

In-Situ Monitoring and Quality Assurance Algorithms for Laser Powder-Bed Fusion using Optical Tomography

by

Osazee Ero

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

- External Examiner: Jin Xiaoliang, Ph.D.
Associate Professor
Department of Mechanical Engineering
University of British Colombia
- Supervisor: Ehsan Toyserkani, Ph.D.
Professor
Department of Mechanical and Mechatronics Engineering
University of Waterloo
- Internal Member: Amir Khajepour, Ph.D.
Professor
Department of Mechanical and Mechatronics Engineering
University of Waterloo
- Internal Member: Soo Jeon, Ph.D.
Professor
Department of Mechanical and Mechatronics Engineering
University of Waterloo
- Internal-External Member: Mohammad Kohandel, Ph.D.
Professor
Department of Applied Mathematics
University of Waterloo

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Osazee Ero was the sole author for Chapters 1, 2, and 6, which were written under the supervision of Prof. Ehsan Toyserkani and were not written for publication.

This thesis consists in part of two manuscripts written for publication. Exceptions to sole authorship of material are as follows:

Research presented in Chapter 4:

Prof. Ehsan Toyserkani and Dr. Katayoon Taherkhani were the primary co-investigators on the research funded by N-SERC, which supported conducting this work. Osazee Ero conducted this research at the University of Waterloo under the supervision of Prof. Toyserkani. The study design was conceptualized by Prof. Toyserkani, Dr. Taherkhani, and Osazee Ero. Osazee Ero was responsible for data collection and analysis, with guidance from Prof. Toyserkani and Dr. Taherkhani. The manuscript for Chapter 4 was drafted by Osazee Ero and reviewed by Prof. Toyserkani and Dr. Taherkhani, who provided intellectual input and revisions.

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Research presented in Chapter 5:

This research was conducted at the University of Waterloo by Osazee Ero under the supervision of Prof. Ehsan Toyserkani. Osazee Ero designed the study with consultations from Dr. Katayoon Taherkhani, who contributed to concept brainstorming and manuscript review. Osazee Ero was responsible for data analysis and drafting the manuscript. Prof. Toyserkani and Dr. Taherkhani provided critical feedback and suggestions for improving the manuscript drafts.

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As the lead author of these two chapters, I was responsible for conceptualizing the study design, carrying out data collection and analysis, and drafting and submitting the manuscripts. My co-authors provided guidance during each step of the research and offered feedback on manuscript drafts.

I would also like to acknowledge my co-authors who contributed to the research described in this thesis:

Prof. Ehsan Toyserkani: Supervising the research, providing the original idea for the thesis, editing and reviewing papers, and providing experimental facilities.

Dr. Katayoon Taherkhani: Guiding the research work in concept brainstorming, manuscript review, and designing samples.

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Abstract

Conventional methods for evaluating the quality of components produced through laser powder-bed fusion additive manufacturing (LPBF) are often costly and resource-intensive. These post-production techniques involve mechanical testing, detailed metallographic examination, and non-destructive methods like X-ray computed tomography (CT) to identify flaws. Recently, there has been a shift towards employing in-situ monitoring systems, such as optical tomography (OT), which capture near-infrared light emissions to detect defects arising during LPBF.

This dissertation introduces innovative approaches for defect detection in LPBF, utilizing OT data alongside machine learning techniques. LPBF processes inherently exhibit random behavior, presenting challenges in developing robust defect detection algorithms adaptable to diverse machine setups and process parameters. The proposed model integrates a self-organizing map (SOM), a fuzzy logic scheme, and a tailored U-Net architecture to detect and predict defect probabilities in LPBF-produced parts using in-situ OT analysis. Specifically, the model is designed to identify common flaws such as lack of fusion and keyhole defects.

The effectiveness of the approach was validated through a series of experiments. Initially, the influence of process parameter selection on recorded in-situ optical tomography (OT) data was investigated. This was followed by the intentional and random recreation of process defects to simulate the stochastic nature of real-world manufacturing processes and to gain a deeper understanding of defect formation. The developed model was subsequently evaluated on a complex geometry to assess its performance in a practical setting. Validation of the model was done by comparing its predictions against computed tomography (CT) scans, to achieve this, Dynamic Time Warping (DTW) technique was used to measure the similarity between porosity curves generated by the model and those from CT scans. The developed model effectively predicted porosity resulting from lack of fusion or keyhole defects across various process parameter settings, achieving average Euclidean distance scores of 0.243 for lack of fusion pores and 0.6 for keyhole pores. Additionally, the model successfully detected defects in complex geometries with internal lattice structures.

A significant advantage of this developed model is its adaptability. Fuzzy logic allows for the integration of soft decision boundaries and expert rules into the model, which is crucial when

dealing with complex phenomena like porosity where the boundaries between the presence of defects in the fabricated part, based on monitoring OT data, are not always clear-cut. Expert knowledge can be encoded into fuzzy rules that mimic human reasoning and decision-making processes. Quality assurance experts can use their experience to provide insights through the application of fuzzy rules, determining how certain visual or measurable features of an image typically correspond to specific types of porosity. They can also adjust the probability threshold for defect detection based on specific quality criteria. This adaptability enhances the approach's utility across diverse manufacturing scenarios, offering flexibility in meeting quality assurance requirements.

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Dedication

To my beloved Family

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1 Introduction

1.1 Research Motivation

3D printing or Additive manufacturing (AM) technology involves transforming a digital model into a three-dimensional physical object by adding material a layer at a time[1]. This method of manufacturing allows the fabrication of complex shapes without the requirement of extra tooling, as well as utilizing minimal material. Due to its unique benefits, it is widely used in several industries such as medical, military, aerospace and tooling for automotive [2, 3]. There exist several AM technologies[4], among is the powder-bed fusion (PBF) process which is normally used for the fabrication of metals such as titanium, copper, and nickel-based alloys. This technology uses a moving heat-source such as laser or electron beams to selectively fuse regions of metallic powder on a substrate placed on a bed, enabling the manufacturing of complex geometry with high accuracy and desirable mechanical properties [1]. Laser powder-bed fusion (L-PBF) uses a laser-beam as its heat-source. Although, this manufacturing method offers considerably advantages over traditional methods of manufacturing, the process repeatability, durability, and reliability still face significant challenges[5]. This can be attributed to the process defects such as voids within the part (undesired porosity), cracks, dimensional errors etc. formed because of the complex nature of the laser-material interactions, which is influenced by over 130 parameters such as laser power, scan velocities, layer-thickness, laser-powder interactions etc., as such inconsistency in finished part quality is a major challenge [1].

Real-time monitoring of the manufacturing process mitigates the occurrence of these defects by keeping track of the process stability on a layer-by-layer basis, such that corrective repair/compensation actions can be taken when required. Optical devices such as high-speed cameras in the visible to the infra-red range are frequently used. However, these monitoring devices produces a large stream of data which could be challenging to manage. Also, effective monitoring algorithms to link these large data with process defects are lacking[6].

Previously, image processing and statistical based methods have been applied for the analysis of these data. These methods though relatively effective, suffer from poor scalability and computation speed when processing large data. A relatively new paradigm shift in computing that

takes advantages of this large datasets and allows a machine to learn useful patterns in an automated manner, making decisions without explicitly been programmed is called machine learning.

This research is an attempt to proffer a novel solution to real-time detection of process defects in L-PBF using optical tomography (OT) with machine learning techniques, and if successfully implemented could allow for increase in process repeatability drastically reducing the cost of post-process quality testing of L-PBF manufactured parts.

1.2 Opportunities and Challenges

In the last few years, machine learning (ML) has elevated the analysis capabilities for expanding datasets and has garnered notable attention in the field of AM[7] ML has demonstrated impressive efficacy in diverse domains, including self-driving vehicles, language comprehension, and health diagnostics. Crucially, ML's effectiveness improves with the volume of data available for training, making it highly suitable for scenarios that naturally generate vast amounts of data, like the Laser Powder-Bed Fusion (L-PBF) AM processes. As previously discussed, components fabricated using L-PBF are prone to various defects, such as unwanted pores from insufficient melting (due to low energy input) or keyhole effects (from excessive energy input), cracks, layer separation, and warping. These issues can accumulate, layer upon layer, compromising the final product's quality[7]; therefore, real-time monitoring becomes indispensable.

Monitoring within these processes typically unfolds across three tiers: observation of melt-pool size and heat influence to identify deviations, temperature checks of the powder bed during the layering process, and post-process inspections aimed at enhancing the quality of the end product [6]. A relatively new, less data-intensive method for this purpose employs optical tomography[8] a technique also prevalent in medical fields for visualizing internal body structures. This monitoring approach captures a singular image per layer, revealing cooling rates and thermal gradients for that specific section. Analyzing this captured data through ML techniques allows for the detection of anomalies, thereby ensuring the quality of the manufactured parts.

1.3 Research Aim and Objectives

This study aims to leverage ML strategies to explore the relationship between optical tomography outputs and potential manufacturing defects. The research goals include:

- Conducting experiments that simulate common defects such as lack of fusion and keyholes by incorporating artificial voids and selecting specific process parameters to induce these defects.
- Assessing how variations in process parameters affect the readings from optical tomography.
- Analyzing how lack of fusion and keyhole defects are reflected in optical tomography data.
- Comparing the performance of different analytical algorithms in identifying these defects with the findings from Computed Tomography (CT) scans.
- Creating ML models that can identify defects in real-time using images from optical tomography, validated against CT scan results.
- Developing ML algorithms capable of estimating the likelihood of defect presence based on optical tomography images.
- Establishing a quality assurance system for parts manufactured via Laser Powder Bed Fusion (LPBF) using insights gained from optical tomography.

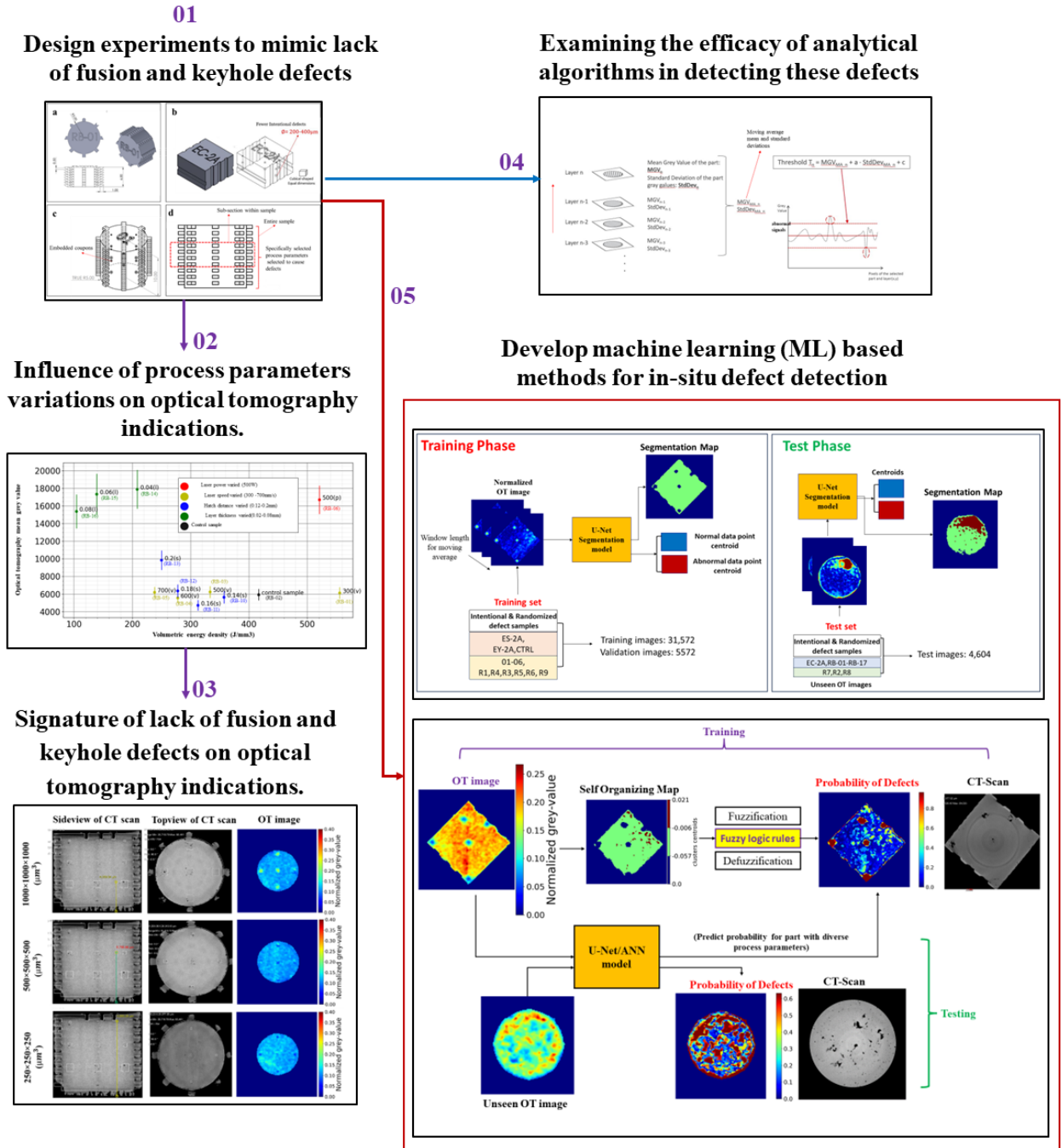


Figure 1-1: Graphical flowchart of the research conducted in the current thesis.

1.4 Thesis Outline

The thesis comprises six chapters. In Chapter 1, the problem definition, motivation, and objectives of the current research are outlined. Chapter 2 reviews the relevant literature on lack-of-fusion and

keyhole defects, in-situ monitoring devices, and monitoring algorithms applied to LPBF studies. Chapter 3 presents Experimental procedures and Analytical Based Methods for correlating Optical Tomography Indications with Porosity Within the LPBF Process. Chapter 4 introduces a machine learning pipeline aimed at addressing various challenges associated with analytical based methods by automatically correlating recorded optical tomography indications with process defects. Chapter 5 delves into fuzzy-machine learning for predicting the probability of actual defects in parts given an abnormal optical tomography indication, noting that such indications do not necessarily lead to defects in actual parts. Finally, Chapter 6 summarizes conclusions drawn from the research and outlines potential future work.

Chapter 4 and Chapter 5 are adapted from the author's published work and manuscripts submitted or will be submitted for publication, as follows:

- Chapter 4 is a journal article published in the Journal of Additive Manufacturing
 - O. Ero, K. Taherkhani, and E. Toyserkani, “Optical Tomography and Machine Learning for In-situ Defects Detection in Laser Powder Bed Fusion: A Self-Organizing Map and U-Net Based Approach,” *Addit Manuf*, p. 103894, 2023 [9]
- Chapter 5 is an article that has been submitted to International Journal of Extreme Manufacturing.
 - An Integrated Fuzzy Logic and Machine Learning Platform for Porosity Detection using Optical Tomography Imaging during Laser Powder Bed Fusion.

The content of these publications has been slightly modified to fit within the scope of this thesis.

