Operational Advancement Through Data-Driven Machine Learning Techniques

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ABSTRACT
The layer-wise production paradigm of additive manufacturing technologies allows for the collecting of a huge number of pieces. This study focuses on the application of data analytics algorithms for real-time monitoring in additive manufacturing processes. The utilization of advanced analytics plays a pivotal role in enhancing the quality control and efficiency of these manufacturing techniques. The research explores how data-driven insights can be harnessed to identify, analyze, and rectify deviations in the manufacturing process, ensuring optimal performance and product quality. By integrating sophisticated monitoring algorithms, the study aims to create a robust framework that continuously analyzes various parameters during additive manufacturing. This includes monitoring factors such as temperature, pressure, and material properties in real-time. The collected data is processed through advanced analytics tools to detect anomalies or deviations from the expected standards. The implementation of machine learning algorithms further facilitates predictive maintenance and proactive adjustments, contributing to the overall reliability and effectiveness of additive manufacturing processes. The outcomes of this research hold significant implications for industries relying on additive manufacturing technologies, providing a foundation for improved process control and product quality. The study contributes to the growing field of Industry 4.0 by showcasing the integration of data analytics as a key enabler for efficient and reliable additive manufacturing.

Keywords
Additive manufacturing, Correlation, Linear Regression, Multiple Logistic Regression, Decision Tree.

1. INTRODUCTION
Additive manufacturing (AM), a tool-free, economical, and digital method of production, offers numerous significant advantages that have the potential to completely transform the industrial paradigm across a range of sectors. Using high-energy heat sources like a laser or an electron beam, powder bed fusion (PBF) is a metal additive manufacturing process that enables the direct fabrication of fully dense, nearly net-shaped metallic objects. Using the PBF method, a powder layer is selectively melted (together with the previously deposited layer, or substrate), leading to the formation of a series of melt-pools on a micrometer spatial scale. These melt-pools are produced on a millisecond temporal scale by severe solidification conditions. Improving the stability and dependability of products made by additive manufacturing as a function of processing parameters is the goal here.

Since it is an indirect indication of interactions between processing factors and intrinsic materials qualities, the melt-pool geometry is essential as a primary criterion for optimizing processing conditions. Geometry-related phenomena like as defect development, microstructure evolution, thermo-mechanical characteristics, and so on must also be understood. The influence of materials and process parameters on melt-pool properties, as well as the underlying physics, have been studied extensively through study and computational analysis. Nonetheless, the PBF method involves over 130 processing parameters that interact intricately with multiple phase shifts across a wide temperature range during the operation. Through well-controlled experiments or simulations using only a few variables, it is difficult to understand the general relationships among the processing factors. Also, it is difficult to quantify which traits are most important and how important they are to the properties of AM-processed parts [1]. In his recent work, Mustaquim (2024) employs a method centered on remote sensing data analysis to scrutinize land surface characteristics. This methodology plays a pivotal role in the analysis and development of our virtual platform, significantly enhancing the educational experience for students. The insights gained from this research contribute to the foundational aspects of our platform's capabilities, ensuring its relevance and efficacy for educational purposes [23].

Since the 1920s, manufacturers have used traditional control charts to monitor the quality of their products. Because of their simplicity and applicability, traditional Statistical Process Monitoring (SPC) methodologies are extensively employed. Traditional quality control systems are no longer effective due to the "curse of dimensionality" because today's production processes are more complicated than ever before. Unlike traditional methods, which limit measurement to physical goods or work in progress, many process characteristics provide sufficient chances for defect prevention and process monitoring. Traditional control charts frequently face high dimensional problems due to the large number of parameters.

