have adequately cited and referenced the sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated, or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.


**Antara Parui** | **Hrishi Inani**

**Roll No. 210103019** | **Roll No. 210103120**


Date: 14/11/2023

# APPROVAL SHEET

This project report entitled "**Fatigue Life Prediction of Additively Manufactured Part Using Machine Learning Algorithms for Varying Deposition Attributes**" by **Antara Parui (210103019)** and **Hrishi Inani (210103120)** is approved for the degree of Bachelor of Technology.

**Examiners**

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**Supervisor**

Prof. Swarup Bag

**Chairman**

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Date: 14/11/2023

Place: Guwahati

# ABSTRACT

Additive Manufacturing (AM) is an advanced manufacturing technique that creates three-dimensional objects by adding layer by layer material, based on a digital 3D model. AM is significant in a wide range of industries, including consumer goods, healthcare, and aerospace due to its ability to rapidly prototype and produce complex geometries. One of the major issues faced by additive manufacturing today is the uneven quality of printed goods, which is primarily determined by different processing parameters such as layer thickness and printing speed. It is crucial to assess the fatigue characteristics of metallic structural materials. Many factors, including AM processing parameters, microstructure, residual stress, surface roughness, porosities, post-treatments, etc., affect the fatigue properties of materials that are additively manufactured (AM). Machine learning models are capable of assimilating information and making inferences from reliable training datasets. Thus, they can be used for predicting fatigue life.

The aim of our study is to predict fatigue life of additively manufactured components by using machine learning algorithms for varying deposition attributes. Different machine learning algorithms, such as support vector machines and neural networks, are used to find relationships between fatigue performance and AM process variables. This study demonstrates how ML can be an effective tool for AM quality control and optimization, which will ultimately expand the technology's use in sectors that demand high-performance parts. The knowledge gained from this study has the potential to enhance the dependability and security of parts made using additive manufacturing (AM), as its application spreads throughout numerous industries.

***Keywords**: Additive manufacturing, machine learning, fatigue strength, fatigue life prediction.*

# LIST OF ACRONYMS USED

| | |
|---|---|
| AM | Additive Manufacturing |
| 3D | Three Dimensional |
| PBF | Powder Bed Fusion |
| DED | Directed Energy Deposition |
| BJ | Binder Jetting |
| ML | Machine Learning |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| RF | Random Forest |
| SVR | Support Vector Regressor |
| CRS | Compressive Residual Stress |

# LIST OF TABLES & FIGURES USED

# CONTENT

# Chapter 1

# Introduction

## 1.1 Introduction to Additive Manufacturing

Additive Manufacturing (AM), also known as rapid prototyping, 3D printing, and freeform fabrication, is capable of depositing, joining or solidifying materials to construct physical objects from computer-aided design (CAD) models [1]. Compared with conventional manufacturing methodologies, such as subtractive manufacturing and formative manufacturing, AM systems show higher efficiency and flexibility within the high-yield production and offer a new perspective for the design and processing of both parts and materials. The first commercial AM system was recognizably emerged in 1987 with stereolithography (SL) by 3D Systems. Since then, AM has become one of the most crucial manufacturing solutions across various industries, such as automobile, aerospace, and construction.

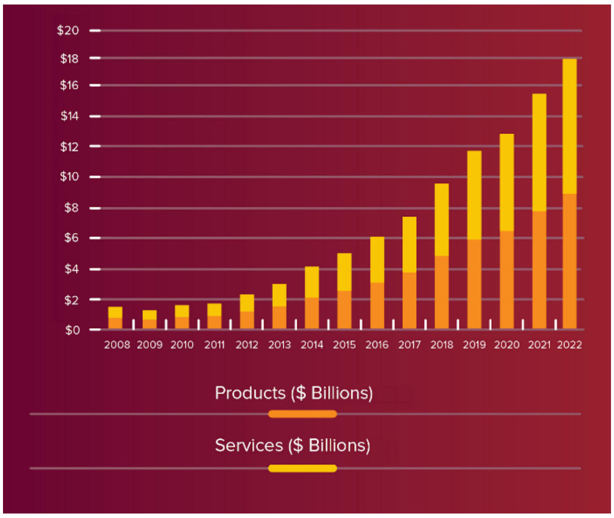


Figure 1: Global Revenue for AM Product and Services [2].

