Defect Prediction in Additive Manufacturing using Machine learning and Artificial Intelligence

B.Tech. Project: Phase 1

Objective: Detecting & Classifying defects in Additively Manufactured components by studying cross-section images using Machine Learning Algorithms & correlating process parameters that contribute to these defects

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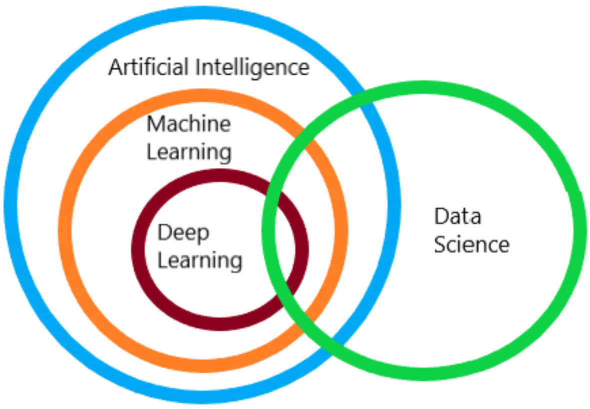
Abstract

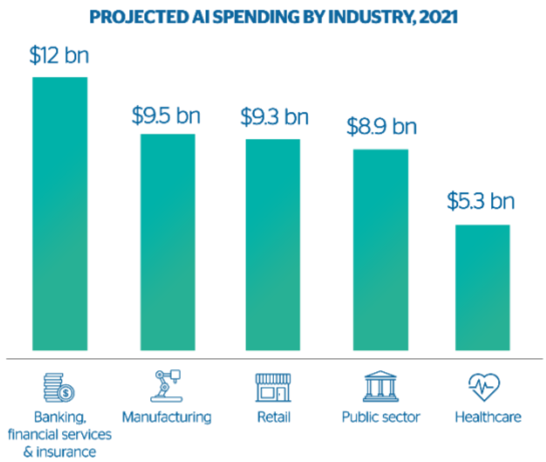
Artificial Intelligence (AI) and Machine Learning (ML) are domains that are growing by leaps and bounds lately. Also is Additive Manufacturing (AM), which has been dominating the manufacturing sector in the last decade. This paper explains how AI and ML could be incorporated into AM, especially in Laser Bed Powder Fusion Process. Manually studying each cross-section microscopic image to understand the defects observed in an AM component is a laborious task. The paper explores the possibilities of using computer vision to study Optical and Scanning Electron Microscopy (SEM) Images of AM components using OpenCV functions and a correlation between process parameters and expected defect representation is also calculated. Image Analysis algorithms are implemented to predict and classify the defects by considering the defect contours. The image is processed to remove unwanted noises and then an Algorithm to classify each contour into specific defect categories was set up. A front end was then created to let the user provide a set of images to estimate the types of defects, their count, and their area percentage. The defects dealt with here in this paper were primarily Blow holes, Lack of Fusion along with Grain Boundary Cracks. The model was able to successfully classify the defects visible in the images, calculate the total area percentage and along with that a cumulative Scatter Plot with all the defect locations was also constructed. The model was tested on datasets having around 50 image samples each and it was able to successfully calculate the total defect count with its classification as well as the area percentage for each set. A front end has also been developed wherein the user could enter either an individual image or a folder of images, and it could give out the defect data. Experiments were done on varying parameters such as laser speed, powder diameter, etc. and a cross-section image of each product was taken to be tested in the model. A correlation between the process parameters and defects observed was done based on the results obtained.

Introduction

Artificial Intelligence, or the ability of a machine to think like a human being, was first coined by John McCarthy. Though before him the English Mathematician, Alan Turing, proposed the idea of machines that are intelligent. He developed the “Turing Test” to categorize if the machine was intelligent. Depending on how it solves problems, AI is divided into two categories: traditional intelligence and computational intelligence. AI is classified as Traditional if it uses knowledge and reasoning, and as Computational if it bases decisions on example data. Machine learning (ML) is a subcategory of Artificial Intelligence (AI) that uses previous data as input to anticipate future output values, enabling software applications to become increasingly adept at making predictions without being expressly designed to do so. Computational Capability, Memory, and Data, all three play a very crucial role in making machines more intelligent. Both ML and AI in turn come under a broader description known as Data Science, which is defined as a field



that uses scientific methods, processes, algorithms, and systems to extract knowledge and insights from noisy, structured, and unstructured data, and apply knowledge and actionable insights from data across a broad range of application domains.