A central processing unit (CPU), for example, is made up of hundreds of processes with thousands of process parameters. Traditional multivariable approaches, such as the T2 chart introduced by Hotelling in 1947, cannot be used effectively in this scenario since it was meant to detect mean variations in a small number of quality indicators, typically less than ten. Since its debut, another important SPC improvement has been the ability to detect subtle process changes faster [2]. Molla et al. (2023) and Hasan et al. (2024) undertake a comprehensive investigation to determine the optimal scenario for job shop production for operational improvement [28,29]. Their findings have significant implications, particularly in the realm of reducing state-by-state accident rates for effective accident mitigation strategies. Building on this foundation, Biswas et al. (2024) employ the Value Stream Mapping (VSM) method, incorporating a robust and effective arithmetic process. This method proves instrumental in our ongoing research, especially in the development of a laboratory platform tailored for students with a keen interest in production activities. The insights gleaned from these studies not only contribute to the enhancement of production processes but also align with our broader goals of promoting safety and efficiency in manufacturing environments, ultimately fostering a rich learning experience for students [30,31,32,33].

Having this context, this paper aims to solve or make a possible solution to the described problem. The result of Polytechnic di Milano and Trumpf's open science collaboration is the QSR Data Challenge Competition. The signals from the two photodiodes used in this competition were collected during a Laser Powder Bed Fusion procedure, in which anomalies were purposely added to bulk specimens by building overhanging regions. The goal of the Data Challenge is to develop a statistical process monitoring method that can identify anomalies in melting fast. [3].

The objective of our work is to develop a model using the methodologies learned in class to analyze how the different variables respond on each layer of the process through the application of a code in Jupyter. The QSR Data Challenge's major goal is to create an SPM technique that can detect the abnormalities as quickly as feasible while obtaining the optimal balance of false positives and false negatives; furthermore, another goal of the competition is to measure the radiation in the melt pool the objective.

2. DESCRIPTION OF THE DATA

For the past ten years, additive manufacturing (AM) has been considered a cutting-edge technology; yet, by utilizing its applications, businesses can save expenses and schedules while simultaneously improving client outcomes. The problem in this competition involves the signals obtained from a single spatially integrated sensor (co-axial monitoring method uses photodiodes that are aligned with the laser's optical path). Noman et al. (2020) have undertaken a commendable and noteworthy project, showcasing a robust data retrieval approach coupled with an advanced framework for predicting data accuracy. This project stands as a valuable augmentation to our continuous efforts in virtual lab research, introducing an array of supplementary features poised to enrich the learning experiences of upcoming students, specifically catering to those pursuing studies in the fields of software engineering and computer science [18, 19, 20, 21, 22]. The photodiode signal was acquired during the fabrication of a single AlSi10Mg (aluminum) specimen using predetermined process conditions. The parameters are the following [3]:

- A Sean speed of 1300 mm/s
- Power of Laser 4600 W
- A diameter of the laser spot of 100µm

By intentionally creating some unexposed blocks, anomalies were purposefully produced levels of the material. After an unexposed block, the initial layer has a sizable overhanging area with loose powder behind it. Because loose powder is less conductive than the bulk material, it has an impact on the heat exchange in this overhanging layer. When a result, when the number of unexposed layers rises, unexposed blocks tend to force heat conduction anomalies with increasing severity.

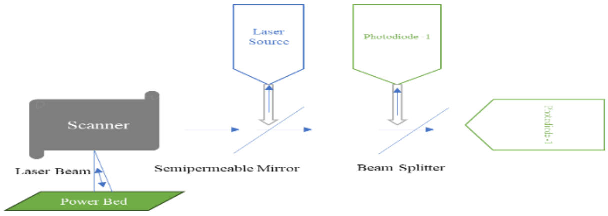

Fig 1. This co-axial monitoring method uses photodiodes that are aligned with the laser's optical path.