Wohlers Report 2023 shows an overall worldwide growth in AM products and services of 18.3%, continuing a trend of double-digit AM industry revenue growth in 25 of the past 34 years [2].

### 1.1.1 Classification of Metal based Additive Manufacturing

Among AM processes, three classes of PBF, DED and BJ, are integrated into mainstream metal manufacturing widely.

**1. Powder Bed Fusion**

The powder bed fusion (PBF) processes consist of thin layers of fine powders, which are spread and closely packed on a platform. One or two thermal sources are employed in the systems to melt and fuse material powder particles in each layer. Subsequent layers of powders are spread across the previous layers using a roller and then fused together until the entire product is built. Selective Laser Sintering (SLS), Selective Laser Melting (SLM), and powder-based Electron Beam Melting (EBM) are the commonly used PBF technologies.

**2. Binder Jetting**

One of the first AM methods developed for polymer powder-based materials was binder jetting (BJ). The liquid binder is sprayed onto the polymer powder using an inkjet print head. The powder material is solidified at an acceptable speed by chemical reaction bonding, traversing the section of the manufactured component layer by layer.

**3. Directed Energy Deposition**

Directed energy deposition (DED) procedures use directed energy, such as a laser beam, electron beam, or plasma arc, to melt and fuse the substrate and the material being deposited into the melt pool of the substrate to build parts. DED procedures can employ both powder-based and wire-based materials.

As per the applications, these AM classes can be used in various applications depending on the size, complexity, and resolution of components. As seen, for large-size components, the powder fed and wire fed DED processes are the most applicable processes, where the printed part may not require high resolution with complex features. In contrast, PBF and BJ can be used for smaller metal parts with higher resolution and complexity [3].

### 1.1.2 Advantages and Disadvantages of Additive Manufacturing

The following are a few of the primary advantages of additive manufacturing:

**1. Rapid Prototyping**

It can take weeks or even months to create a prototype using some traditional methods. With additive manufacturing, prototypes can be produced in a matter of days. Before committing to a production run, you can quickly make revisions and print multiple prototypes.

**2. Enhanced Precision**

Comparing additive manufacturing to conventional procedures, accuracy can be increased. Because it doesn't involve human involvement, there is less opportunity for error.

**3. Minimizing Waste and Conserving Energy**

By adding layers of material as needed, additive manufacturing produces items with minimal waste. It is also possible to recycle any extra powder or filament. Furthermore, machines for additive manufacturing are smaller, require less energy, and do not require additional tools.

**4. Environmentally Friendly**

Conventional manufacturing techniques frequently generate large amounts of carbon dioxide, which adds to pollution. Additive manufacturing is a useful technique for manufacturers looking to enhance their sustainability practices because it uses less energy and produces less trash.

**5. Unique and Customizable Design**

Unique designs that are challenging or impossible to achieve with conventional manufacturing procedures are made attainable via additive manufacturing. With additive manufacturing, you can produce parts that would be too costly or complex to produce using conventional methods.

The following are the primary drawbacks of additive manufacturing:

**1. Restricted Resources**

Sometimes this method isn't the ideal choice, as you're usually restricted to using certain materials with the machinery if you pick additive manufacturing. One has to make sure that the parts for the final assembly are made of materials that are appropriate for the job.

**2. Entrance Fee**

Compared to conventional methods, the initial setup for additive manufacturing may be more costly. For startups or small organizations looking to implement these procedures, it may not be as advantageous to invest in the necessary machinery and personnel training.

**3. High expense of production**

Even though production costs have gone down as technology has proliferated, some may find it costly to obtain specialized materials. Production costs can also increase due to slow processes.

**4. Slow Procedures**

Additive manufacturing is not scalable enough to produce large quantities of parts, and it can have slow build rates. While traditional manufacturing takes seconds, additive manufacturing can take hours, depending on the product.