2 Background And Literature Review

2.1 Introduction

The American Society for Testing and Materials (ASTM) [4] standard divides AM processes into seven distinct categories based on the layer-creation techniques and the material states involved. A significant barrier to the broader acceptance of AM technologies is the variability in the quality of the produced parts [10], often due to randomly occurring defects during the production phase. Gaining insight into how these defects develop and identifying their potential triggers are crucial steps toward establishing a robust quality assurance system for monitoring AM processes. This chapter discusses the challenges of LPBF, in-situ monitoring sensing devices and monitoring techniques for collecting useful data from the process, then finally statistical and machine learning method to detect abnormal signatures in these data would be introduced.

2.2 Laser Powder-Bed Fusion (LPBF) Additive Manufacturing

Powder Bed Fusion (PBF) is an AM technique that employs a concentrated energy source, like a laser or electron beam, to fuse material powder on a platform layer by layer [1]. This method is particularly effective for producing advanced materials including titanium [10,11], iron-based alloys, nickel-based superalloys [12, 13], aluminum, and stainless steel [15]. Sub-categories of PBF, includes Selective Laser Sintering (SLS), Selective Laser Melting (SLM), and Electron Beam Melting (EBM). Specifically, SLM, also referred to as L-PBF, involves converting a computer-aided design (CAD) file into thin cross-sections. The thickness of these sections is a critical parameter that must be evaluated before initiating the print process. A fine metal powder layer (with a thickness between 30 to 50 μm) is spread over a base plate or atop previously solidified layers. Following the CAD model's contours, a high-energy laser beam selectively melts the powder. After each layer is fused, the build platform lowers to add a new powder layer, continuing until the part is complete [15], [16]. This entire procedure is conducted in a chamber filled with inert gas, like argon or nitrogen, to prevent any oxidation and maintain the quality of the powder. Given the intricacies of this process, defects such as voids and cracks can emerge, underscoring

the importance of understanding these imperfections for the development of effective quality control measures.

2.3 Fundamental Challenges of LPBF

Despite the significant advancements in the LPBF technique, several challenges persist, including undesired porosity, dimensional errors, layer delamination etc. Part quality transcends mere shape; it lies in a part's ability to fulfill its intended function while preserving its structural integrity. Typically, part specifications encompass factors like geometry, surface finish, and mechanical properties, all integral to quality assessment. Despite extensive research and diverse approaches aimed at enhancing fabricated part quality through material characterization, many issues persist, particularly in predicting and controlling internal defects. Inner defects notably undermine mechanical properties, and current experimental methods heavily rely on trial and error, which prove costly and inefficient.

Additionally, the multitude of parameters involved in LPBF presents another challenge, as some parameters, though uncontrollable, can significantly impact process quality (e.g., gas flow pressure and powder uniformity), leading to reduced repeatability. Conversely, controllable parameters also demand optimization through experimental refinement rather than a straightforward solution.

2.4 Defect Formation in LPBF

In L-PBF fabricated parts, undesired porosity is a frequent problem which can largely be attributed to instability in melt-pool dynamics [10],[15]. These porosities are usually present in three distinct variations [17]; Lack of fusion (LoF) porosity occurs when there is an incomplete fusion between two successive built layers or scan vectors, primarily due to insufficient energy applied to the powder material. Also, weak bonding between layers because of oxidation and insufficient material either because of material shrinkage or uneven powder spread can cause this defect. [18][6]. The melt-pool formed is usually small, resulting in thin and irregularly shaped voids within part [19]. When the energy input is high another type of defect called “Keyhole porosity” is formed. The high energy input into the material results in temperatures higher than the boiling point of the material, which causes evaporation of the material, creating metallic bubbles leading to a deep keyhole depression to be formed. This depression is unstable and can collapse, trapping

inert shielding gas forming typically round or spherical pores[6],[19]. The melt-pool formed is usually large. Gas pores, typically petite sizes with a spherical shape, occur due to gas entrapment of shielding gas, the porosity of powder particles, or alloy vapors inside the molten pool[17] [20].

Other defects that can occur during the layer-wise process include the ejection of liquified molten metal to form spatter. This molten material may solidify into spherical shapes preventing the bonding of adjacent melted previous layers [16]. Geometric and dimensional errors are also common because of shrinkage caused by cyclic heating and cooling.

The melt-pool typically has three types of electromagnetic radiation emanating from it as shown in figure 2.3. The backscattering (reflection) of the laser beam and plasma radiation (400-600nm) are an undesirable phenomenon are eliminated by installing suitable mirrors [6]. The thermal emission (900 – 2300nm) contains the useful information about the melt-pool stability.

2.5 Quality Assurance in LPBF

In the literature, quality assurance is usually done at three levels[21]

- **Incoming quality assurance methods** where the suitability of the powder material for the fabrication process is determined and the build environment is conditioned to ensure the success of the build process.
- **In-situ quality assurance methods** which involve integration of sensing devices during the layer-wise process to detect potential defects and take corrective actions. At this level, if successfully implemented would largely reduce the cost of post-process quality assurance methods which is the last level of quality assurance check.
- **Post-processing quality assurance methods** are usually the final stage of quality check of the fabricated parts to ensure it meets the desired requirements for its intended application. It usually involves parts inspection using non-destructive methods such as computed tomography (CT) for detecting pores within the part, surface finishing methods, residual stresses measurement and treatment.

2.5.1 In-situ Sensing Devices in Laser Powder-Bed Additive Manufacturing (L-PBF)

At present, the verification of quality and the validation of metal additive manufacturing parts predominantly depend on time-consuming and costly post-production assessments. These evaluations may consist of extensive mechanical tests, in-depth study of the parts' cross-sections through metallography, and the use of non-destructive methods like X-ray computed tomography (XCT) to detect potential flaws within the components. Concurrently, there are ongoing efforts to create and refine in-situ monitoring systems and the analytical methods that accompany them, presenting new or complementary options for quality assurance. These systems aim to detect anomalies during the additive manufacturing process, layer by layer, with the possibility of incorporating feedback loops for corrective actions. Achieving this requires the development of empirical models that can correlate observed deviations with specific manufacturing defects in the produced parts. These deviations are usually recorded by sensors integrated into the manufacturing equipment, which are divided into radiative or non-radiative types [22], [23]. This classification depends on whether the sensors detect emissions from the manufacturing process or monitor its physical attributes and convert them into electrical signals. Examples of radiative sensors include cameras, photodiodes, and pyrometers, while non-radiative sensors comprise acoustic devices and thermocouples, among others.

2.5.1.1 Mounting strategy

Several of the in-situ sensing devices includes vision-based systems such as high-speed digital cameras and infrared (IR) thermal cameras for capturing the melt-pool properties along with the layer-wise surface images. Photodiodes and pyrometers are sometimes used to provide supplementary process information. These optical devices are usually arranged either co-axially (on-axis) [9], [10], [24] - [30] where they are mounted in the same axis as the optical path of the laser beam (Figure 2-1a), or off-axially [10], [27], [31] - [35] where they are placed outside the optical path and mounted separately at a specified angle [16] (Figure 2-1b). The on-axis setup arrangement usually provides detailed observation of the melt-pool dynamics and it's usually the preferred. Because of the fast melt-pool dynamics of the layer-wise build process, the optical

sensing device is required to have very high frame rates resulting in large amount of data to be stored and analyzed.

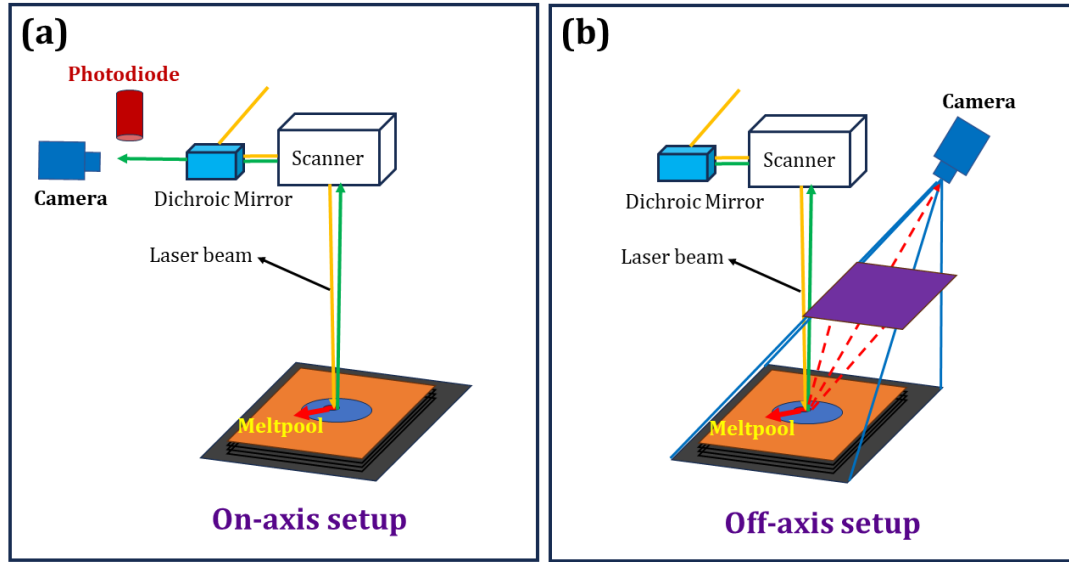


Figure 2-1: On-axis and Off-axis setup in L-PBF

To optimize the data collection rate of optical sensors without compromising the integrity of the process signatures captured, Berumen et al. explored the potential of using the laser machine's scan-head for direct observation of the melt pool, narrowing the focus to a specific area of interest [36]. This setup captures the thermal emissions from the melt pool by equipping the laser scan head with an optical sensor and a semi-transparent mirror, which then directs the thermal radiation to a high-speed camera. Additionally, they utilized a photodiode to measure the melt pool's temperature, complementing the non-thermal vision system. Further research into coaxial monitoring systems, as discussed in [37], [38], aims to control melt pool characteristics, like its size, by matching the observed signals against target properties established through experimentation. Investigations into off-axial monitoring configurations have also been conducted [39], which involve placing cameras within the visible spectrum at an angle to the build platform to capture images of the powder bed and the areas being scanned. These setups also feature an LED lighting system to ensure the build chamber is well-lit, with the light's intensity designed to surpass all other light sources except for the laser's impact zone. Coaxial (on-axis) arrangements offer the benefit of pinpointing defects directly by maintaining a clear line of sight to the melt pool, thereby enabling the precise localization of any irregularities. In contrast, off-axis sensor

placements may not pinpoint defects with the same accuracy but can detect broader process anomalies, such as metal spatter or deviations in the geometry's dimensions.

2.5.1.2 Optical Tomography for In-situ Monitoring In L-PBF

Optical Tomography (OT) is a technique within computed tomography that captures 2D images of a target object using a light source, which are then transformed into a 3D volumetric digital model through specialized software. During this process, the object is rotated around a specific axis, with images taken at predetermined angular intervals. OT operates under the principle that an object, when exposed to light, will both reflect and scatter some light, while transmitting another portion of it [8]. The components of a tomographic monitoring system fall into three primary categories:

- The **sensors** serve the dual purpose of emitting light towards the object and detecting the light that is scattered back. These include transmitters such as LEDs, lasers, or infrared sources, and receivers like photodiodes and optical systems. Key considerations in sensor selection include response time, noise level, and operational wavelength [40].
- A **data acquisition** system that converts the gathered signals into digital data for subsequent processing.
- An **image reconstruction** algorithm that reconstructs the captured digital signals into images.

In the context of process monitoring for LPBF process, the working principle of OT is as follows: the interaction between the laser beam and the metal powder results in the emission of three distinct types of electromagnetic radiation from the melt pool. These are the reflected laser radiation (wavelength 1064nm), plasma radiation (wavelength 400 - 600nm) resulting from the high energy input, and thermal radiation (900 to 2300nm) [6]. The OT camera's sensor is designed to continuously capture the thermal radiation emissions while ignoring the other two types, thanks to the implementation of appropriate filters. These filters block unwanted radiation, allowing the sensor to concentrate on specific wavelengths. The strength of the captured signal reflects the intensity of the process radiation, aggregated over the sensor's capture duration for each layer. Image processing techniques are then applied to synthesize these signals into a singular OT image

for each layer, aiming to link the collected data with potential defects in the process. This method is represented diagrammatically in Figure 2-2.

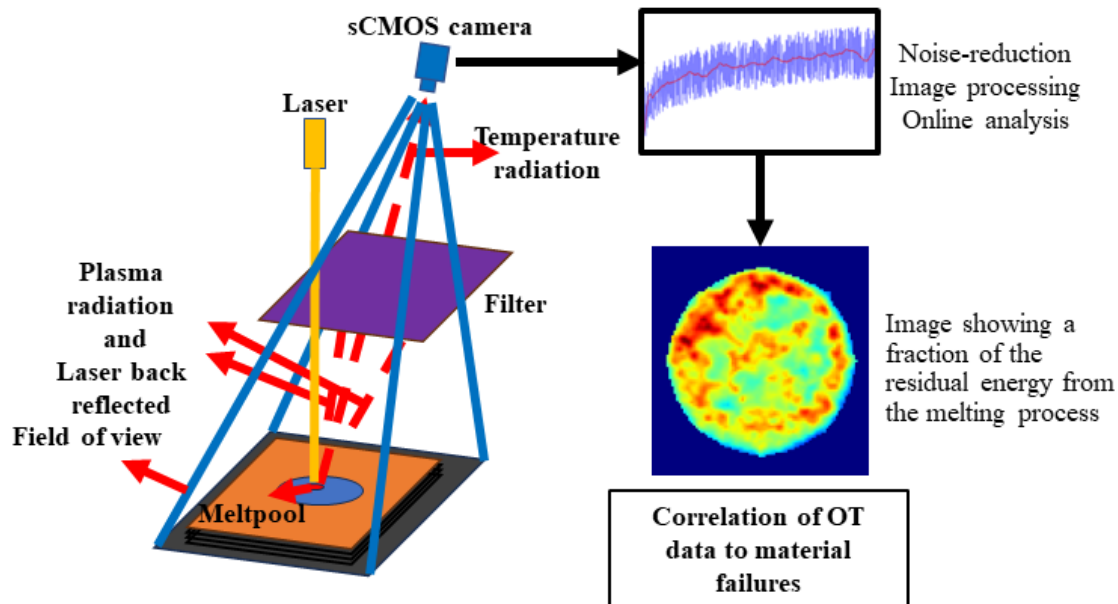


Figure 2-2: Illustration of Optical Tomography (OT) monitoring setup in L-PBF

An optical tomography (OT) image reveals the stability of the process and any variations that could result in flaws. The data collected encapsulates the cumulative effect of the process's radiation over a specific period. It highlights areas of intense interaction between the laser beam and the material in the melting phase, showcasing these interactions with varying intensities. Deviations from the norm are identified as either cold spots or hot spots, as depicted in Figure 2-3.