The dataset consists of one file per layer in HDF5 format. Every layer has a data matrix, where different factors are indicated by distinct columns and photodiode measurements are represented by each row. Data obtained during the manufacture of such bottom layers is not included in the dataset since the process was still not operating under regime circumstances in the lower levels, which correspond to the tapering base region. Jamil et al. (2024) delve into the intricacies of supply chain strategy minimization and address the bullwhip effect. Concurrently, Mustofa (2020) contributes insights into integrating these strategies with Industry 5.0, establishing a comprehensive framework. This integration seamlessly incorporates machine learning and robots while emphasizing the crucial facet of human intelligence interaction. The synergistic approach not only optimizes supply chain processes but also aligns with the transformative advancements of Industry 5.0, creating a dynamic and efficient ecosystem. [25,26]. Within each unexposed block, the number of unexposed layers increases from 1 to 10 along the z-axis. The object is a parallelepiped that was created vertically using the L-PBF process, measuring 10 x 10 x 25 mm. Initially collected at a sampling rate of 100 kHz, the photodiode signal was down sampled to one datapoint per 30 m along the laser scan path. The orientation of the laser scan route and direction were altered for every layer, as is customary in L-PBF. The X and Y coordinates of the laser spot, or the coordinates of the photodiode's field of vision, are recorded concurrently with the photodiode signals in this collection.

3. METHODOLOGIES

To analyze our data, we needed to pre-process it. Our initial dataset consisted of 13 columns and 378 observations. For importing necessary library, we have imported the necessary libraries firstly to make the data process for our coding:

```
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import pandas as pd
from sklearn.linear_model import LinearRegression
from scipy import stats
import random
import seaborn as sb
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
import seaborn as sn
```

Fig 2: Necessary Libraries Imported

Our first step was to visualize all the parameters that we would be using in the methodologies. The variables we used were IDBulkLayer, x, meanSIG, and meanLPC. To visualize them, we created a simple scatterplot to see the correlation between the variables figure 3 to 5. Researchers have extensively explored and delved into the application of advanced deep learning and machine learning algorithms for the precise and effective diagnosis of a spectrum of diseases, including but not limited to breast cancer, brain cancer, and various other intricate medical conditions [4-9]. Ullah and colleagues (2023) have eloquently presented insights across four distinct papers, delving into the realms of manufacturing excellence, operational scheduling, and equipment efficiency. Their contributions stand as crucial pillars for advancing operational improvements within our industry. The meticulous exploration of manufacturing excellence sets the stage for optimized production processes, while the insights into operational scheduling contribute to enhanced resource utilization and efficiency. Additionally, their focus on equipment efficiency provides valuable guidance for maintaining and improving machinery performance that has a great impact on our research paper. These collective findings establish a cohesive connection in our ongoing efforts to elevate operational standards. The integration of Ullah and colleagues' research into our industry practices ensures a holistic approach to operational enhancement, fostering a culture of continuous improvement and innovation. Their work serves as a cornerstone for shaping a robust and efficient operational framework within our industry [34].

The existing literature meticulously elucidates the intricacies and nuances of the methodologies adopted for comprehensive sentiment analysis and the simulation of real-time scenarios. This involves the adept utilization of predictive simulation modeling software, showcasing its multifaceted capabilities. It is noteworthy that this software, designed with an emphasis on robustness, ensures not only highly secure encryption for real-time speech signals but also plays a pivotal role in enhancing safety protocols during the intricate operations of nuclear power reactors [10-17].

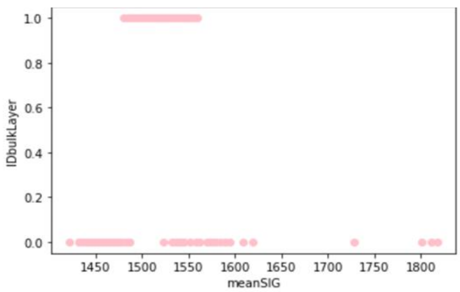

Fig 3. Correlation between "IDbulkLayer" and "meanSIG"

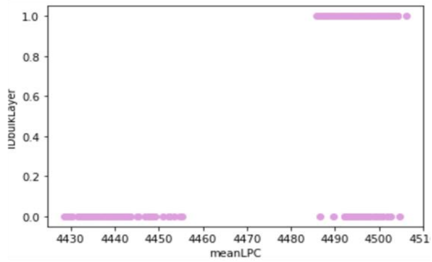

Fig 4. Correlation between "IDbulkLayer" and "meanLPC"