Since the advent itself, both ML and AI have observed tremendous progress in terms of their prospects. Complex Mathematical functions and programs have contributed significantly to the exponential growth of AI and ML. The projected growth of AI has shown its potential to be used in the Manufacturing Sector, and it could contribute to over 21% of the total. As it is also evident that Additive Manufacturing is also a field that has experienced exponential growth in the last decade, owing to the ease of operation and faster output, the prospects of using AI and ML in AM are unimaginably huge. ML and AI could find applications in areas such as data visualization, image recognition & system modeling to better understand this process, and could be used in the areas of process optimization, design correlation, design improvement, defect detection, and microstructural design. As AM leads to very less wastage, the production efficiency, as well as the Carbon Emission, is also significantly lower. The opportunities are vast but as of now, the implication is very minimum or nonexistent. The primary reason behind this discrepancy is the lack of quality and reliable data, that could be used to train the model. The creation of ML algorithms for AM must prioritize reliable data gathering, storage, and sharing. If cutting-edge AM machines and data were more predominant and easily available, integrating ML and optimization techniques could enhance product quality many folds. Defects detection, the ability to create a 3D image of the build during the build or the ability to monitor the microstructure and grain orientations are some examples that are still not fully explored. The project aims at incorporating ML algorithms to automatically compute the defects in a given image and correlate it with different parameters that contribute to these defects. It serves as a stepping stone to exploring the possibilities of using Machine Learning and Artificial Intelligence in Additive Manufacturing.

Project Tasks

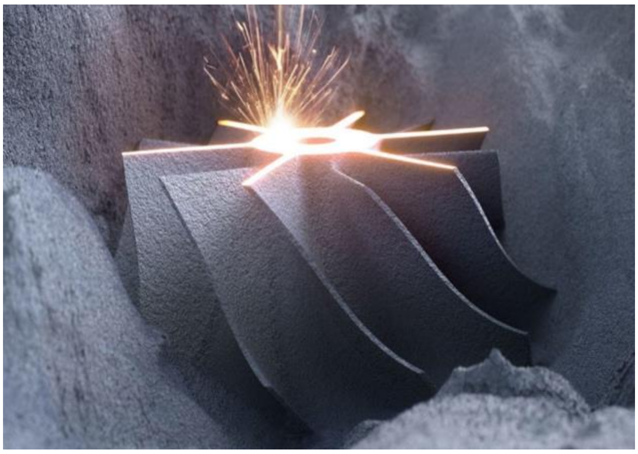
The project could be broadly classified into 4 tasks.

- Using image analysis tools to classify the defects from Optical, Scanning Electron Microscopy, and Transmission Electron Microscopy Images of the Laser Powder Bed Fusion process.
- Training an ML model to predict the defects and classify them into Blow holes, Lack of Fusion, and Grain Boundary Cracking.
- Front-end creation where the user could input a folder of images which then would be analyzed and the program would return the defect percentage and the number of defects in the image folder.

- Correlating with the processing parameters and how each contributed t the defect percentage and location.

Outline of the Project (till now)

Literature Review

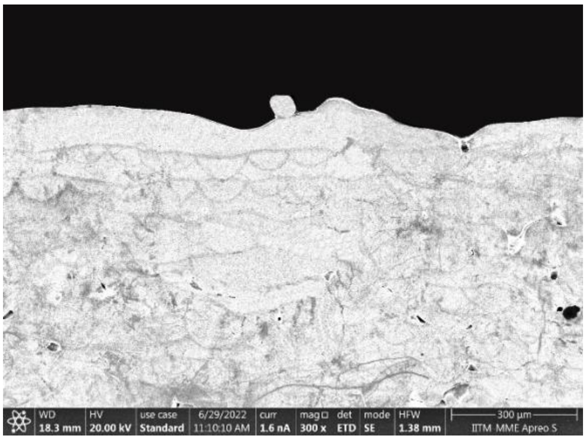


The initial part of the project required a comprehensive literature survey that was essential to understand the basics of Additive Manufacturing as well as to understand the prospects and implementation of ML and AI in AM. The project primarily focused on Laser Powder Bed Fusion (LPBF) Process. In powder bed fusion, a container of powder is treated selectively using an energy source, most frequently an electron or scanning laser beam. It is a very widely used AM technique and is excellent to produce Polymers (such as Polystyrenes, Elastomer Thermoplastics, flame retardant polyamides, Biodegradable polymers - Polycaprolactone, Polylactide, Poly-L-lactide), Metals and Alloys (basically any metal that can be welded such as Low carbon steels, SS and tool steels, Ti and its alloys, Ni-based superalloys) and even Ceramics and Composites. It can produce products with a good surface finish, though it completely depends on how optimized the process parameters are. The major process parameters are:

- Laser parameters- such as laser power, beam size, pulsing frequency, etc.
- Scanning parameters- hatch distance, scan speed, and scan pattern
- Powder parameters- Shape, size and distribution, powder bed density, layer thickness
- Temperature- Powder bed temperature, powder feeder temperature, temperature homogeneity, and so on.

Data Collection

The materials I worked with were primarily H13 tool steels and Inconel 625. A major portion of the work required a large variety of microscopic images that could be used to train a model to predict the defects. The images were usually cross-section views of cubes formed by LPBF which were processed and viewed under an Optical or Scanning Electron Microscope to visualize the surface abnormalities. Two separate models were planned to operate on both Optical and SEM images separately as both their scales and image orientation were hard to capture from a single model alone. Hence a separate list of Optical and SEM cross-sections of samples was taken. For the project, around 200 Optical and 75 SEM images were collected and these images served as the base for the algorithms that were developed.



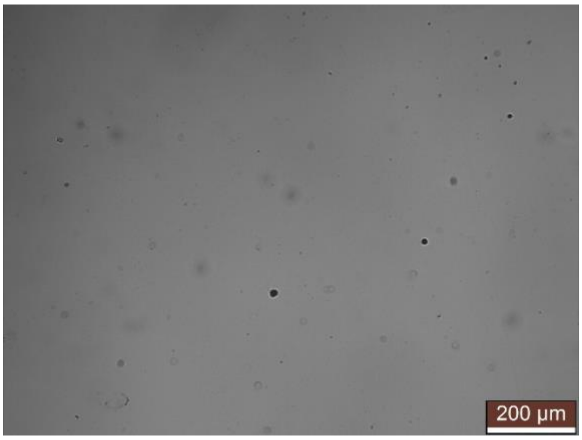


Image Processing

Most of the processing was done using the OpenCV library. The first step entailed converting the images to Black and White scale. Next, each image underwent a Gaussian Blur that helps in reducing the background noise. Gaussian Blur acts as a low-pass filter that attenuates high-frequency signals by using a Gaussian function for calculating the transformation to apply to each pixel in the image. The Equation involved is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

After Blurring, the images undergo binary thresholding, which creates a binary image by setting a threshold value for each pixel. Finally, Image Dilation was performed, which adds extra pixels along the boundaries of the images for more clarity. Some code snippets-

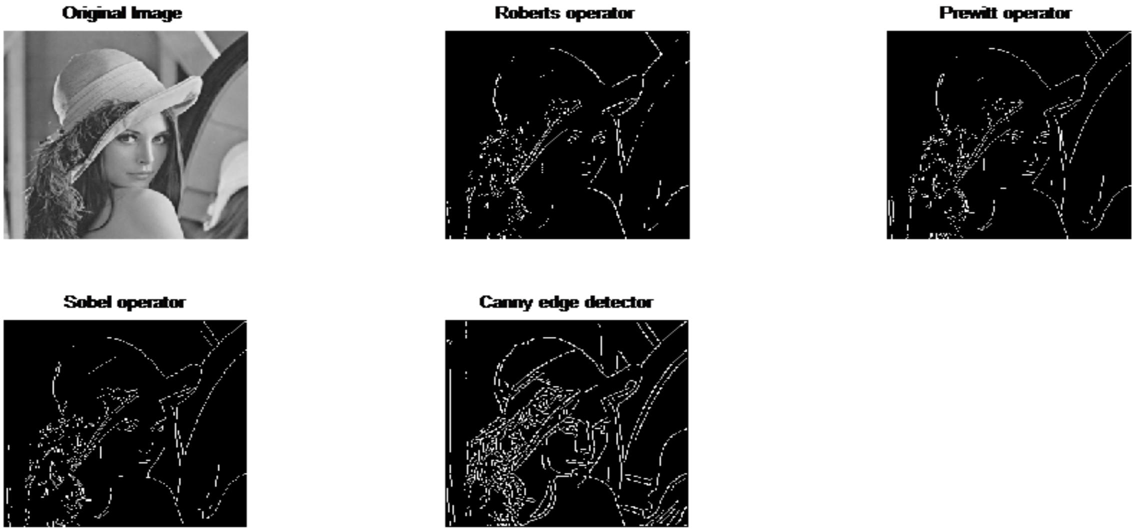
```
def process(img, show = False) -> dict:
    img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    img = cv2.GaussianBlur(img, (3,3), 0)
    ret,thresh = cv2.threshold(img,70,255,cv2.THRESH_BINARY)
    edges = cv2.Canny(image=thresh, threshold1=100, threshold2=200) # Canny Edge Detection
    img_dilation = cv2.dilate(edges, None, iterations=4)
    contours, hierarchy = cv2.findContours(img_dilation, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
    contour_img = np.zeros(np.shape(img))
```