## 1.2 Fatigue Strength

Under cyclic loading, materials or structures experience local damage accumulation, which leads to the initiation of cracks after a sufficient number of cycles. This phenomenon is called fatigue failure, which involves the stages of fatigue crack initiation, propagation, and final fracture. In high cycle fatigue, most of the lifetime is consumed in the crack initiation stage, while the crack propagation stage mainly dominates the low cycle fatigue failure. Generally, cracks mainly originate from singularities or discontinuities, such as slip bands, pores, inclusions, and machined surfaces [4].

Figure describes the fatigue crack growth behaviour in the framework of continuum mechanics. As the crack length increases, the corresponding physical mechanism undergoes a significant transformation, generally divided into three stages: discontinuous mechanism, continuous mechanism, and fast fracture [5].

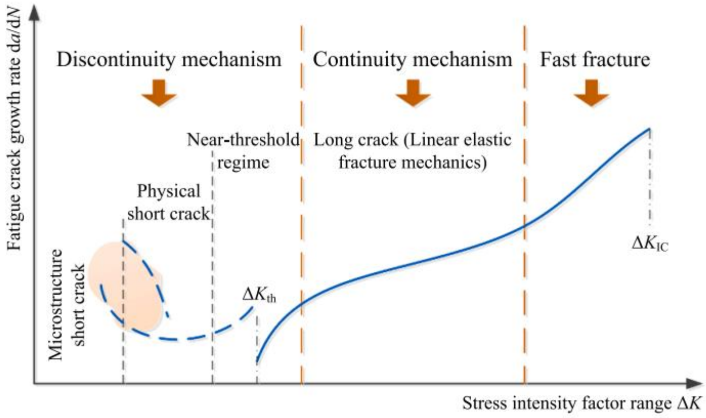


Figure 2: Fatigue crack propagation mechanism in the framework of continuum mechanics [5].

### 1.2.1 Fatigue life

Fatigue life refers to the number of cycles in which a material or structure fails under alternating loads [6]. Different failure criteria of materials and structures lead to different scales of fatigue life. In the case of materials, the localized permanent damage gradually accumulates under cyclic loading, and the fatigue life is the number of cycles required to cause the formation of cracks or sudden fractures. Fatigue failure of a structure is the loss of its load-bearing or force-transmitting function due to fatigue, i.e., the functional failure of the structure. Therefore, structural fatigue life is the number of cycles when its service function is destroyed under alternating load.

### 1.2.2 Deposition Attributes for Fatigue Strength Analysis

Fatigue strength in Additive Manufacturing (AM) is influenced by a combination of factors related to material properties, geometric features, and build orientation. Understanding and optimizing these factors is crucial to ensure the durability and reliability of AM-produced components. Major attributes affecting the fatigue strength of additively manufactured metals are Yield Stress, Ultimate Stress, Elongation, Relative density, Surface hardness, Depth of Hardness variation, Surface CRS, Maximum CRS, Depth of CRS, Surface Modification factor, Surface Roughness, Stress Amplitude [7]. Using these attributes as input, we will be predicting the fatigue life cycle of additively manufactured parts or metals.

## 1.3 MACHINE LEARNING

Machine learning (ML), a subset of artificial intelligence (AI), is defined as computer programming that uses sample data or prior knowledge to optimize a performance criterion [8].

Table 1: Categories of Machine Learning [9].

| Supervised Learning | Unsupervised Learning | Semi-supervised Learning | Reinforcement Learning |
|---|---|---|---|
| Provide input, output and feedback to build model.<br><br>Example Algorithms<br><br>Linear regressions<br>i. Sales forecasting.<br>ii. Risk assessment.<br><br>Support vector machines<br>i. Image classification.<br>ii. Performance comparison.<br><br>Decision trees<br>i. Predictive analytics.<br>ii. Pricing. | Use deep learning to arrive at conclusions and patterns through unlabelled training data.<br><br>Example Algorithms<br><br>K-means clustering<br>i. Performance monitoring.<br>ii. Searcher intent.<br><br>Artificial neural networks<br>i. Generate new, synthetic data.<br>ii. Data mining and pattern recognition. | Builds a model through a mix of labelled and unlabelled data, a set of categories, suggestions and exampled labels.<br><br>Example Algorithms<br><br>Generative adversarial networks<br>i. Audio and video manipulation.<br>ii. Data creation.<br><br>Self-trained Naïve Bayes classifier<br>i. Natural language processing. | Self-interpreting but based on a system of reward and punishments learned through trial and error, seeking maximum reward.<br><br>Example Algorithms<br><br>Q-learning<br>i. Policy creation.<br>ii. Consumption reduction.<br><br>Model-based value estimation<br>i. Linear tasks.<br>ii. Estimating parameters. |