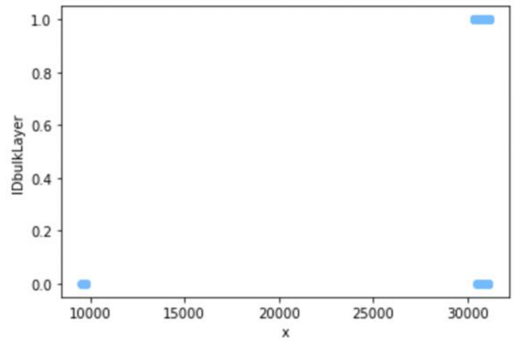

Fig 5. Correlation between "IDbulkLayer" and "x"

Based on the scatterplots above, we can notice that our dataset consists of 1s and 0s. To get a good dataset, we will split it into training and testing dataset. To get an equal amount of 1s and 0s in our training and testing dataset, we split the original dataset to create two dummy datasets, where one was going to contain only the data for 1 and where the other one was going to contain the values of 0. Once we had our two datasets, we proceeded to divide both into training and testing; afterwards, we merged them together so that in the end, we would have two datasets: one with our training data and another one with our test data. The dataset we used in our methodologies was the testing dataset.

3.1 Simple Linear Regression

Our first methodology is the simple linear regression. Modeling the relationship between a scalar answer and one or more explanatory factors using a linear technique is known as linear regression. This approach is helpful to understand to what extent each variable is affecting the response variable; additionally, to understand under what conditions the response variable performs best. A crucial characteristic of a linear regression is for the data to be continuous; otherwise, the linear regression will not be useful. Once we had our dataset prepared, we were able to run our code. As a response variable, we used the column named "IDbulkLayer"; this column indicated whether the layer analyzed was going to be a good or bad layer as shown in below figure from number 6 to 8:

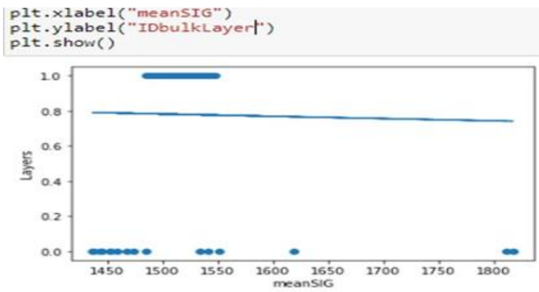

Fig 6. Linear regression plotted for "meanSIG" and "Layers"

```
plt.xlabel("x")
plt.ylabel("IDbulkLayer")
plt.show()
```

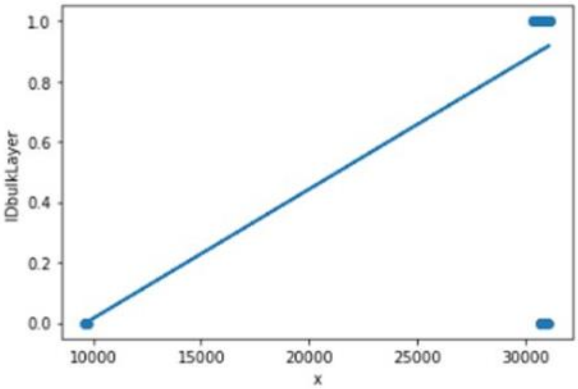

Fig 7. Linear regression plotted for "x" and "IDbulkLayer"

```
plt.xlabel("meanLPC")
plt.ylabel("IDbulkLayer")
plt.show()
```

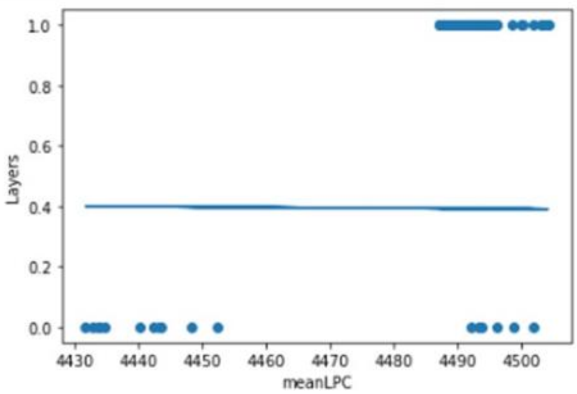

Fig 8. Linear regression plotted for "meanLPC" and "Layers"