For SEM images, as the images had a color discrepancy, the background and the defects had the same pixel intensity. So, along with the defects, the backgrounds were also taken into consideration which significantly reduced the accuracy. To prevent this, the background alone was converted to white and then only the image processing was performed. Apart from this, the image processing was similar for both Optical as well as Scanning Electron Microscopy images.

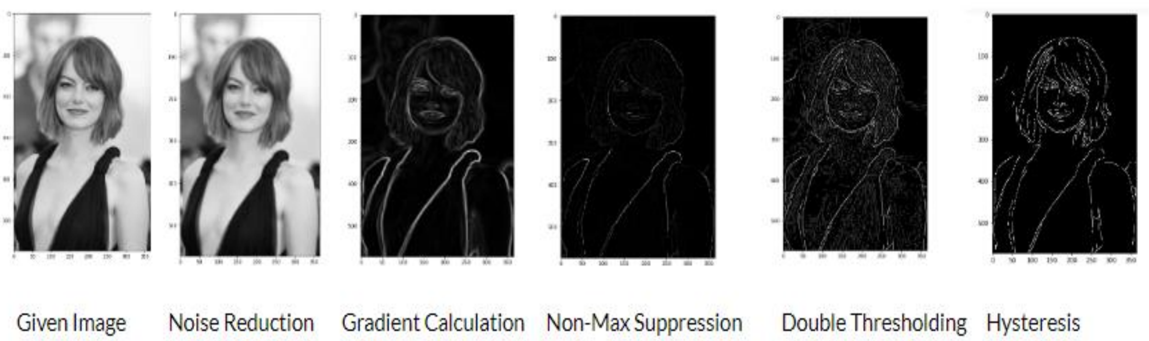
After the images are processed, then the contours present in each defect in the image have to be traced out automatically. For this Contour detection was done.

Contour Detection

The contour could be traced by the sudden variation in pixel intensities along the intersection line. For this, initially, the Prewitt and Sobel operators were tested. In both cases, at each point in the image, the result of the Prewitt and Sobel operator was either the corresponding gradient vector or the norm of this vector. Sobel showed better results as Sobel parameters were adjustable according to the need. But, both of these techniques could not yield satisfactory contour detection. Finally, Canny Edge detection was tested.



It produced excellent results due to the 5-step comprehensive examination that it performs. It involves Noise reduction, Gradient calculation, Non-maximum suppression, Double threshold, and Edge Tracking by Hysteresis. To begin, the image undergoes further noise reduction by using image convolution techniques. Gradient change is measured by how pixel intensity varies between neighboring pixels and then the contours are identified. To thin out the edges, non-maximum suppression is performed which initially detects the largest intense pixel and compared with that, starts reducing pixel intensities for better and thin contours. In Double Thresholding, strong, weak and medium intense pixels are identified and then weak gets removes while strong is taken into consideration. The medium pixels get converted to strong ones er by adding more pixels in the Hysteresis step.