### 1.3.1 Different Types of ML Models Used

1. **Artificial Neural Network Model**

The artificial neural network is modelled on the biological neural network. Analogous to neurons, the ANN is an interconnection of nodes, like the biological neural network. Three essential elements make up every neural network: node character, network topology, and learning rules. Node character determines how signals are processed by the node, such as the number of inputs and outputs associated with the node, the weight assigned to each input and output and the activation function. The arrangement and connectivity of nodes are determined by the network topology. The initialization and adjustment of the weights are determined by learning rules. ANNs are used for a variety of tasks, including predictive modelling and pattern recognition [10].

### 2. Random Forest Regression Model

Within the class of ensemble machine learning algorithms falls Random Forest (RF), a supervised machine learning algorithm. It is a regression technique that classifies or predicts a variable's value by combining the performances of several Decision Tree algorithms. In other words, RF builds K regression trees and averages the outcomes given an input vector consisting of the values of the various evidential features examined for a specific training region. The RF Regression model is well known for being accurate and flexible [10].

### 3. Support Vector Regressor Model

SVR is derived from the supervised ML algorithm called support vector machines (SVM), which is used for classification problems. The basic idea under the SVM method is to transform the input features into a higher-dimensional space where the two classes can be linearly separated by a high-dimensional surface, known as hyper-plane. The SVM model for regression is defined then to cope with non-separable features by allowing misclassification errors. SVR adopts an $\varepsilon$-insensitive loss function, penalizing predictions that are farther than $\varepsilon$ from the desired output. The value of $\varepsilon$ determines the width of the tube; a smaller value indicates a lower tolerance for error and also affects the number of support vectors and, consequently, the solution sparsity [10].

### 4. K-Means Clustering model

K-Means is an unsupervised learning algorithm used for clustering. It is an iterative algorithm that divides a dataset into clusters, or non-overlapping subgroups. The value of k, a hyperparameter that is selected prior to the algorithm's execution, controls how many clusters are produced. Even with limited information available, K-means can group data points. Thus, it is a good option for large datasets because of its high speed. It is useful for segmentation and pattern discovery [10].

### 5. XGBoost Algorithm

The boosting algorithm XGBoost employs bagging, which involves training several decision trees and combining the outcomes. It is an ensemble learning method. It uses Gradient Descent as the underlying objective function. Multiple cores are used to create individual trees in XGBoost, and data is arranged to reduce lookup times. As a result, the model's training time is shortened, improving performance. It uses computing power as efficiently as possible to produce the intended results while offering a great deal of flexibility.

### 1.3.2 Application of Machine Learning in Additive Manufacturing

Additive manufacturing is facing a major issue today, i.e., the uneven quality of printed goods, which is primarily determined by different processing parameters such as layer thickness and printing speed. Two approaches to address this issue are experiments and high-fidelity simulations. Both offer reliable data and support processing parameter optimization, but they are expensive and time-consuming. Another method to ensure part quality and process reliability is to use in situ monitoring systems. However, an efficient method is needed for defect detection using in situ data, such as images. Both methods depend on an efficient and productive tool for data mining and analysis. This need is being met by machine learning (ML) [11].

Machine learning models are capable of assimilating information and making inferences from reliable training datasets. One the one hand, the trained machine learning models can effectively identify the optimal processing parameters and make predictions. It can, however, also handle in situ data for defect detection in real time. A few other machine learning applications, such as quality evaluation, cost estimation, and geometric deviation control, are also covered in recent literature. Applications of machine learning are typically regarded as the art of data manipulation.

### 1.3.3 ML for Prediction of Fatigue Properties of Additively Manufactured components

Many attributes mentioned in the section 1.2.2 affect the fatigue properties of materials that are additively manufactured (AM). These elements must unavoidably be combined in order for them to be evaluated, which leads to low efficiency and high costs. Their evaluation through the application of machine learning (ML) has drawn more attention in recent years.