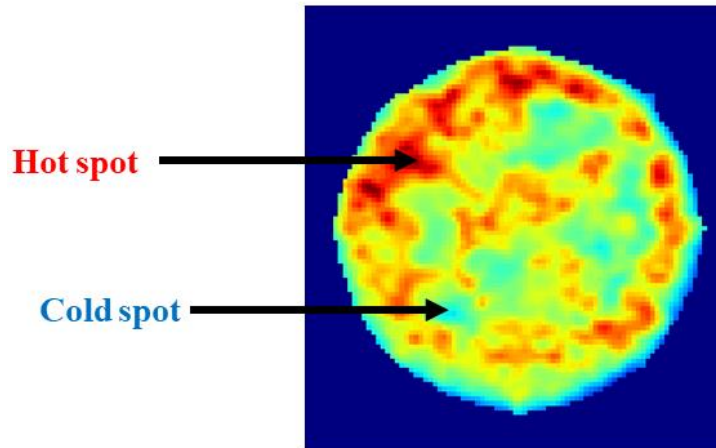


Figure 2-3: Examples of indications in recorded optical tomography monitoring data

Cold spots, represented as darker areas in monitoring images, emerge from lower energy application to the material, leading to less intense signals. This condition can result from inadequate process parameter settings or unpredictable events like plume generation or laser backscatter, which in turn lead to a superficially formed melt pool. Typically, such indications are precursors to lack of fusion defects.

Conversely, **hot spots**, depicted as brighter areas, occur due to excessive energy input into the material or poor heat dissipation, particularly above the Downskin area, prolonging the solidification period due to elevated temperatures. Interestingly, hot spots can also emerge from low energy input, as explained by the Raman scattering phenomenon where particles in the smoke generated by laser-material interaction emit radiation of different wavelengths than the incident light. This interaction, coupled with the inert gas flow in the chamber, broadens the emission area, leading to enhanced signals in optical tomography readings [41].

However, the self-corrective capability of the L-PBF process means that not all deviations detected by optical tomography necessarily result in defects. The influence of varied process parameters and the strategy of exposure on OT signal outcomes makes the direct association between these signals and potential defects a complex task. Abnormalities observed in a single layer may be rectified in subsequent layers due to the process's self-healing nature, whereas persistent anomalies over multiple layers are more indicative of actual defects in the final product.

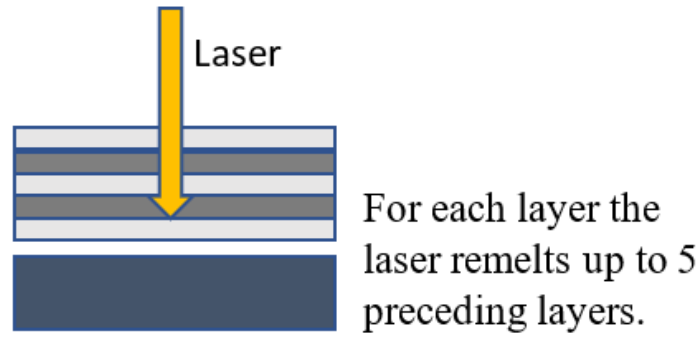


Figure 2-4: Self-healing nature of L-PBF

Zenzinger *et al.* [42], Gunther *et al.* [43] and Alexander Ulbricht *et al.* [44] explored the effectiveness of an off-axis installed optical tomography monitoring system in detecting process defects. Lukas *et al.* at EOS GmbH- Germany [45] assessed the sensitivity and efficacy of the EOSTATE on-axis Melt-pool and off-axis OT monitoring modules for identifying process deviations. Findings revealed that the OT monitoring system displayed heightened sensitivity to deviations in scanning speed and variable hatch distances, whereas the photodiode-based melt-pool monitoring system exhibited greater sensitivity to laser power fluctuations. Both systems could detect process deviations before defects emerged, with the melt-pool system capable of pinpointing defects' locations, while the OT's localization capability was determined by the camera chip's spatial resolution. Schwerz *et al.* [46] also employed this monitoring technique to identify spatters ejected from the melt-pool due to recoil pressure, aiming to establish a correlation with the occurrence of fusion defects within the process.

2.5.2 Monitoring techniques in Laser Powder-Bed Additive Manufacturing (L-PBF)

After collecting the in-situ data set, it's essential to analyze this data to identify any disruptions in the process. Research into the data acquired during the LPBF process has historically utilized image processing techniques [47], [48] and statistical methods [49], [50], [51]. These approaches involve a series of steps aimed at isolating relevant features from the data, such as the dimensions of the melt pool and its temperature distribution. Operations like thresholding, erosion, and dilation

have been applied in these methods. Despite the progress made through statistical approaches, these techniques face difficulties. They may not adequately capture the complex, nonlinear dynamics present in the data, nor efficiently adapt to new, unseen data or different circumstances. A major challenge for current commercial in-situ monitoring systems is managing the large amounts of data they generate, especially for printing processes that extend over several hours or days, which complicates data storage and analysis. Therefore, developing a quick and efficient method for processing this data and pinpointing any anomalies is crucial. This research effort will categorize the investigation of these monitoring methodologies into statistical and machine learning techniques, detailed in sections 2.5.2.1 and 2.5.2.2.

2.5.2.1 Statistical techniques for in-situ quality assurance in L-PBF

After the in-situ data collection phase, there's an immediate need to refine and examine the sensor data to identify relevant insights. Foster et al.[52] and Abdelrahman et al. [47] utilized image segmentation techniques on images captured by DSLR cameras to identify porosity. Foster integrated image processing with 3D X-ray scanning to draw parallels with computed tomography (CT) scan data [52]. Conversely, Abdelrahman et al. took a distinct route by segmenting and normalizing images for analysis, employing the level set segmentation method [47]. They validated the detection of 28 artificially induced defects through comparison with CT scans, employing a confusion matrix to gauge accuracy. Despite achieving a high rate of true positives, the confusion matrix also highlighted a significant rate of false positives. Zenzinger et al. [53] applied optical tomography (OT) methods using a CMOS camera outfitted with an appropriate filter to capture thermal emissions. The anomalous signals detected by OT were then matched with CT scans and digital radiography data of the part. The OT setup boasted a spatial resolution of 0.1mm x 0.1mm, enabling the capture of fine details with high temporal resolution.

2.5.2.2 Machine Learning for In-situ Quality Assurance in L-PBF

The adoption of ML techniques[54], [55], [56], [57], within the field of additive manufacturing has surged in recent years. These methods are driven by data, which means their effectiveness enhances as the training dataset size grows, making them suitable for AM process monitoring. Machine learning algorithms can be classified into three categories: Supervised, Unsupervised, and Semi-Supervised. In the first category, models learn from labeled training data to predict new,

unseen data. The second type autonomously discovers meaningful features in data without supervision, while the third approach blends labeled and unlabeled data for learning, which could be quite effective in AM-based applications as it would allow a human expert input in the learning process while still complementing automatically learned patterns by the machine.

Numerous studies employing supervised machine learning (ML) techniques in additive manufacturing have been conducted. Gobert et al. [58] and Petrich et al. [59] utilized supervised ML techniques, including Support Vector Machine (SVM) and Neural Networks (NN), to detect overheating, pores, and unmelted powders. The labeled dataset was validated through computed tomography (CT) scans, and both SVM and NN were trained for classification tasks, with NN demonstrating superior performance in all test cases. Imani et al. [60] explored SVM, K-Nearest Neighbor (KNN), and NN algorithms for identifying process parameters leading to porous parts. Aminzadeh et al. [61] employed Bayesian inference to predict defective layers using frequency domain features extracted from collected data.

Zhang et al. [62] employed high-speed camera monitoring system to record melt pool, plumes, and spatters. These images were used to train SVM and Convolutional Neural Network (CNN) models for abnormality detection. CNN was also applied to detect defects like delamination and spatter in thermographic images [63]. Similarly, CNN was used with acoustic signals to identify defects, where the recorded acoustic signal was transformed into the frequency domain for training a spectral CNN [64]. Shuo et al. [65] utilized tree-based ML models to predict porosities within optical tomography images. Conditional Generative Adversarial Networks (CGANs) were trained by Shuo et al. [66] to generate new optical tomography in-situ images based on conditional inputs, simulating probabilities of defects' locations before printing. While the network mimicked several in-situ data characteristics, it didn't fully capture the stochastic nature of images. Snow et al. [67] employed visible-range cameras alongside the EOSTATE Meltpool module to establish a link between spatter particles and stochastic lack of fusion through the application of a Dynamic Segmentation Convolutional Neural Network (DSCNN). The U-Net model is a convolutional neural network architecture designed for image segmentation tasks, featuring a contracting path to capture context and an expansive path for precise localization [56]. In a separate investigation, Zhang et al. [68] conducted pre-processing of optical tomography (OT) images by employing the Otsu binarization algorithm and layer packaging to accentuate contour information. They then used

an integrated OT approach to train a U-Net model using mean absolute error (MAE) for predicting radiation patterns in the LPBF process, relying on the contours of the designed parts.

The most prevalent forms of unsupervised learning include K-means, Self-Organizing Map (SOM), agglomerative hierarchy, principal component analysis (PCA), and singular value decomposition (SVD). Grasso et al.[69] employed principal component analysis (PCA), a dimensionality reduction technique, and the K-means clustering algorithm to identify instances of localized overheating along the laser scan path [70]. A self-organizing map (SOM) is a type of artificial neural network that maps high-dimensional data onto a lower-dimensional grid while preserving the topological relationships within the data[71]. Taherkhani et al.[72] demonstrated the application of the SOM algorithm in detecting lack of fusion based on deviations in signals measured by photodiodes, while Fathizadan et al.[73] utilized the agglomerative hierarchy method to distinguish between anomalies and normal processes.

To identify heightened intensity in in-situ optical tomography (OT) data, a semi-supervised machine learning approach was adopted, involving a K-means clustering algorithm and K-nearest neighbor classifier. These intense regions, referred to as hotspots, are widely recognized for harboring the highest likelihood of defects in the final part [74] . Knaak et al [75]. and Wasmer et al [76] similarly utilized this approach to respectively pinpoint surface roughness and detect porosity resulting from the LPBF process.

Semi-supervised machine learning approach takes advantages of having both labelled and unlabeled dataset. Gaussian Mixture Model-Expectation Maximization (GMM-EM) which is a probabilistic based clustering model was applied in certification of L-PBF manufactured parts as either faulty or acceptable based on the ultimate tensile strength of the parts[77]. A semi-supervised CNN model was applied in monitoring the laser scan track width and continuity. Image processing was first employed to generate a small amount of labelled dataset before using CNN model based on temporal ensemble method[78].

Table 2-1:Machine learning algorithms

Machine Learning	ML algorithms
Supervised	Artificial neural networks. (ANN) Convolutional neural network. (CNN) Recurrent neural networks Support vector machines. (SVM) Decision trees, Random Forest Linear and Logistic regression Bayesian networks
Unsupervised	Self-organizing maps. Kmeans, hierarchical clustering. Principal component analysis (PCA) Autoencoders Generative adversarial networks (GANs)
Semi supervised	Gaussian Mixture Model-Expectation Maximization K-means clustering

Table 2-2:Machine learning techniques as applied to defect detection in L-PBF

Reference	Recorded data	Monitoring quantity	ML technique
[58] [59]	Build images	Overheating pores, unmolten powder	SVM, NN
[60]	Process parameters such as laser power, hatch distance and scanning speed	Porosity	KNN, SVM,NN
[61]	Build images	Porosity	Bayesian inference
[62]	Melt-pool, plume and spatter images	Process anomalies	SVM & CNN

[64]	Acoustic indications	Defective indications	sCNN
[65]	Plume images	Abnormal melt-pool states	Thresholding and Kmeans
[69]	Build images	Overheating defect	PCA,Kmeans
[77]	Photodiode indications	Tensile strength	GMM-EM

2.6 Summary, and relevance of research

We discussed the formation of defects in LPBF processes and the need for in-situ monitoring system to improve part quality and promote process repeatability. We also showed that current monitoring setup usually requires a high-sampling rate in order to efficiently monitor the melt-pool signatures as such requires large data storage requirements and may pose a challenge for analyzing such data. We discussed about the advantages and challenges of using optical tomography for detecting abnormal process deviations. Examining the presented studies, it's evident that machine learning techniques have found extensive application in LPBF process quality control. However, many of the published works concerning recorded optical tomography data have concentrated solely on specific process parameters. This calls for method adaptation when dealing with diverse parameter selections, or even the same parameters due to the stochastic nature of the process. Also, fluctuations in pixel intensities in optical tomography images may not always signify defects. as, the self-healing characteristics of the process imply that anomalies observed at a specific layer do not necessarily translate into defects. In essence, the occurrence of colder spots and hotspots in the image generally raises the likelihood of defects in the printed part. Furthermore, most of these studies have employed supervised machine learning approaches, necessitating the creation of labeled datasets which can be arduous and time-consuming. Adding to the complexity, the self-healing nature of the LPBF process poses challenges in establishing effective quality control methods.

3 Investigating Optical Tomography images for Porosity Detection Within the LPBF Process

3.1 Introduction

In this chapter, the OT monitoring systems and equipment used in this study will be discussed. We will systematically develop several experiments to garner better understanding of optical tomography indications relative to lack of fusion and keyhole defects within the process. We will conduct preliminary experiment to study the effectiveness of analytical based approaches for correlating the recorded optical tomography data to these defects. CT scans will be used for non-destructive testing of fabricated parts for validation.

3.2 Monitoring systems and Methodologies

3.2.1 Optical Tomography (OT) monitoring system

The additive manufacturing process was monitored using the EOSTATE Exposure OT system, which consists of an off-axis 5-megapixel Scientific Complementary Metal-Oxide-Semiconductor (sCMOS) camera that records the light emitted from the LPBF process in the near-infrared range. The emitted radiation from the melt-pool typically consists of three components; (i) the reflected laser radiation (1064 nm), (ii) plasma radiation (400-600 nm) due to evaporation and ionization of gases, and (iii) thermal emissions which ranges from visible (380-789 nm) to near infrared (≈ 1400 nm) spectrum [42]. The thermal emissions are the radiation of interest as such bandpass filter of $900 \text{ nm} \pm 12.5 \text{ nm}$ [46] is placed on the camera to only gather the thermal radiation and eliminate the reflected laser, plasma, and visible light to avoid the detection of process noises and undesired optical effects. Instead of a high-speed image capture, a long-time exposure is used, stored as grey images. The camera has a resolution of 2560×2160 pixels achieving a spatial resolution of $125 \mu\text{m}$ /pixel across the entire build platform. The system also records images at 10 frames per second which are then permanently superimposed to form a single image per layer representing the heat distribution information.

There are two types of images that can be captured from the monitoring system.

- 1) The integral image: which shows the thermal radiation in the near-infrared wavelength range emitted from the process that integrated over the duration of exposure. Using the integral image, observing the relative cooling rates of different sections of the part could be achievable.
- 2) The max image: which shows the positions of maximum thermal radiation emitted from the process for a given layer.