3.2 Multiple Logistic Regression

Multiple logistic regression is the second methodology applied in this project. A statistical test predicts a single binary variable using one or more additional inputs. The goal of this strategy is to comprehend the relationship between the responsive and predictive variables since it is also used to determine what numerical relationship exists between a collection of variables. Multiple logistic regression is an estimator of probabilities of odds ratio and discrepancy in the data. This analysis provides discreet output and predicts binary outcomes as some of their functions. Ahmed et al. present a comprehensive exploration of brain tumor classification, elucidating the intricate workings of the methodology employed, which holds paramount importance for our ongoing research in classification examination. The deep learning approach they detail not only provides valuable insights into the complexities of brain tumor classification but also serves as a foundational reference for our own methodologies. The thorough examination and elucidation of their deep learning techniques contribute significantly to advancing our understanding and enhancing the efficacy of classification methodologies in the context of brain tumor research [24].

The first step for this method was to set the test values, which are the 20 percent of the entire dataset. We called this data set "testing data", the remaining 80 percent of the dataset was the "training data". Once we determine the testing data, we set "x" as the values of testing data for "meanSIG", "meanLPC", and "x", then we determined the "y" variable as "IDbulkLayer" testing values. By determining this variable, it is easier to plot them in the next step. The second step was to have another variable with four different characteristics, which are "X_train", "X_test", "y_train", and "y_test"; we splitted all these characteristics containing "x" and "y". By creating a variable that contains "x" and "y", we identified a confusion matrix using only "y_test" and "X_test"; thus, we obtained the following results at figure 9:

```
y_predicted = model.predict(X_test)

cm = confusion_matrix(y_test, y_predicted)
cm
```

```
2]: array([[ 4,  0],
           [ 0, 12]], dtype=int64)
```

```
plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True)
plt.xlabel('predicted')
plt.ylabel('Truth')
```

```
3]: Text(69.0, 0.5, 'Truth')
```

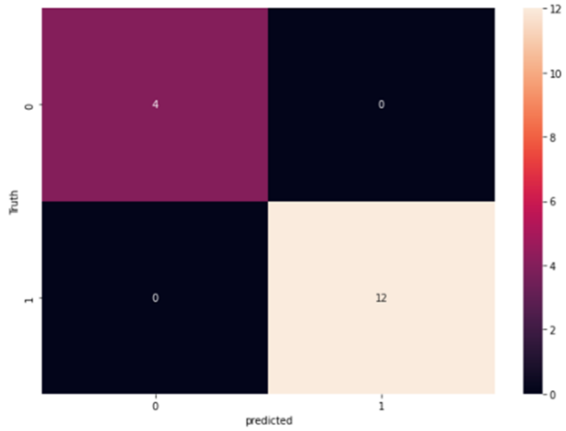

Fig 9: Multiple logistics regression

3.3 Decision Tree

As our third methodology, we created a decision tree classifier. Choice trees are a non-parametric supervised learning technique used in regression and classification that aims to build a model that predicts the value of a target variable by learning basic choice rules from data attributes. By constructing a decision tree, a decision tree classifier generates the classification model. It may be applied to various forms of data and improves the visual comprehension of the dataset. It functions as a flowchart, as seen in Figure 10 below, that starts with a single fundamental concept and branches out based on the decisions we make.