The data-driven approach is predicated on the data and highlights the correlation between targets and influencing factors. A data-driven model, like the machine learning (ML) model, is a black-box model that predicts fatigue life and identifies characteristics of the current damage state using data from simulations and experiments [12].

## 1.4 Motivation and Objective of the Study

It is now well established that additive manufacturing is more advantageous than conventional machining to create complex shapes. Therefore, it becomes essential to have more control over the features of the printed goods. But because there are many more parameters, it is not as convenient as conventional machining. Furthermore, it is still unclear how different parameters influencing the output relate to one another.

The goal of this study is to accurately and consistently predict the output parameters based on various input variables and produce the intended product specifications using ML. Using the datasets that are available, basic algorithms can be created with the help of various AI technologies, and the most effective model can then be used in order to successfully predict the fatigue life of additively manufactured parts.

# Chapter 2

# Literature Review

A thorough review of recent advancements in AM metal fatigue life prediction is given in this section, with a focus on machine learning (ML) modelling methods.

## 2.1 Challenges and Considerations in Fatigue Life Prediction

It is crucial to assess the fatigue characteristics of metallic structural materials. The foundation of fatigue analysis and anti-fatigue design, or the stress-life approach, is the relationship between applied stress and fatigue life. The S-N curve that results is one of the key tools for characterising fatigue behaviour. Nevertheless, it is still expensive and time-consuming to obtain S-N curves through experimental testing. To make matters more complicated, the evaluation of fatigue properties is further complicated by the fact that fatigue testing involves multiple test conditions, including R-value and frequency [13].

Many studies conducted recently have demonstrated that defects serve as the source of cracks in AM parts and determine their fatigue strength. Manufacturing flaws will cause a large scatter in the fatigue life and drastically lower the fatigue resistance of AM metal parts [13]. Within this framework, one of the main areas of focus for research is quantifying the connection between defects and fatigue resistance. The location, size, and shape of defects can have a substantial impact on the fatigue performance of AM metals, as demonstrated by prior research [13]. The critical defect that causes crack initiation and propagation is determined by the combined effect of these geometrical parameters. The degree to which defect type, size, distribution, location, and quantity affect the fatigue life of AM parts is different.

## 2.2 Some Empirical Fatigue Models and their Limitations

Some of the universal fatigue models for fatigue life prediction, for example the Basquin and Coffin–Manson equations, are essentially empirical equations [14]. A significant amount of experimental data is used to formulate them. The relationship between the fatigue limit, Vickers hardness, and inclusion or defect size parameter—that is, the square root of the inclusion or defect's projection area to the direction of maximum applied stress—was highlighted by Murakami. Next, in order to forecast the fatigue limit, a Murakami model was created [14]. The ratio of applied stress level to the Murakami model is used in place of the ordinate of the S-N curve to further explain the scatter of metal fatigue life in additive manufacturing.

Sanaei and Fatemi [15] used the Pairs law, which is based on the defect-induced crack growth mechanism, to predict the fatigue life of L-PBF metal parts. Nevertheless, the limited utilization of computed tomography (CT) by these semi-empirical models hinders their ability to fully capture numerous minute morphological details of defects. Zhu et al. [16] developed a Z-parameter model after taking into account the relative positions of defects in the life prediction model. The Z-parameter model was modified to include the defect circularity in order to more precisely characterize the defect morphology. In a similar vein, Hu et al. [17] developed the fatigue life model with X parameters. By taking into account the finer morphological details of defects, the models mentioned above provide an explanation for the fatigue life scatter of AM metal.

## 2.3 ML-Assisted Fatigue Predictions

Data handling and analysis have become exponentially cheaper and faster in recent times due to advances in computing power and data storage capacity. Consequently, sophisticated techniques for interpreting data have been employed to resolve the intricate nonlinear damage mechanics issues. The domains of mechanical and material science make use of machine learning (ML) algorithms since they can estimate patterns present in the data, classify the data, and cluster the data. The literature demonstrates that predictions and estimates of mechanical properties in the fields of fatigue and fracture mechanics have been made using data-driven modelling. Many researchers are investigating the use of machine learning and deep learning models to speed up the predictions of material properties as data availability increases.