There is no loss of information in the integral image, as such would be the focus of this research. Low grey values in the integral image, also known as cold spots, can be caused by a lower energy deposition in the material, leading to less intense indications in the OT monitoring. This can be caused by improper process parameters or randomly occurring phenomena such as plume formation and laser backscattering, resulting in a shallow melt-pool. These indications typically result in lack of fusion defects. On the other hand, high grey values in the integral image, known as hotspots, can be caused by high energy input in the material, leading to keyhole defects. They can also be created by low energy input and Raman scattering of particles in the smoke [45]. These particles may have different wavelengths from the incident light and when they meet the flow of inert gas in the chamber, it increases the area of emittance and leads to an increase in recorded OT grey-value. It should be noted that variations in intensity do not always result in defects. For example, an increased emission can be detected within the narrow geometries due to short scan vectors and may result in distortions or local metal vaporization [66], but laser-scan stripe overlaps are expected to have higher emissivity and usually do not lead to defects. Additionally, the self-healing nature of the process causes that deviations seen at a particular layer do not always lead to defects. The colder spots and hotspots present in the recorded in-situ data, the higher the probability of defects in the fabricated part. For clarification, Figure 2-2 illustrates the schematic of the monitoring setup. Preprocessing of the OT images was conducted to reduce the effect of natural occurring phenomena within the process such as gas flow effects, part edge borders, and spatter on the powder-bed that were detected by the monitoring system. To do this, a region of interest was selected around the samples and a binary image mask was generated by applying image thresholding and erosion morphological operation to detect part edges and remove unwanted edge borders from the sample as shown in Figure 3-1. Additionally, since the camera system is off-axially positioned, it could result in gathering data from different angles and distances, resulting in geometric distortions. Thus, a geometric correction is necessary to align the

machine coordinate system with the camera coordinate system [45]. This calibration is typically applied by the EOS service qualified staff and is not a focus of this research.

3.2.2 Computed tomography (CT-scanning)

To validate defect distribution, the printed samples were μ CT-scanned using Zeiss Xradia Versa 520 X-ray μ CT system with a source power of 10 W, source voltage of 140 KV, pixel size of 14.97 μm , and exposure time of 2 seconds. A HE6 filter was used, where the X-ray optics was 0.4 $\times$ lens. Additionally, Dragonfly Pro v4.0 software package was used to analyze the CT images and register the X-ray CT images with the Optical tomography data. Figure 3-2 represents an example of reconstructed X-ray CT part and slice, and 3D-reconstructed OT images.

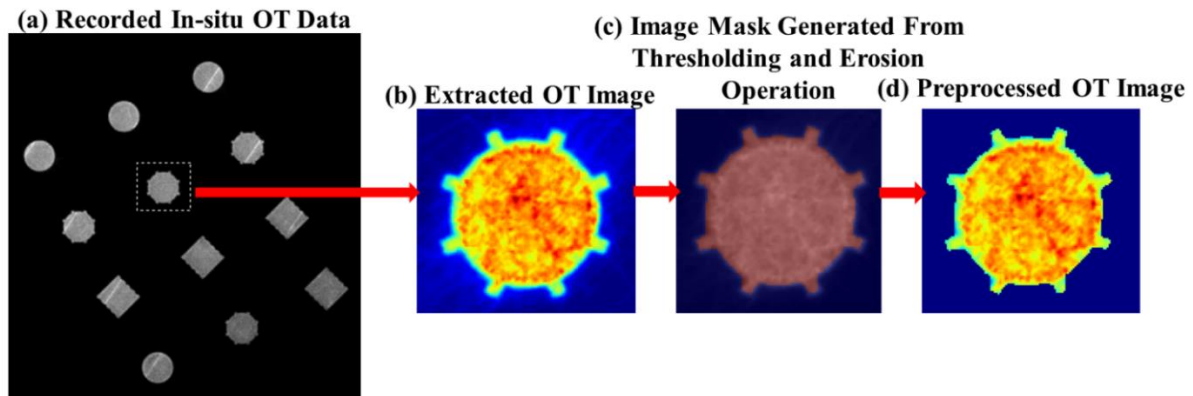


Figure 3-1:Preprocessing of in-situ OT data (a) Recorded OT image showing the extraction of region of interest (b) Extracted OT image, (c) Mask generated from applying thresholding and erosion operations to eliminate background noise (d) Processed OT image gotten from multiplying the mask with the extracted OT image

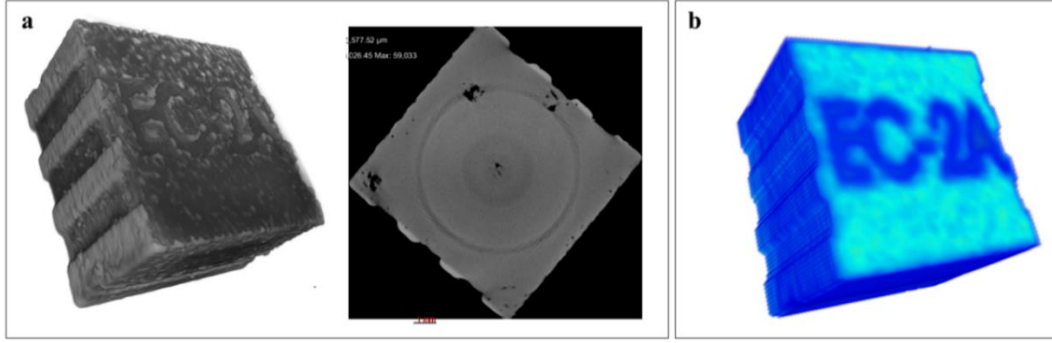


Figure 3-2:(a) reconstructed X-ray CT and example of CT slice (b) 3D reconstructed OT images

3.2.3 Design of experiments

The experiments were conducted using a customized EOS M290 (customized by AMCM)) LPBF machine, which is equipped with a 1000 W Yb fiber continuous laser beam working in a wavelength range of 1060 – 1100 nm. The machine has a nominal beam diameter of $100\ \mu\text{m}$ with a build capacity of $250\ \text{mm} \times 250\ \text{mm} \times 250\ \text{mm}$. In this study, five sets of design of experiments (DOE) were devised using Copper Chromium Zirconium alloy (CuCrZr):

The first consisted of sixteen cylindrical coupons (RB-01 to RB-16), each measuring 5mm in radius ($\emptyset$) and 6mm in height (H), printed using diverse process parameters to assess their impact on recorded optical tomography (OT) images. These parameters, detailed in Table 3-1, encompassed laser power, scanning speed, hatch distance, and layer thickness, all adjusted during fabrication to regulate the energy density ($\text{VED} = \text{Laser power} / (\text{Speed} \times \text{Hatch distance} \times \text{Layer thickness})$ (J/mm^3)) of the laser's interaction with the powder bed. A stripe scan strategy was employed with specific parameter values for contour, up-skin, and down-skin regions as outlined in

Table 3-5. The second DOE focused on studying lack of fusion phenomena in captured optical tomography data. To simulate this phenomenon, artificial voids of different shapes and sizes (Table 3-2) were embedded in $10\text{mm} \times 10\text{mm} \times 6\text{mm}$ coupons (Figure 3-3 b). These voids imitated lack of fusion defects[51] as the locations immediately after artificial voids would have less energy, thus leading to weak fusion of the powder material, thus causing lack of fusion. To elaborate, by intentionally reducing the energy input in the layers immediately preceding the voids, the powder material in these regions experienced weak fusion. This process replicates the lack of fusion phenomenon observed in actual manufacturing defects, providing a controlled environment for studying their characteristics and effects. Control samples were printed, along with adding

additional features like grooves for CT scan registration. The stripe scan strategy along with specific parameters for contour, up-skin, and down-skin regions as shown in

Table 3-5 was also used. The third DOE involved creating six cylindrical samples (Sample 01-06) to replicate the keyhole phenomena by embedding cubic coupons of varying sizes at different heights. Standard print parameters (Power= 900 W, Hatching Distance=0.2 mm, Laser speed=800 mm/sec, and Layer thickness= 0.2 mm) were used for all samples except for the artificial keyhole locations, where laser speed was reduced to increase energy density and induce keyhole formation (See Figure 3-3c and Table 3-3). A control sample was printed without embedded voids, and the stripe scan strategy was employed for all samples with specific laser power, speed, and hatch distance settings (see

Table 3-5). The fourth DOE aimed to explore the impacts of randomized lack of fusion and keyhole phenomena. Several cylindrical specimens with specific process parameters, specifically selected to provoke the formation of these defects. Some samples from the first DOE (RB-15 and RB-16) and a new sample (RB-17) were used for investigating the lack of fusion phenomena (Table 3-4). Cylindrical samples, with specific sub-sections printed with reduced laser speed (see Figure 3-3d), were utilized to study randomized keyhole phenomena. Three control samples were also included, and process parameters similar to intentional keyhole experiments were employed (Table 3-4). Similar contour and skin parameters to intentional keyhole DOE was also used.

The final DOE aimed to validate the effectiveness of the developed model on a complex geometry. Four samples with an internal lattice structure (see Figure 3-4) were printed using standard print parameters as the third DOE at four different locations on the build plate.

Table 3-1: Types and print parameters of first DOE (influence of process parameters on in-situ OT data)

Sample	Laser power (watt)	Hatching Distance (mm)	Speed (mm/sec)	Layer thickness (mm)	Number of images processed
RB-01	400	0.12	300	0.02	300
RB-02	400	0.12	400	0.02	300
RB-03	400	0.12	500	0.02	300
RB-04	400	0.12	600	0.02	300
RB-05	400	0.12	700	0.02	300

RB-06	500	0.12	400	0.02	300
RB-07	600	0.12	400	0.02	64
RB-08	700	0.12	400	0.02	64
RB-09	800	0.12	400	0.02	64
RB-10	400	0.14	400	0.02	300
RB-11	400	0.16	400	0.02	300
RB-12	400	0.18	400	0.02	300
RB-13	400	0.2	400	0.02	300
RB-14	400	0.12	400	0.04	150
RB-15	400	0.12	400	0.06	100
RB-16	400	0.12	400	0.08	75

Table 3-2: Types and print parameters of second DOE (investigating intentional lack of fusion signature on in-situ OT data)

Sample #	Type of artificial voids	Size of artificial voids (μm)	Laser power (watt)	Hatching Distance (mm)	Laser speed (mm/sec)	Layer thickness (mm)	Number of images processed
EC-2A	Cubical	400×400×400	550	0.17	650	0.04	6924
		300×300×300					
		200×200×200					
ES-2A	Spherical	$\varnothing = 400$	550	0.17	650	0.04	6924
		$\varnothing = 300$					
		$\varnothing = 200$					
EY-2A	Cylindrical	$\varnothing, H = 400$	550	0.17	650	0.04	6924
		$\varnothing, H = 300$					

		Ø, H= 200					
CTRL	Control sample	None	550	0.17	650	0.04	3536

Table 3-3: Types and print parameters of third DOE (investigating intentional keyhole signature on in-situ OT data)

Sample #	Size of artificial voids (µm)	Laser speed of embedded artificial voids (mm/sec)	Number of images processed
01	1000×1000×1000	500	550
	500×500×500		
	250×250×250		
02	1000×1000×1000	550	550
	500×500×500		
	250×250×250		
03	1000×1000×1000	600	550
	500×500×500		
	250×250×250		
04	1000×1000×1000	500	550
	500×500×500		
	250×250×250		
05	1000×1000×1000	550	550
	500×500×500		
	250×250×250		
06	1000×1000×1000	600	550
	500×500×500		
	250×250×250		
C-1	None	None	550

Table 3-4: Types and print parameters of last DOE (investigating randomized keyhole porosity signature on in-situ OT data)

Sample #	Laser power (watt)	Hatching Distance (mm)	Laser speed (mm/sec)	Laser speed for sub-sections (mm/sec)	Layer thickness (μm)	Number of images processed
R1	900	0.2	800	700	0.02	465
R2	900	0.2	800	700	0.02	465
R3	900	0.2	800	700	0.02	465
R4	900	0.2	800	600	0.02	465
R5	900	0.2	800	600	0.02	465
R6	900	0.2	800	600	0.02	465
R7	900	0.2	800	500	0.02	465
R8	900	0.2	800	500	0.02	465
R9	900	0.2	800	500	0.02	465
C-1	900	0.2	800	None	0.02	465
C-2	900	0.2	800	None	0.02	465
C-2	900	0.2	800	None	0.02	465
RB-17	400	0.12	667	None	0.02	745

Table 3-5: Additional Process parameters for DOE

S/N	Experiment	Additional Process parameters
1	Influence of process parameters on OT images	stripe scan strategy contour laser power - 400 W, contour speed- 350 mm/s

		hatch distance-0.11 mm up-skin laser power-700 W up-skin laser speed-600 mm/s up-skin hatch distance-0.13 mm down-skin laser power-74.3 W down-skin laser speed-951.2 mm/s down-skin hatch distance-0.09 mm
2	Investigating intentional lack of fusion phenomena on OT images	Same as 1
3	Investigating intentional keyhole phenomena on OT images	stripe scan strategy contour laser power - 100 W, contour speed- 1000 mm/s hatch distance-0.125 mm up-skin laser power-500 W up-skin laser speed-800 mm/s up-skin hatch distance-0.125 mm down-skin laser power-500 W down-skin laser speed-800 mm/s down-skin hatch distance-0.0125 mm
4	Investigating randomized lack of fusion and keyhole phenomena on OT images	Same as 1 and 3

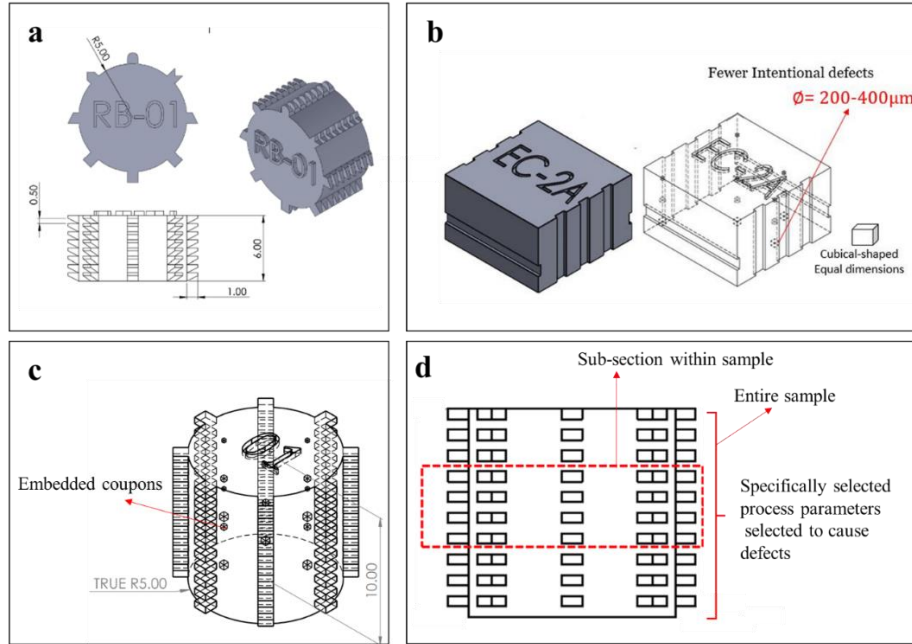


Figure 3-3: The example of CAD model of parts printed for investigating influence of a) process parameter changes, b) intentional lack of fusion porosity, c) intentional keyhole porosity, and d) randomized lack of fusion and keyhole porosity on recorded in-situ OT data

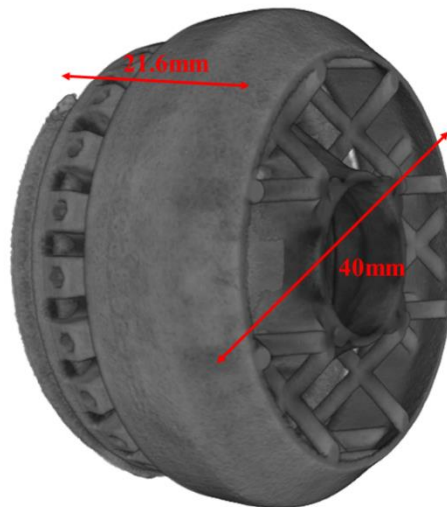


Figure 3-4: Complex geometry with internal lattice structures.