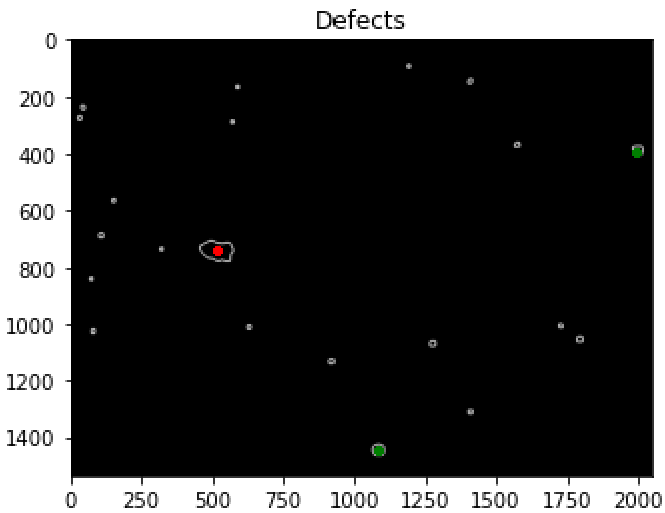
Algorithm Development

After the contours are detected, the next task was to differentiate the detected contours into Blow Holes and Lack of Fusion. Blow holes are holes in the material caused by a bubble of gas captured during solidification. It is a very common defect in AM as it involves solidification. As the bubbles are spherical, the blow holes are also spherical and the cross section would yield a circular defect on the surface. Coming to Lack of Fusion, is the failure of the weld metal to fuse with the side wall or joint or the incomplete joining of two weld beads. It is more irregular in shape and would possess usually a tapered or oval shape that would be larger in size than a usual blow hole. The task now was to use computer vision to categorize these defects based on only their geometry and pixel intensity.

```
if (area > area_thresh):
    m = ((np.sum(contour, axis=0))/len(contour)).squeeze()
    median.append(m)
    contour_thresh.append(contour)
    cnt = contour.squeeze()
    d = []
    for a in cnt:
        d.append(dist(m, a))
    mean_d.append(np.mean(d))
    std_d.append(np.std(d))
```

For achieving this, initially, the Hough Transformation method was implemented, but it did not produce satisfactory results. The problem was that the method could not identify the minute defects contours and it started neglecting those and time complexity was also an issue. Then a method from scratch was developed to identify contours that were circular. For this, each contour was selected separately and the median of each one was found using inbuild library functions. Then, the Euclidean distance between this median point and the outer contour was found, for each point in the contour. If the distance remained constant within a certain tolerance limit, set up by trial and error, then the contour was labeled as a circle and thereby categorized as a Blow Hole. If the detected contour was not a circle, then it was categorized as a Lack of Fusion. In addition, to remove defects that did not contribute to material failure, an area threshold was set, that filters each contour if it was below the limit.

This algorithm was able to detect defects that were not even visible by the naked eye and was also able to successfully categorize them as a Blowhole and Lack of Fusion.