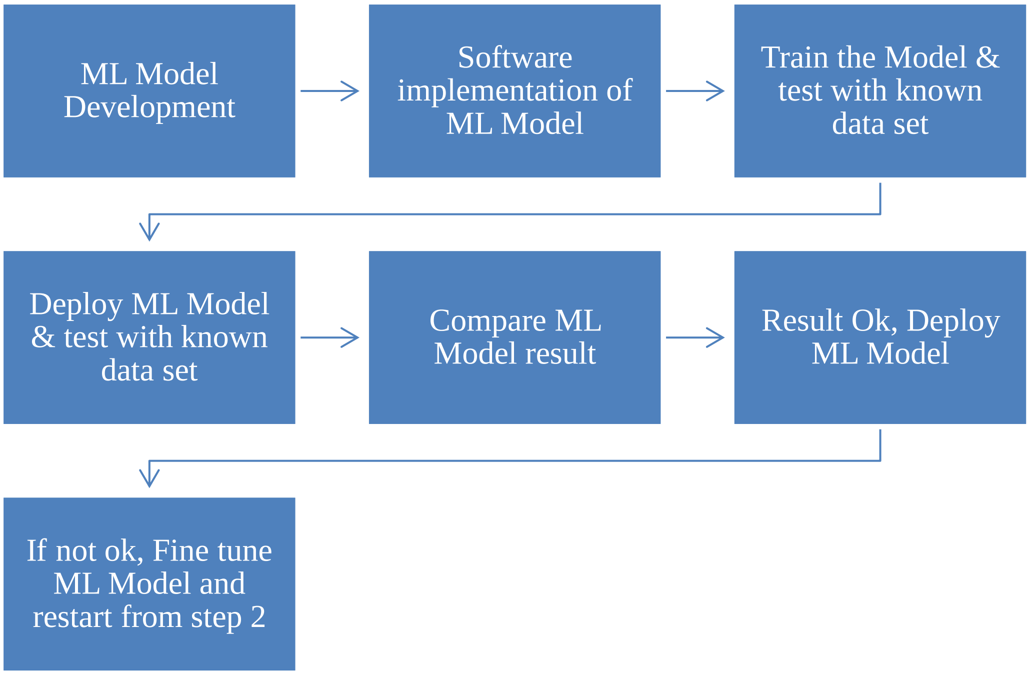


Figure 3: General Workflow of Machine Learning applications [18].

A comprehensive review of the literature presents machine learning-assisted predictions of the fatigue crack growth rate (FCGR) of Ti6Al4V (Ti64) after post-processing and laser powder bed fusion (L-PBF). A versatile method for explaining the intricate mathematical relationship between the processing, structure, and property of the materials has been made possible by a variety of machine learning techniques. Four machine learning (ML) algorithms were used in this work to analyze the fatigue crack growth rate (FCGR) of Ti64 alloy: K-Nearest Neighbor (KNN), Decision Trees (DT), Random Forests (RF), and Extreme Gradient Boosting (XGB) [19].

Generally speaking, the KNN algorithm bases its prediction on the closest neighbours of the unknown, which can be adjusted in accordance with the needs. The decision trees are the tree-based algorithm that splits the data based on the lowest mean squared error, whereas the other two algorithms are used as ensemble techniques that create multiple decision trees that collectively make the predictions. The main purpose of these tree-based algorithms is to determine whether the data set contains any nonlinearity [19].

For the ML model analysis, the experimental FCGR data of the Ti-64 alloy published by V. Cain et al. [19] were used. The stress intensity factor, the built orientation during fabrication, and the post-processing method are the independent variables. These three parameters are independent of one another and have a significant impact on the FCGR [3,11,30–33]. The FCGR of Ti-64 alloy is estimated using the ML models given these three independent variables. It was discovered that the trained models could estimate the unseen data just as well as the trained data after the hyperparameters for these algorithms were adjusted.

Based on their mean squared error and R2 scores, the four tested machine learning models were compared to one another during both the training and testing phases. In comparison to other models, Extreme Gradient Boosting has outperformed the FCGR predictions, resulting in lower mean squared errors and higher R2 scores. The feature importance analysis was conducted using the algorithm that performed the best. The rankings of the independent variables according to their significance are provided by feature importance analysis. This analysis demonstrated that the built orientation and post processing technique are the most influential parameters for the FCGR behaviour of Ti64 alloy fabricated using LPBF, with SIF coming in second [19].