3.2.4 Influence of process parameter changes on recorded in-situ OT data.

As previously discussed, the laser-material interaction is affected by several parameters, including laser power, scan velocity, hatch distance, and layer thickness, which largely influence

the amount of energy input in the process given by Equation 3-1 to measure the volumetric energy density (VED) [22]. Thus, understanding the effects of variations in process parameters on recorded in-situ OT data is crucial in developing effective monitoring algorithms.

$$VED_{spot} = \frac{p}{vdl} \quad \text{Equation 3-1}$$

As discussed in Section 3.2.3, 16 coupon samples were designed and printed with the process parameters listed in Table 3-1. For each of these samples, the histogram plots of corresponding recorded OT gray values were calculated and are shown in Figure 3-5. Also, Figure 3-6 shows the Fisher-Pearson coefficient of skewness [79], which is a measure of the asymmetry of the probability distribution of the samples' OT grey value. In Fisher-Pearson coefficient of skewness, a distribution is skewed if it has a long tail on one side compared to the other. A skewness value of 0 indicates a perfectly symmetric distribution where the tails are the same length. A positive skewness value indicates a distribution with an asymmetric tail extending to the right (the positive direction), meaning the right tail is longer or fatter than the left. A negative skewness value indicates a distribution with an asymmetric tail extending to the left (the negative direction), meaning that the left tail is longer or fatter than the right tail.

According to Figure 3-5 and Figure 3-6, the following results could be drawn:

- When laser scan speed was varied from 300 mm/s to 700 mm/s (samples RB-01 to RB-05), we see that the data is positively skewed, with skewness factor showing a downward trend from about 3.2 in sample RB-01, to 3.05 in sample RB-05, implying that as the laser speed is increased, less energy is deposited on the powder, resulting in lower grey values recorded. This can also be observed in the histogram plots, where most of the grey-values are distributed at the left tail, which is the lower grey value direction (0-direction) with normalized mean OT gray values of 0.15, 0.11, 0.12, 0.10 and 0.10 for samples RB-01, RB-02, RB-03, RB-04 and RB-05 respectively.
- In samples RB-06 to RB-09, where the laser power was varied between 400 W and 800 W, the low skewness score for samples RB-07, RB-08, and RB-09 was because the print failed as such, there was little data available for capturing the probability distribution for those samples. But for sample RB-06 where the laser power was 500 W, we observe a significantly higher

normalized mean OT gray value of 0.27, which implies that we have more energy in the powder. Also, we noticed that though sample RB-01, with a higher VED than RB-06, the mean grey value for the latter was still significantly greater than the former, showing the sensitivity of the monitoring system to specific process parameters.

- Increasing the hatch distance from 0.14 mm to 0.2 mm in samples RB-10 to RB-13, resulted in relatively the same positively skewed score for samples RB-10, RB-11, and RB-12. Although, for sample RB-13, where the hatch distance was 0.2 mm, we had a significantly lower skewness score of about 1.79 relative to the former samples (RB-10, RB-11, and RB-12) whose skewness scores were about 2.3. This shows that when the hatch distance is increased, we would have less energy applied to the powder. Also, the latter sample (RB-13) had a slightly higher normalized mean OT gray value of 0.15, relative to the other samples, which were about 0.12.
- In samples RB-14- RB-16, where the layer thickness was increased from 0.04 mm to 0.08 mm, relatively the same normalized mean OT gray value of about 0.29 was recorded, showing that the monitoring system might be less sensitive to changes in layer thickness.

Additionally, Figure 3-7 shows the plot of the mean OT gray-value and volumetric energy density (VED). It should be added that the print of samples RB-07, RB-08 and RB-09 failed, and they are not included in Figure 3-7.

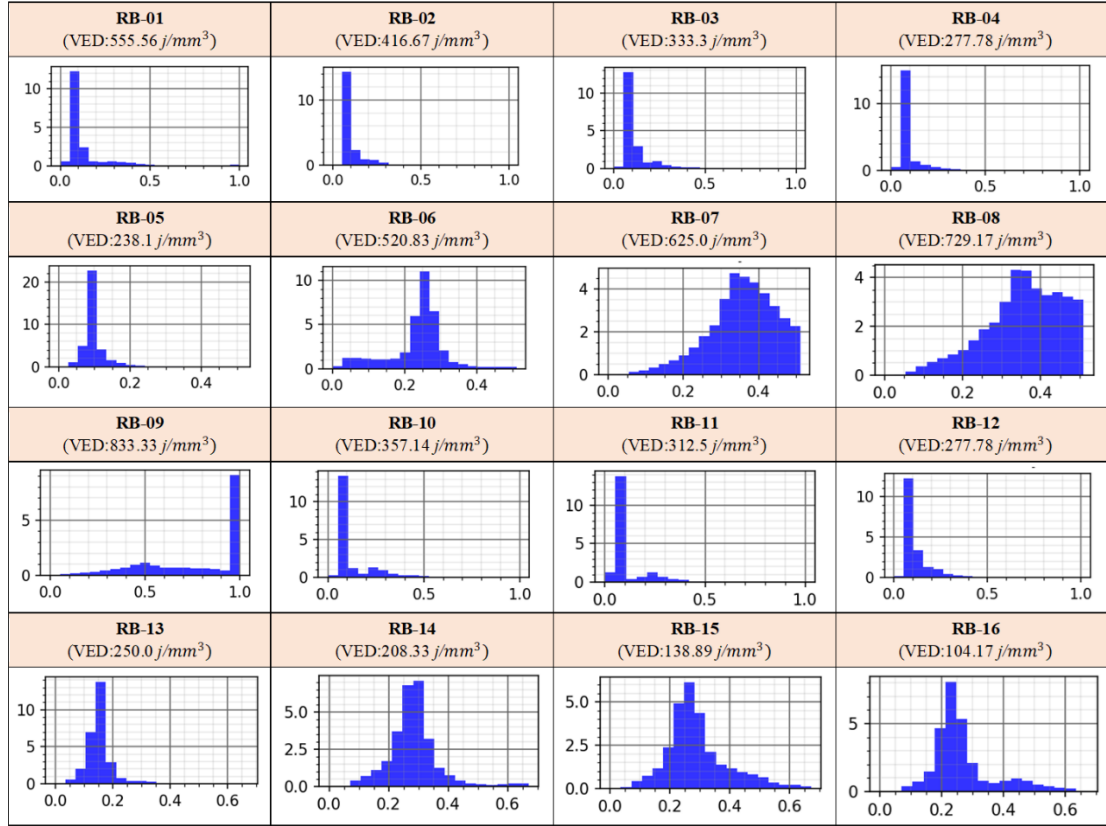


Figure 3-5: The histogram distribution of OT images corresponding to samples RB-01: RB-16 in which x-coordinate and y-coordinate represent normalized OT grey value and probability density, respectively.

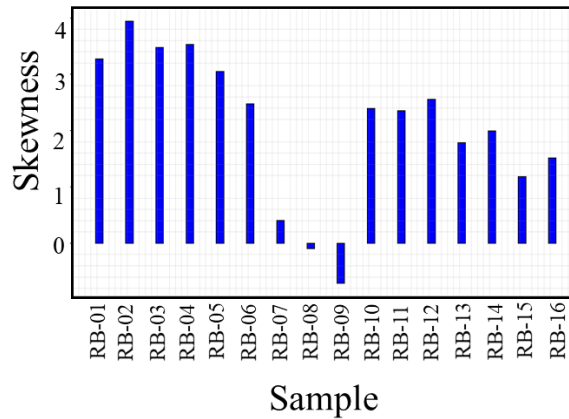


Figure 3-6: Fisher-Pearson coefficient of skewness for samples RB-01: RB-16

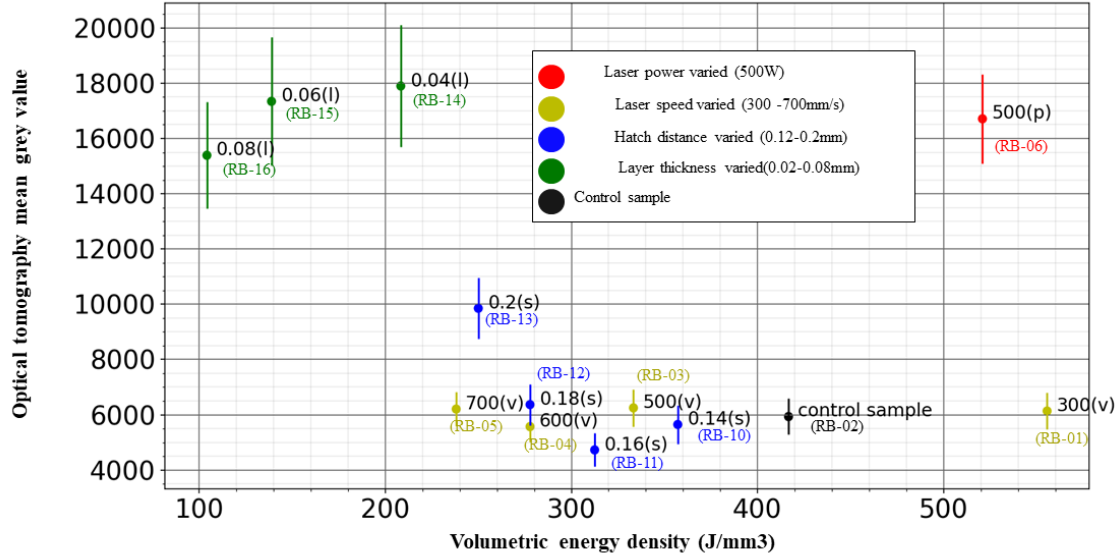


Figure 3-7: The influence of changes in volumetric energy density on recorded mean OT grey value

Figure 3-7 proves the huge impact of energy density on the OT gray-values. For example, in sample RB-01 where the computed VED was 555.56 J/mm^3 , a mean grey value of about 6000 was recorded, while in sample RB-06, with a lower VED of 520.83 J/mm^3 a higher recorded grey value of about 17000 was observed. Additionally, for the same VED (sample RB-04 and RB-12), the captured grey value (600 (v) and 0.18 (s)) were not similar. Apart from the process parameters considered, other parameters, such as the hatching method, stripe width, stripe overlap, *etc.* could significantly impact the signal magnitude.

To determine the relationship between the process parameters and the recorded mean optical tomography, the Pearson correlation coefficient [80] was used. The Pearson correlation coefficient is a statistical metric that quantifies the degree of the linear association between two data sets. It is a widely used tool to assess the strength and direction of the relationship between two variables, with values of 1 signifying a perfect positive correlation, -1 indicating a perfect negative correlation, and 0 denoting no linear relationship. Table 3-6 shows the computed Pearson correlation coefficient for the entire samples (RB-01 to RB-16).

Table 3-6: Pearson correlation coefficient for the influence of process parameters on mean optical tomography grey values

	Power	Speed	Hatch distance	Layer thickness
Normalized Mean OT grey value	0.94	-0.27	-0.32	0.034

From Table 3-6, a negative relationship between the hatch distance and laser speed was observed, implying that selecting a larger speed or hatch distance would lead to low grey values and vice versa, which confirms the result of Figure 3-5 and Figure 3-6. Also, a strong positive correlation between the laser power and the recorded OT grey value was observed. The layer thickness has negligible influence on the mean OT grey value with a correlation coefficient of 0.034, implying the monitoring system might not be sensitive to changes in layer thickness.

As a result, this analysis confirmed that parameters that lead to higher mean OT gray values include relatively high laser power, slow laser speed, and small hatching distance. While parameters leading to lower OT gray values include relatively low laser power, fast laser speed, large hatching distance. Thus, the average grey values in optical tomography images change significantly depending on the process parameters.

3.2.5 Correlation between CT-scan and recorded OT image for Process defects

In this section, the signature observed in optical tomography images for the detection of lack of fusion and keyhole porosities within the LPBF process is investigated. Thus, Section 3.2.5.1.1 and Section 3.2.5.1.2 will discuss the intentional lack of fusion and keyhole porosities, respectively.

3.2.5.1 Intentional defect

3.2.5.1.1 Lack of fusion

- Preliminary observation

Lack-of-fusion is caused by insufficient energy applied to the powder material. To replicate this defect, intentional voids were embedded within a sample. As approved previously [51], [72], when the laser penetrates the preceding layer after the intentional defects, less energy is applied to the material. Similar observation was made here. For instance, Figure 3-8(a) and Figure 3-8(b) show the OT image for two sizes of the intentional voids and their preceding layer (voids are cubical-shaped with the size of $400\ \mu\text{m} \times 400\ \mu\text{m} \times 400\ \mu\text{m}$ and $300\ \mu\text{m} \times 300\ \mu\text{m} \times 300\ \mu\text{m}$). As observed, there is a significant drop in OT grey value at the intentional defect zones (locations 1 to 5). These regions are called cold spots due to lower energy deposition in the material, resulting in dimmer monitoring indications. Additionally, Figure 3-8 (c) and Figure 3-8 (d) represent the CT scan slice of the same layer as Figure 3-8(a) and Figure 3-8(b), which confirms the above conclusion. The largest pore volume size, as seen on the CT scans for the $400\ \mu\text{m} \times 400\ \mu\text{m} \times 400\ \mu\text{m}$ defect size, was $7.6 \times 10^7\ \mu\text{m}^3$, which was about 18.75% increase from the intentional defect volume of $6.4 \times 10^7\ \mu\text{m}^3$ ($400 \times 400 \times 400$). While the largest pore volume size for the $300\ \mu\text{m}$ defect size was $1.9 \times 10^7\ \mu\text{m}^3$, which was about 29.63% decrease from the original defect volume of $2.7 \times 10^7\ \mu\text{m}^3$. The same observation is made for the $200\ \mu\text{m}$ defect size where the largest pore volume was $2.6 \times 10^6\ \mu\text{m}^3$ in contrast with the original pore volume of $8 \times 10^6\ \mu\text{m}^3$, showing a 67.5% decrease. This was also captured on the recorded OT images, where the drop in the grey-value intensity were less visible. This implies that the severity of pores on the actual part as detected by the OT monitoring system is dependent on the grey-values magnitude and resolution of the monitoring system. Also, the differences in the defect volume size on the actual part and the original volume size might be because of the self-healing nature of the process.