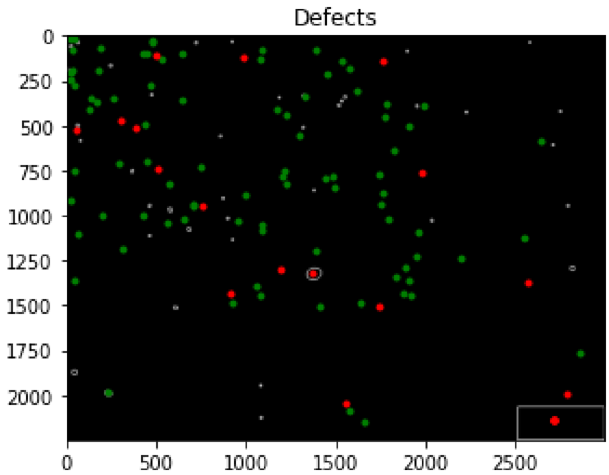


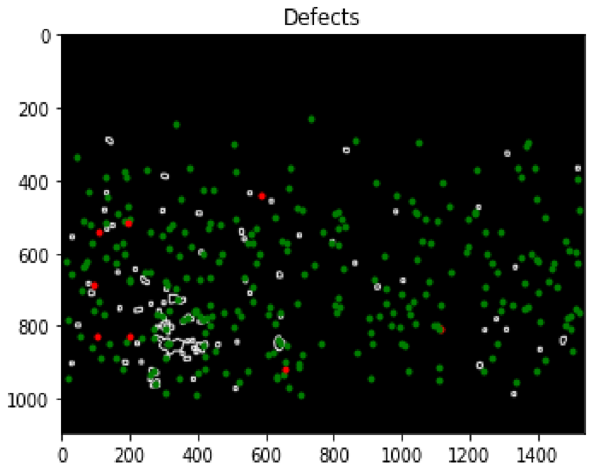
Plotting Defects

To visually represent the defect location, a graph was overlayed on the image plane and then each contour was plotted as scatter plots on it, with the X and Y axis being the resolution of the image. Along with the graph, for each image, the corresponding number of defects identified, their categorizations, and even the area percentage of each defect were calculated. The latter was done using pixel counts. The number of pixels within each contour was identified and finally, this results in the area of each defect with respect to the total area of the image. Hence, now the algorithm could detect the number of defects present, categorize them, find the area percentage of each defect, and even plot the defects graphically. Here, red color was marked to represent the Lack of Fusion and green to represent the Blow Holes.

Cumulative Results

As of now, the defects for a single image could be identified and labeled. The next task was to make it more comprehensive and make it suitable for a folder of images or even a folder consisting of folders of images. For this, using dictionaries, each image in a folder was processed and the results were again added to a dictionary. A loop was set up for taking in an image folder, rather than a single image. In addition, a cumulative plot was set up, wherein each defect location on every image could be plotted on the same plot.





This could be very essential to correlate the parameters with the defect location, for example, say whether a certain set of parameters could lead to more blowholes in the right corner or something similar. For achieving this, the user should upload a folder of images that has a constant scale. The program could also count the total defects present in all the images combined in the folder, how many of these could be classified as Blow holes and Lack of Fusion, their average area percentage, etc. to calculate the area percentage of the entire folder, the area percentage of each individual image was found and it was divided by the total number of images in the folder to get the average value. If the user requires it, the program could also provide him/her with individual data of each image as well, separately.

```
{'A1': {'bottom.jpg': {'def_count': 5,
   'lof_count': 1,
   'lof_area_percent': 1.3209925925925925,
   'bh_count': 4,
   'bh_area_percent': 0.06774074074074074},
  'bottom_0002.tif': {'def_count': 0,
   'lof_count': 0,
   'lof_area_percent': 0,
   'bh_count': 0,
   'bh_area_percent': 0},
```

In addition, the program could transfer the results obtained onto a CSV file on the user's device. This would comprise a comprehensive data report on the total defects and their localization.

condition	def_count	lof_count	bh_count	lof_area_percent	bh_area_percent	n_images
A1	108	21	87	0.162057	0.054086	50
condition	def_count	area_percent	n_images			
A	271	0.366162	31			

Front End Creation

To make the program more user-friendly, a front end was created using a Streamlit open-source app framework. The user could choose whether an Optical or SEM image was being entered and he/she could upload single images, a folder of images, or even multiple folders simultaneously and the results could be saved on their respective device. The user could select whether to view the plots or just observe the results.

Future Work

The base is set up and the code to detect and classify defects is also up and running successfully. In the next phase, I would be focusing on correlating parameters and how each parameter would result in the defects observed in the samples produced. For this, the tasks pending are:

- Training the model to improve efficiency by training on more images, maybe high-resolution Transmission Electron Microscopy Images to further classify the defect to Grain boundary cracks as well.
- Conducting sample printing experiments using various process parameters of Laser Powder bed Fusion and visualizing the cross-section view of each, using SEM or Optical microscopy.
- Processing these images by using the developed algorithm to detect the total defects, their areas, and locations.
- Correlating how each parameter leads to a certain defect and how they contribute to the defect localization in a particular area.
- Extrapolating the graph to obtain the optimum parameter for the least observed defect parameters.
- Compiling the results obtained into a research article that would be published in a metallurgy journal.

Summary

The project aimed at exploring the possibilities of introducing Artificial Intelligence and Machine Learning into Additive Manufacturing. It deals with defect prediction and analysis of the Laser Powder Bed Fusion process and cross-section images of each product were taken and observed under an Optical or Scanning Electron Microscope. An algorithm to process these images and identify the number of defects present and their defect type based on geometry was also calculated. A plot showing the defect locations for single as well as multiple images was developed. A front was created to make it easier to implement. The task now pending is to train a model to improve accuracy and add more classification to the defects, perform experiments to identify how process parameters, such as laser power, powder diameter, etc. contribute to these defects, and obtain an ideal parameter with the most reduced number of defects.

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