Z. Zhan et al. predicted the fatigue life of additively manufactured AlSi10Mg, Ti6Al4V, and SS316L using ANN and RF models. They used the Multi Layered Perceptron algorithm to examine the effects of processing parameters on Additively Manufactured SS316L and compared the results with SVM and RF models. [20] In order to comprehend the influence of surface and pore characteristics on the fatigue life of laser powder bed fusion fabricated Ti6Al4V alloy, S. Moon et al. [21] employed dropout neural networks.

In a study, the fatigue strength of a nickel-based superalloy GH4169 under various temperatures, stress ratios, and fatigue life in the literature were predicted using the gradient boosting regression tree model, the long short-term memory model, and the polynomial regression model with ridge regularization in machine learning. The impact of the training set's data composition on the machine learning method's predictive capacity is examined through the division of distinct training and testing sets. The findings suggest that the machine learning approach has a lot of promise for predicting fatigue strength from limited data by learning and training. This could lead to the development of new techniques for predicting fatigue performance that take into account intricate influencing factors [22].

Using a model based on an artificial neural network (ANN), Iacoviello et al. [23] investigated the impact of the stress ratio R on the fatigue crack growth resistance of PM duplex stainless steel and accurately predicted the fatigue crack propagation. ANN was employed by Durodola et al. [22] to assess the impact of mean stress on the fatigue life of metal alloys. Their findings demonstrated that, in comparison to the other methods in use, the ANN method had a higher resolution and consistency. Based on a modified bagging method, Yan et al.'s hybrid model [22] to predict the fatigue strength of steels demonstrated significant promise in increasing the prediction accuracy of the fatigue strength.

One of the primary raw materials used to create sophisticated engine turbine disks and turbine blades—which are exposed to fatigue loadings during operation—is the Ni-based superalloy GH4169. The fatigue strength prediction of the Ni-based superalloy GH4169, taking into account multiple influencing factors, was investigated using three common machine learning techniques: the polynomial regression model with ridge regularisation (PRRR), the long short-term memory (LSTM) model, and the gradient boosting regression tree (GBRT) model. The LSTM model is a part of the deep neural network architecture, whereas the GBRT and PRRR are classified as machine learning models. LSTM and PRRR are single models, but GBRT is an integrated model [22].

Examining the machine learning method's predictive capacity in handling the impact of multiple factors on fatigue performance was the goal of this study. It was discovered that there is a strong correlation between the training set and the predicted outcomes of the machine learning method after dividing the training and testing sets. All three models provided reasonable predictions when the anomalous data was not present. Additionally, a comparison of the three machine learning techniques' predictive capacities was made. It demonstrated that the best predicted results for fatigue strength were provided by the PRRR.

Nevertheless, limited works study the relationship between manufacturing defects and fatigue life through ML models. In order to identify the optimal input variables based on errors and correlation coefficients, Dang et al. [24] developed an AM metal fatigue life prediction model based on fracture surface analysis using the SVR algorithm. They then compared the model's performance under various input variables. Based on the RF algorithm, Peng et al. [10] identified the four most crucial defect geometry parameters that influence AM metal fatigue life and developed an XGBoost algorithm-based fatigue life prediction technique. When sufficient training data are available, semi-empirical modelling for fatigue prediction can be replaced with a reliable machine learning model.

Chapter 3

# Conclusion And Future Scopes

## 3.1 Conclusion

This phase of our BTP was mostly learning about additive manufacturing, fatigue strength of different materials and machine learning algorithms used in prediction of fatigue strength of additively manufactured parts. The report has also provided a comprehensive overview of recent developments in fatigue life prediction for additive manufactured metals, with a specific focus on machine learning (ML) modelling techniques.

## 3.2 Future work

In the following phases we plan to apply different machine learning algorithms /models to predict the fatigue strength of additively manufactured parts and refine them to improve the predictive accuracy. We will focus on understanding how different deposition attributes, such as layer thickness, deposition speed, build orientation, etc. impact the fatigue behaviour of additively manufactured parts.

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