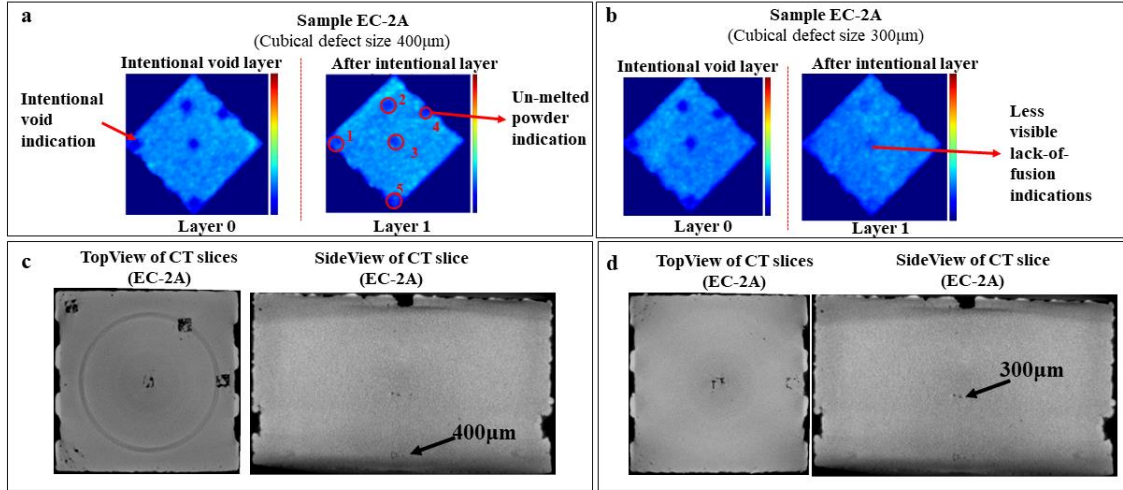


Figure 3-8: Example of lack of fusion intentional defects signature in OT image in sample EC-2A for the layers of/after a) $400\mu\text{m} \times 400\mu\text{m} \times 400\mu\text{m}$ and b) $300\mu\text{m} \times 300\mu\text{m} \times 300\mu\text{m}$, and top view of Micro-CT scan and side view of CT slice for defect size of c) $400\mu\text{m} \times 400\mu\text{m} \times 400\mu\text{m}$ and d) $300\mu\text{m} \times 300\mu\text{m} \times 300\mu\text{m}$

Besides the visualization approach discussed above, the consecutive layer of intentional lack of fusion defects was also analyzed with a colour-coding approach. This approach would enable us to observe the number of layers that the lack of fusion signature persists across the layer sequence. Thus, Figure 3-9(a) shows the colour coding mean OT grey value of the defect locations (3×3 -window) before and after introducing the artificial void sizes of $400\mu\text{m} \times 400\mu\text{m} \times 400\mu\text{m}$ in sample EC-2A (cubical-shaped defects). Figure 3-9 (b) demonstrates the same phenomenon with a line plot.

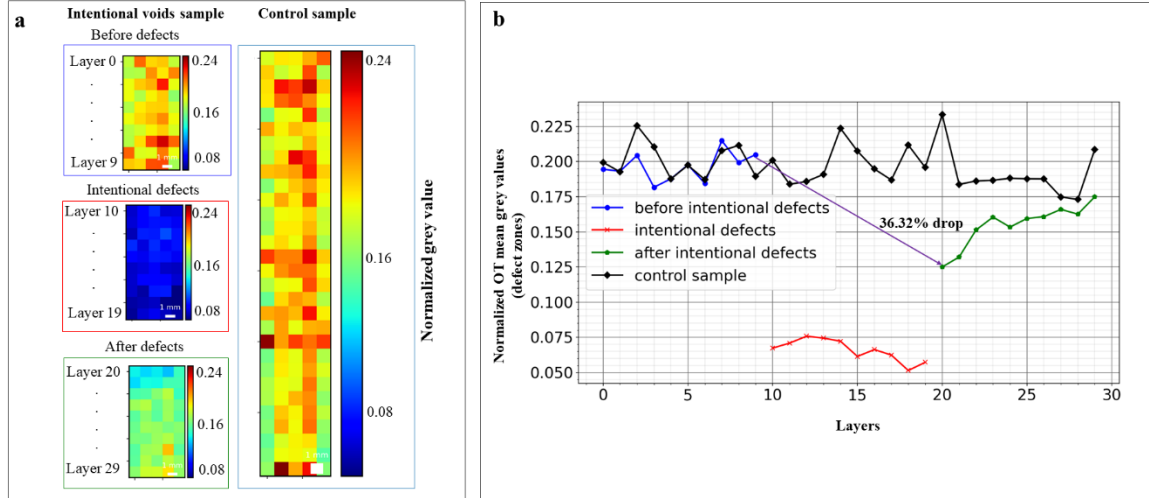


Figure 3-9: Visualization of falling in recorded in-situ OT grey value at defect zones (3 by 3 window) after introducing intentional cubical defects of size $400\mu\text{m} \times 400\mu\text{m} \times 400\mu\text{m}$ in sample EC-2A with a) color coding and b) line plot approaches

According to Figure 3-9, layer 0 to layer 10 are the mean grey values for the zones before introducing the $400\mu\text{m} \times 400\mu\text{m} \times 400\mu\text{m}$ intentional voids, layer 11 to layer 19 are the intentional defect zones, and layer 20 to layer 29 are the layers after introducing the intentional voids. According to Figure 3-9, immediately after the intentional defect's layers (layer 19), there is a significant drop (up to 36.32% drop) in mean OT grey value relative to the control sample (without embedded voids), which persists visibly over about 3 to 4 layers. This is because of less penetrative laser energy into those regions due to the un-melted powder (voids) from the previous layers, thus these layers with low energy density could suffer from lack-of-fusion phenomena. An effective monitoring algorithm needs to consider regions where the OT grey values significantly fall to accurately detect the lack-of-fusion phenomena.

3.2.5.1.2 Keyhole

- Preliminary observation

Keyhole defects can occur when excessive energy is applied to the powder during printing. To recreate the defect, cubical coupons of different sizes ($1000\text{ }\mu\text{m} \times 1000\text{ }\mu\text{m} \times 1000\text{ }\mu\text{m}$, $500\text{ }\mu\text{m} \times 500\text{ }\mu\text{m} \times 500\text{ }\mu\text{m}$, and $250\text{ }\mu\text{m} \times 250\text{ }\mu\text{m} \times 250\text{ }\mu\text{m}$) were imbedded in samples and their laser speed was reduced to increase energy density in the material. Figure 3-10 displays optical tomography images and CT slices for the embedded coupons of $1000 \times 1000 \times 1000\text{ }\mu\text{m}^3$, $500 \times 500 \times 500\text{ }\mu\text{m}^3$, and $250 \times 250 \times 250\text{ }\mu\text{m}^3$ in sample 1 (Table 3-3).

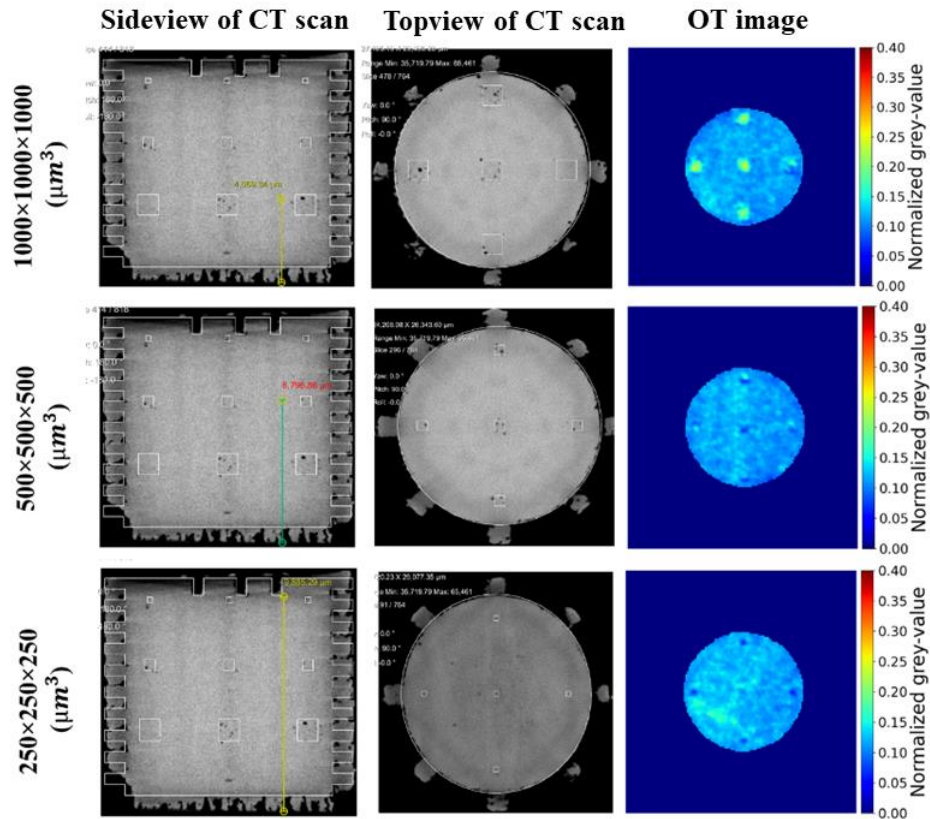


Figure 3-10: Comparison of CT scan and OT image for intentional keyhole defects for sample 1

According to Figure 3-10, the coupon size of $1000 \times 1000 \times 1000\text{ }\mu\text{m}^3$ showed a significant increase in recorded OT grey value, leading to the formation of spherical pores or keyhole defects seen in the CT scan. However, coupon sizes of $500 \times 500 \times 500\text{ }\mu\text{m}^3$ and $250 \times 250 \times 250\text{ }\mu\text{m}^3$ showed a

decrease in recorded OT grey value, possibly due to selecting a large hatch distance of 200 μm , as such the laser might not have melted those coupons while printing, resulting in lack-of-fusion pores seen in the CT scans. From the CT scans, the keyhole pores formed were relatively small, with a maximum pore volume of 960 μm^3 distributed sparsely within the embedded coupon. This implies that the formation of keyhole defects requires sustained high-energy input to the powder.

Similar to section 3.2.5.1.1, a colour coding approach to visualize the grey value levels within the locations of increased energy density is drawn in Figure 3-11(a), and Figure 3-11(b), showing the mean OT grey-value before and after reducing laser speed to increase energy input.

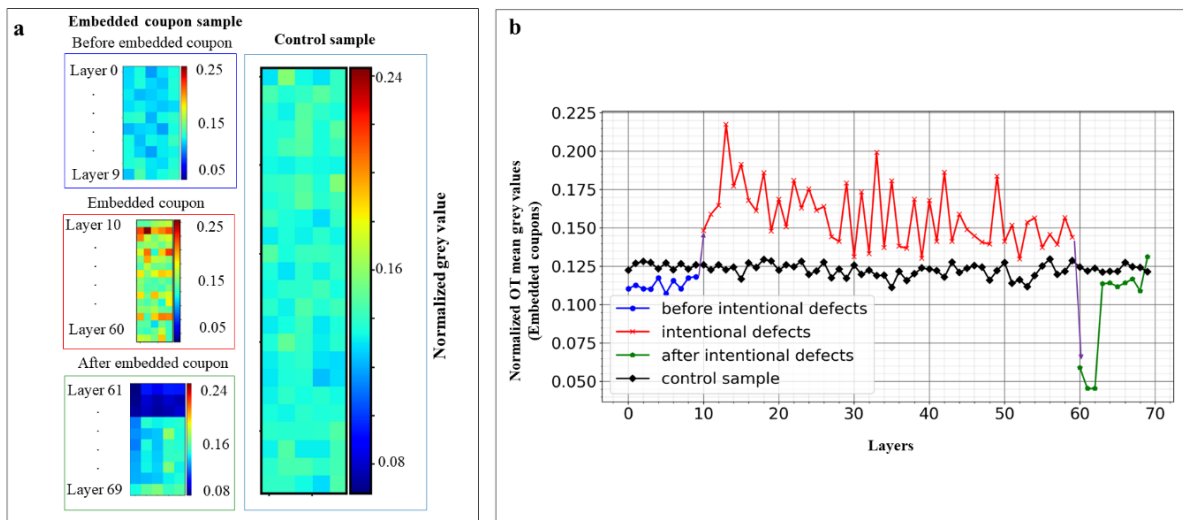


Figure 3-11: Visualization of increasing energy in recorded in-situ OT grey value at defect zones (5 by 5 window) after embedding 1000 μm ×1000 μm ×1000 μm coupons in sample 1 with a) color coding and b) line plot approaches.

According to Figure 3-11, the high energy layers have a corresponding increase in recorded OT grey value, which spikes as the layer-wise images progress (e.g., from layer 13 to layer 60 in Figure 3-11b). As previously mentioned, the CT scans show smaller and randomly scattered pores in the coupons, with a higher concentration at the spike locations, suggesting keyhole defects take longer to form and require sustained high energy grey values over more layers compared to lack-of-fusion defects. Another observation was the drop in OT grey values in three layers (61 to 63) immediately after the high energy density layers as seen in Figure 3-11. This could be because of the high thermal difference between high energy layers and the preceding layer, causing the evaporation of powder deposited at those locations resulting in the lack of fusion pores, as seen in layer 64 in

Figure 3-12. Another explanation could be the geometry mismatch between the embedded coupons and the sample; the coupons might have been shifted in the Z-axis during printing.

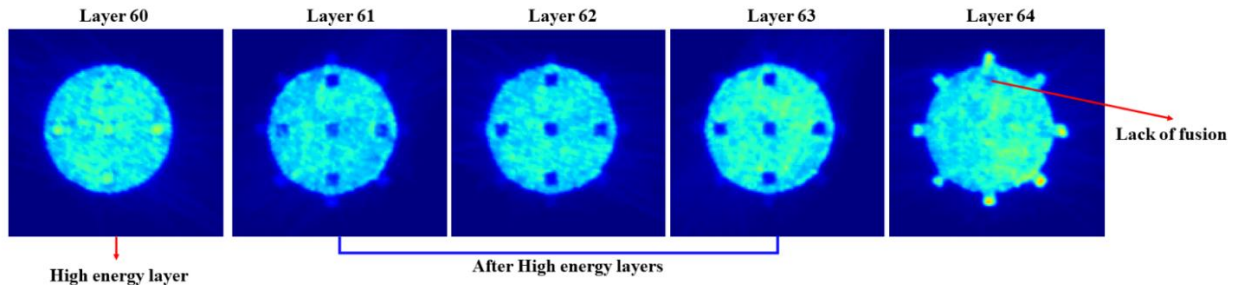


Figure 3-12: Low OT grey values at layers immediately after high energy input

3.2.6 Statistical algorithms

In this section, several statistical algorithms for detecting these abnormal signatures in optical tomography images is presented. An effective monitoring algorithm needs to consider regions where the optical tomography signal gray values significantly fall, and the number of layers this persist to accurately detect the lack-of-fusion phenomena. As such using the moving average mean could be quite effective in detecting these abnormal indications by setting a threshold, such that when the mean optical tomography signal for a given layer exceeds the threshold could indicate possible undesired process phenomena.