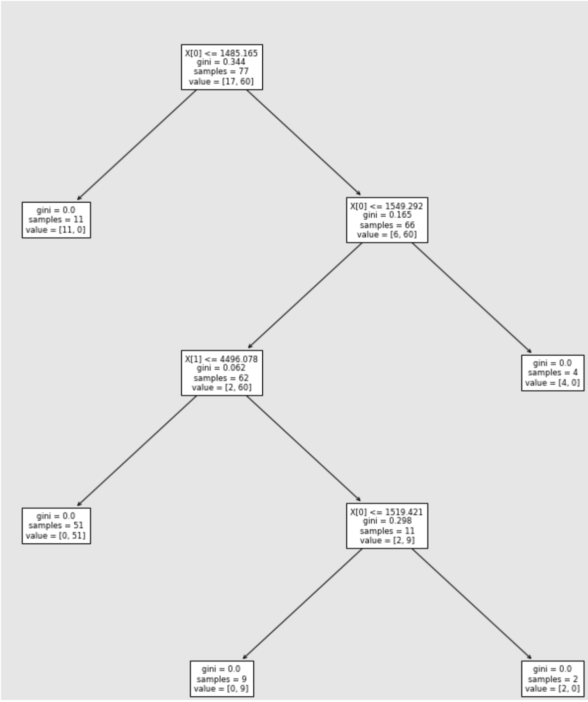

Figure 10: Decision tree

4. RESULTS AND FINDINGS

The first step on the procedure to reveal the several differences throughout the process was to show the characteristics of the data "all_layers_summary.csv". The total information was composed of 379 rows and 13 columns. First, the table with organized data was presented to have a better visualization of the information provided. Getting the table let us move the data easily to compare the columns labeled as 'meanSIG,' 'meanLPC,' and 'x' with 'IDbulkLayer, which was the primary value to split the data in two distinct categories. The first category was 1 that represents a bulk layer, and the second category is 0, which means to unexposed blocks. By conducting the algorithms, the charts express the discrepancy of the results, this means that the values are not well distributed, and changes need to be made to conduct the analysis of anomalies of the mechanism. Data processing was used to create a variable named "dummy," it only shows the values used for all the methodologies. Separation of data in two classifications was needed; the first class was a list of training data and testing data of "IDBulkLayer" being on category 1, the second class was a list of training data and testing data again, but in this case, the category 0 was used. The separation of the categories was required to acquire the most accurate values using both. If this step was skipped, category 0 would probably not be part of the methodologies as below table 1.

Table 1. Training and Testing Dataset

Class	Train Dataset	Train Dataset	Total
Good Layer	237	60	297
Defect Layer	65	17	82
Total	302	77	379

5. CONCLUSION

Throughout the investigation in search of improvement of anomalies about the process of a material being exposed to a laser to be able to melt, three methods were formulated, which demonstrated different results and determined which of these methods were more efficient and which would yield a more accurate outcome. Since the investigation of the three was carried out, the result reveal that the best method is Decision Tree, since it adapted very well to the dataset, the results were the closest to what we were looking for, apart from being a machine learning algorithm. It is also simple since it has better statistics compared to the other methods. This methodology can be used for projects with a larger dataset to help processes find product variations and find complexities in the system. Once the algorithm is done, it is only a matter of changing the dataset and making some adjustments so that it can work with another process. Visually it was possible to analyze and find the problems easily and quickly. Furthermore, it is important to mention that it can make a significant difference in the time it takes to signal each anomaly; it can be concluded that the faster, the better results you will obtain. Another important detail consists of the number of measurement points scanned since the start of the over melting layer; having as an example, the first overhang layer formed after one block of unexposed layers; it can be concluded that it will be counted. Overall, we as a team obtained many benefits through this analysis. We learned how to look for patterns and insights in raw data, and at the same time we employed a variety of tools and approaches that can help assist organizations in making decisions and achieving success.

6. FUTURE WORKS

This paper provides a comprehensive exploration of how emerging trends in ML/AI, including edge computing, reinforcement learning, integration with IoT, and human-machine collaboration, can drive operational advancement. Through practical examples, case studies, and discussions on future directions and challenges, it aims to inform and inspire practitioners, researchers, and students to harness the transformative potential of ML/AI in optimizing operational workflows.

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