3.2.6.1 Part Threshold Indication Detector

As previously mentioned, because of the self-healing nature of the L-PBF process, process deviations using optical tomography does not necessarily lead to defects. Indications which show up once is likely to be healed during the next layer, while indications that persist over several layers are likely to show up as defects in the fabricated part. As thus, the moving average mean could be effective in detecting abnormal OT indications.

This algorithm is based on the moving average of a part, such that at any layer where the part mean is outside a set threshold, could be an indication of possible process deviations. The

algorithm is diagrammatically shown in Figure 3-13. It is a shape invariant algorithm, which implies that it can detect defects of relatively any shape. To effectively apply this method, over 8 parameters must be carefully tuned. Parameters such as the number of layers to be considered for computing the moving average mean, the constants a and c which determines how far away the indications is from the mean before it can be considered abnormal, the minimum size of defect detectable, and parameters that must be excluded from computing the moving average mean such as stripe overlap thickness, and part border thickness.

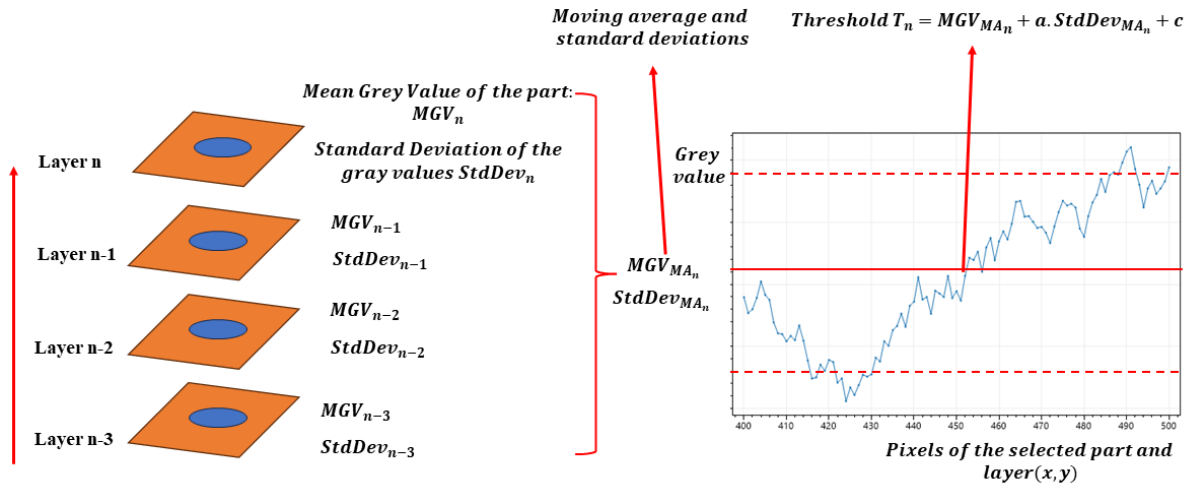


Figure 3-13: Thresholding based detector using moving average mean

This method was applied to detect lack-of-fusion indications in both the intentional and randomized lack-of-fusion experiment. Figure 3-14 shows the moving average mean for EC-2A sample from the intentional defect experiment. A window size of 5 layers was used in computing the moving average mean. We can observe that the moving average mean is like the smoothened version of the mean grey values of the part such that outside certain threshold set by parameter a and c could be an indication of possible abnormal process phenomena. Figure 3-15 shows the thresholds computed when $a = 2, c = 100$ for a layer preceding the intentional void layers, and Figure 3-16 shows the output of the algorithm.

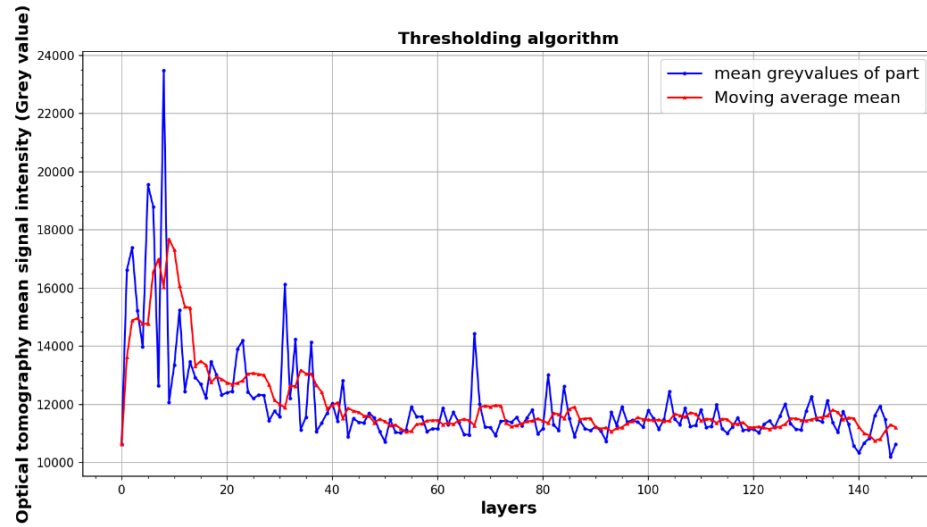


Figure 3-14 Moving average mean illustration

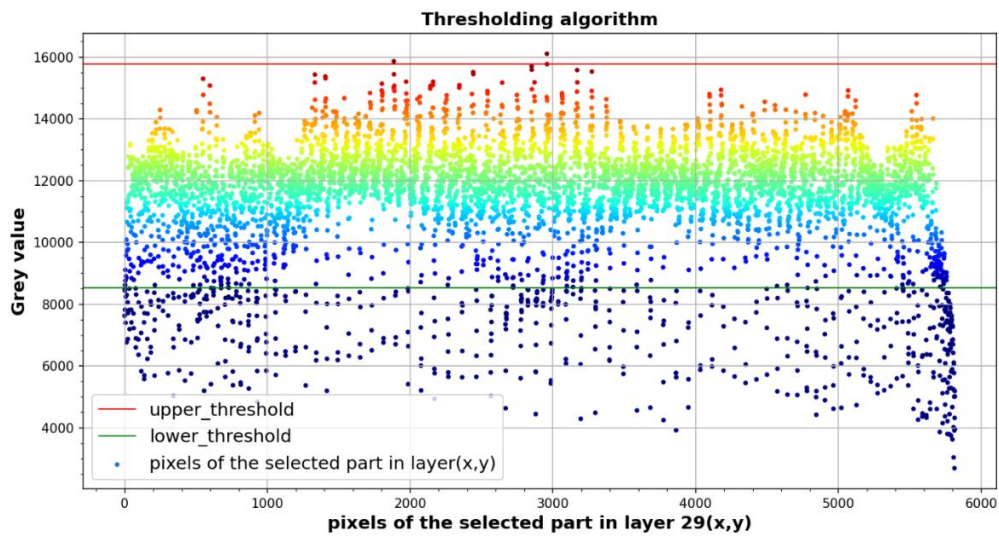


Figure 3-15 Upper and lower thresholds for part pixels of layer 29

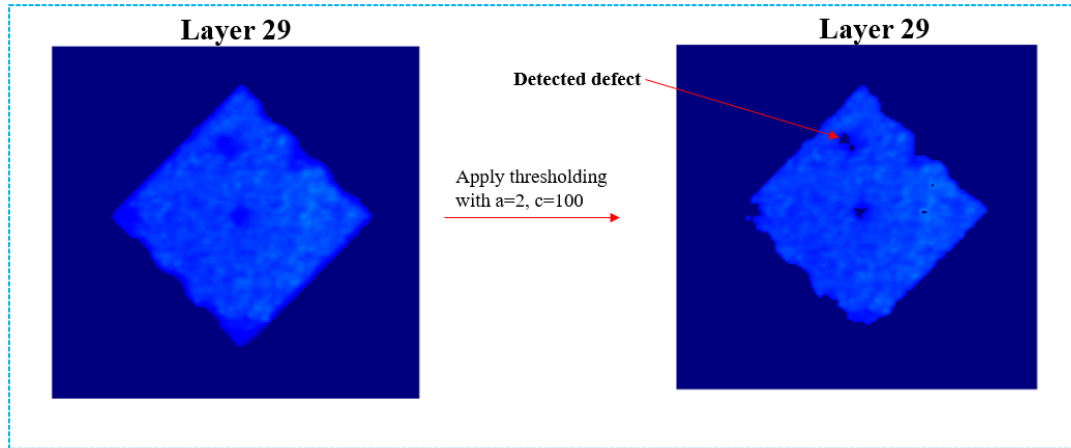


Figure 3-16 Thresholding applied to a layer

As previously mentioned, the thresholding algorithm uses over 8 parameters that must be carefully fine-tuned, among these parameters are the part border thickness, stripe overlap thickness, which are indications that must be excluded from the part to avoid false positives before calculating the moving average mean. Without having the machine coordinates, these parameters might be difficult to exclude with needing extra advanced image processing. To avoid this challenge, we can instead use the pixel-based mean instead of the part-based mean when computing the moving average mean.

3.2.6.2 Pixel-Based Threshold Indication Detector

This is a slight modification to the part-based thresholding described above, instead of using the part-based mean, we use the pixel-based mean for computing the moving average mean and standard deviation. Using this approach, natural occurring phenomenon within the process such as overlap lines, edges, contours, powder-bed regions can automatically be considered in the analysis. Also, it could be useful when machine coordinates are unavailable for excluding several unwanted parts of the signal.

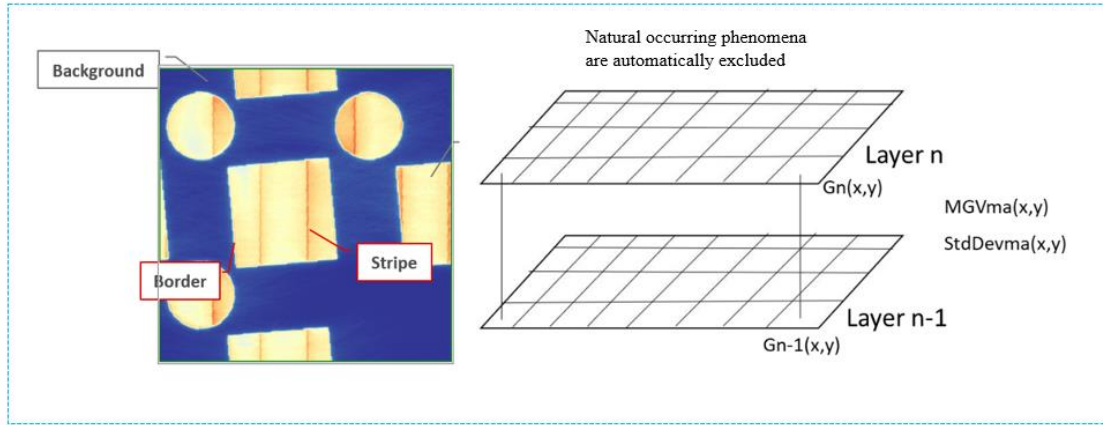


Figure 3-17:Pixel-based thresholding.

Like the part-thresholding method, the threshold for the detection criterion can be set as follows:

$$\text{Threshold} = T_n = MGV_{ma(x,y)} + a \cdot StdDev_{ma(x,y)} + c$$

This method was applied to detect lack-of-fusion indications as shown in Figure 3-18. A drawback of this approach is that the detection criterion is very sensitive to changes in parameters of the algorithm.

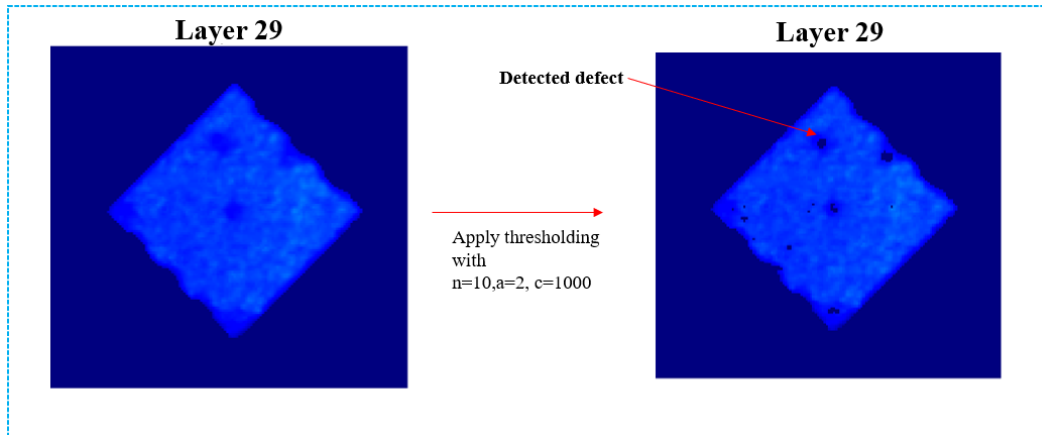


Figure 3-18 Pixel-based thresholding applied to a layer

3.2.6.3 Automatic Derivation of Parameters for Thresholding-Based Monitoring Algorithm

The most important parameters for the thresholding-based algorithm include the:

- m – Number of layers for calculating the moving average mean.
- The constant “ a ” for determining how far away from the standard deviation would a signal be considered abnormal.
- The constant “ c ” which allows more flexibility in setting an optimal threshold.

Selection of these parameters are crucial for effective correlation of recorded optical tomography data with possible process defects. We would attempt to derive an optimization model that can assist the user of these algorithms to automatically select proper values depending on the given recorded optical tomography data. Given successive layers of recorded optical tomography image, the goal is to maximize the correlation or minimize the variation between them.

Goal: Homogeneous signals

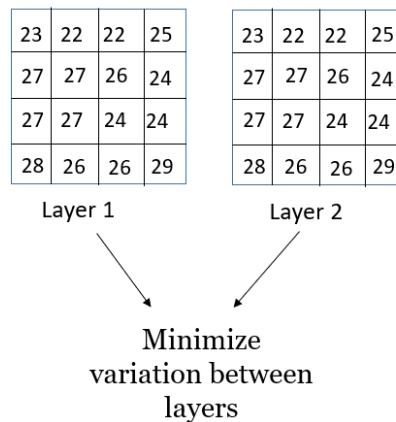


Figure 3-19: Basic objective function for thresholding algorithm parameters optimization.

The basic idea is to maximize the moving average mean optical tomography signal for a particular threshold value, such that the moving average window would have similar mean.

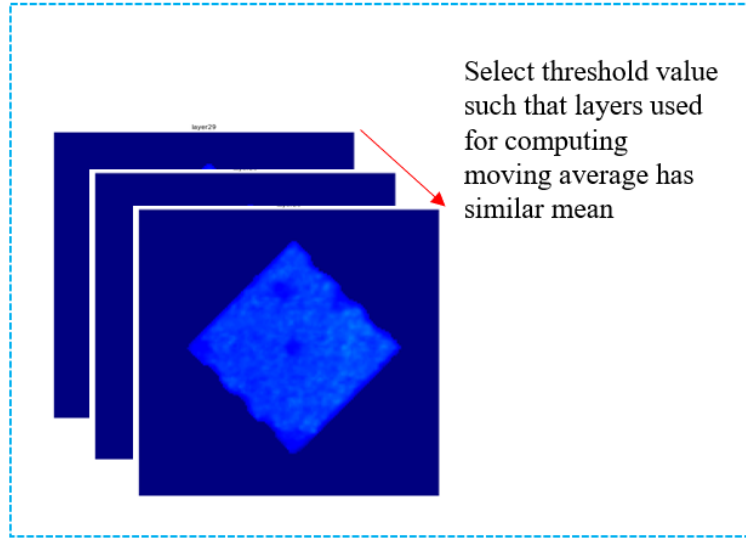


Figure 3-20 Similar mean for moving average layers after thresholding

Let's X_{ij} be a given optical tomography image, then the objective function can be written as:

$$Z = \max \sum_{i=1}^N \frac{1}{m} \sum_i^m \bar{X} \quad \forall x_{ij} \in X: L \leq x_{ij} \leq U \quad \text{Equation 3-2}$$

where $N =$ Total number of recorded OT layers

$m =$ Number of layers for calculating the moving average mean

$X =$ Recorded OT indications for layer j

Equation 3-2 is subject to

Subject to:

$m < N,$ $N =$ Total number of recorded OT layers

$L \leq x_{ij} \leq U$ where $x_{ij} \in X_j, L \& U -$ lower and upper thresholds for OT signal

$L = \bar{X}_j - a * \text{std}(\bar{X}_j) - c$

$U = \bar{X}_j + a * \text{std}(\bar{X}_j) + c$

$$\bar{X}_j = \sum_m mean(X_j)$$

$$a \geq 0, c \geq 0$$

Solving Equation 3-2 would yield optimal values for m, a, and c.

3.2.6.3.1 Solution of Optimization Model using Genetic Algorithm

The objective function from the previous section was solved using genetic algorithm, which are adaptive heuristic search algorithms based on the idea of natural selection and genetics. We then reapplied these optimization model for parameter selection for the thresholding based. Figure 3-21 shows the results derived from running the optimization model. The optimization model was ran using a population size of 100, mutation probability of 0.1 and crossover probability of 0.5. Using the model, we were able to automatically tune the thresholding detector to identify both the intentional and randomized defects. The objective function used in this optimization process seeks to maximize the similarity between the moving average signals of successive layers. Specifically, the objective is to maximize the moving average mean signal while ensuring that the variation within the moving average window is minimized. This approach helps in maintaining consistent signal strength across layers, which is critical for accurate defect detection. The objective function for the model is still a work in progress, with ongoing efforts to refine and improve its performance. Future work will focus on enhancing the accuracy and reliability of the model by incorporating additional parameters such as input process parameters, also other statistical analysis would be explored.

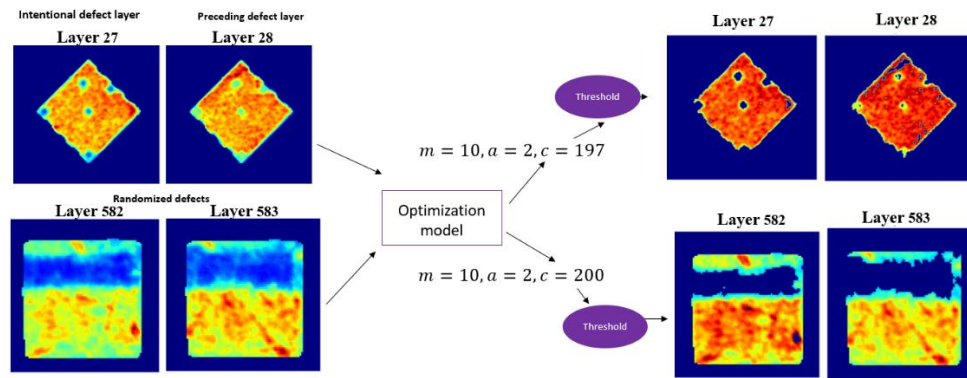


Figure 3-21 Application of optimization model for automatic parameter selection for part-thresholding detector

3.2.6.4 Other Methods

Other analytical-based methods for correlating optical tomography data with process defects such as lack of fusion and keyhole includes:

- **Simple Indication Detector**

Another method for correlating optical tomography indications with possible process defects is based on the second-order derivative that identifies gradient changes. The method assumes that defective optical tomography indications would significantly stand out from the normal indications as such would have an abnormal gradient change at that region. It involves convolving the second-derivative kernel over the recorded image to detect abnormal gradient changes. It is a multi-scale indication detector that can be used to detect circular abnormal indications at any scale. The algorithm is diagrammatically shown in Figure 3-22.

- **Hand-Designed Kernels**

Another effective approach for correlating optical tomography indications to abnormal process deviations involves using hand-crafted kernels to convolve the recorded OT image. It has the advantage of requiring only two parameters for its detection criterion. The kernel is shown in Figure 3-23. The algorithm compares the difference between the average of the neighborhood pixel, with the pixel of interest at the center of the kernel, then the neighborhood average is multiplied by a constant between 0 and 1. If the difference is less than 0, then it implies the surrounding pixels are of a greater magnitude than the pixel of interest, as such that particular pixel could be considered as suspicious. If the detected indication shows up for multiple specified layers, then we can assume that it may be an abnormal signal. This approach has the advantage of requiring only 2 parameters for fine-tuning. A drawback of this approach is that we can detect defect sizes within a 3×3 window, and the threshold parameter must be carefully selected for optimal detection criterion.

- **Simple Indication Detector**

This algorithm is based on OpenCV SimpleBlobDetector[81] that detects an indication by checking how prominent an object stands out against its background. It is a shape-invariant detector used for analysis of single layer without considering other previous or subsequent layers.

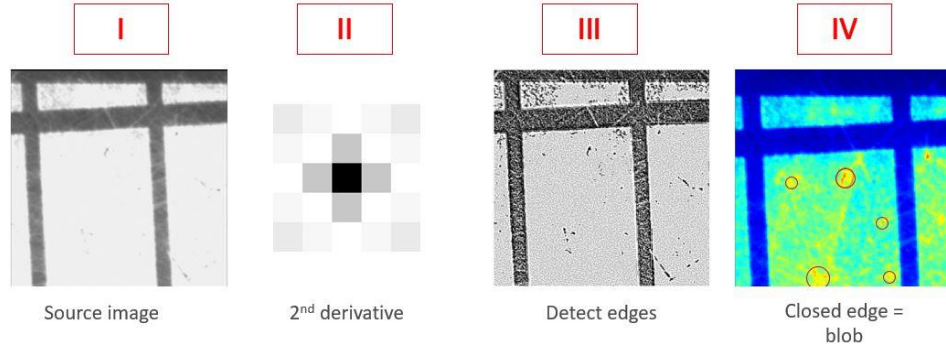


Figure 3-22: Derivation indication detector illustration.

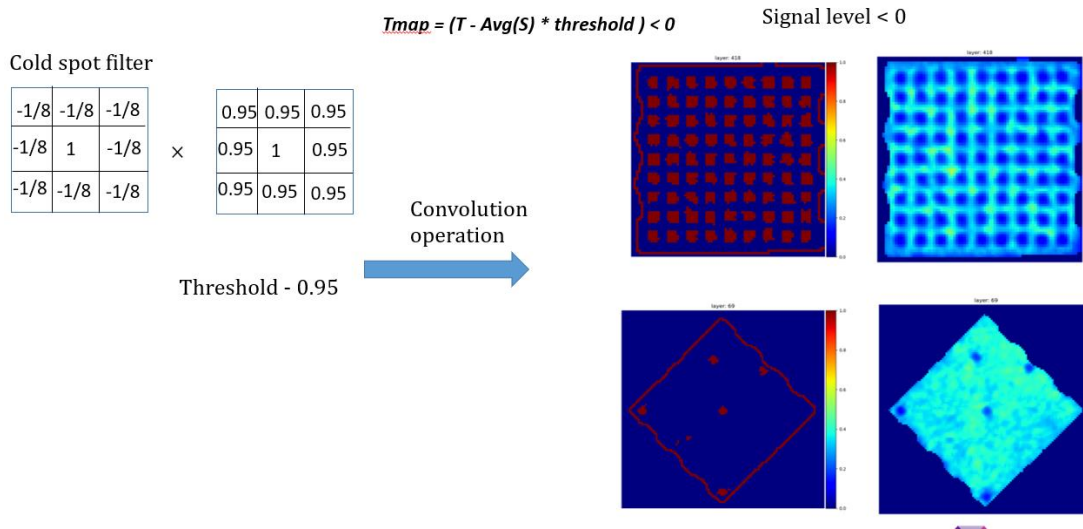


Figure 3-23 Hand-designed kernels

3.2.7 Accuracy of Monitoring Algorithms for Identification of Defects within the Process.

The part-based thresholding, derivation and simple indication algorithm are the three monitoring algorithms available in the monitoring suite (EOS) used in this research for correlating the indications to process defects. Before developing our custom ML algorithm, we would determine the effectiveness of these algorithms. We labelled the intentional voids locations as 1 to 5, and we only considered locations at the preceding layer, immediately after the intentional voids, since as previously mentioned, because of less penetrative laser energy into those regions because of the

un-melted powder (voids) from the previous layers, thus may result in the lack-of-fusion phenomena. For determining the effectiveness of the monitoring algorithms, we used the accuracy metric which is computed as:

$$Accuracy = \frac{Identified\ defects}{Total\ number\ of\ defects}$$

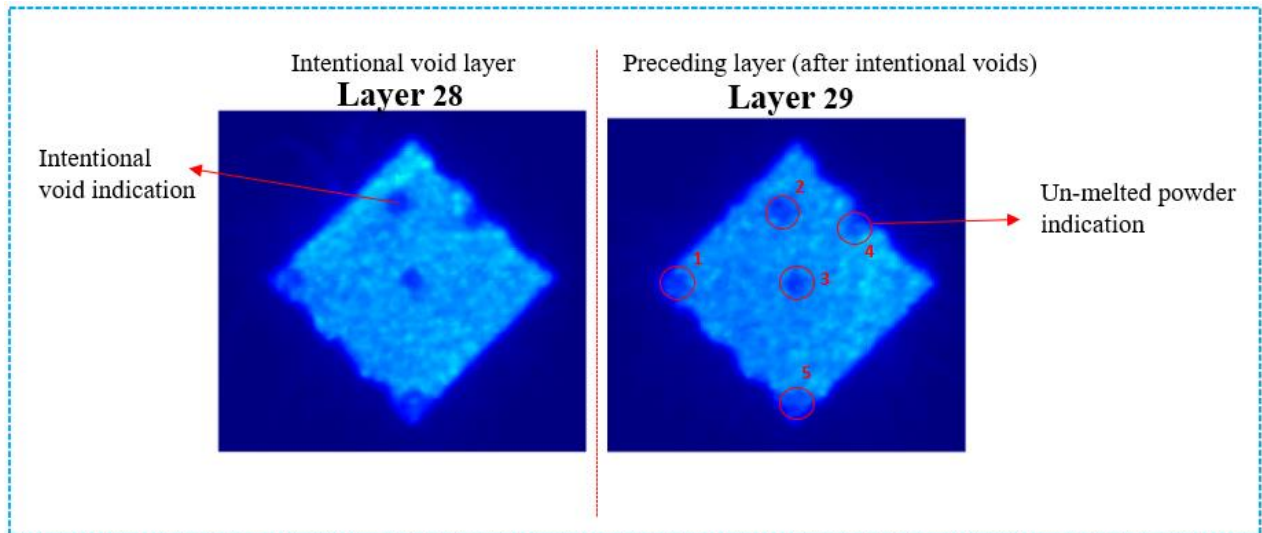


Figure 3-24: Defect locations

Table 3-7, and Table 3-8 show the accuracy of the different monitoring algorithms available in the EOS monitoring system in detection of intentional lack of fusion defects. The two main parameters for this algorithm are the hot and cold spot constant and standard deviation thresholds for determination of the detection criteria. Varying this parameter improved the accuracy of the monitoring algorithm, but also resulted in increase in the number of false indications registered as seen by the increase in the total number of indications.

Table 3-7: Accuracies for threshold Indication detector for several parameters' selection

Parameters	Defect size (um)			
Part border thickness		3	3	3
Stripe Overlap thickness		3	3	3
Moving average layers		5	5	5
Cold spot threshold constant		100	50	50
Cold spot threshold std multiples		2	2	1
Hot spot threshold constant		100	50	50
Hot spot threshold Stdv multiples		2	2	1
Minimum extent		5	5	5
Part statistics border		3	3	3
Time run		1/30/2022 19:22	1/30/2022 21:24	1/30/2022 21:54
Detection	Cold spots	locatons detected (capping layers)		
EC-2A	400	1,2,5,4	4,5,2,1	1,5,3,4,2
ES-2A	400	4	4,	5,3,1,2,4
EY-2A	400	2,5,1,4,3	5,3,2,1,4	2,4,3,1,5
EC-2A	300	None	None	4,1,5,3
ES-2A	300	None	None	1,4,2,5,3
EY-2A	300	None	None	1,5
EC-2A	200	None	None	None
ES-2A	200	None	None	4,2
EY-2A	200	None	None	5
	Accuracy	0.23	0.23	0.65
	Total number of indications	2059 indications	2251 indications	29373 indications

Table 3-8 Accuracies for derivation Indication detector for several parameters' selection

Parameters	Defect size (um)					
Part border thickness		3	3	3	3	3
Stripe Overlap thickness		3	3	3	3	3
Minimum radius		3	3	2	3	3
Maximum radius		50	50	50	50	50
Scale space step		1	1	1	1	1
Threshold Minimum		0	0	0	0	0
Threshold Maximum		50	50	50	25	75
Max border distance		0.7	0.4	0.4	0.4	0.4
Detection Criterion		Determinant of Hessian	Determinant of Hessian	Determinant of Hessian	Determinant of Hessian	Determinant of Hessian
Time run		1/31/2022 10:58	1/31/2022 11:55	1/31/2022 12:30	1/31/2022 14:54	1/31/2022 15:52
Detection	Cold spots	locatons detected (capping layers)				
EC-2A	400	4,2	2,4	2,3	2,4	2
ES-2A	400	None	None	5,1,3,4	4	None
EY-2A	400	4,3	3,4	3,1,4,2	4,3	4,3
EC-2A	300	None	None	None	None	None
ES-2A	300	None	4,1	4,1,3,5	4,1	1,4
EY-2A	300	None	None	None	None	None
EC-2A	200	None	None	None	None	None
ES-2A	200	None	None	4,1,3,5	4,	None
EY-2A	200	None	None	None	None	None
	Accuracy	0.09	0.14	0.4	0.18	0.12
	Total number of indications	2429 indications	2574 indications	10322 indications	7028 indications	1070 indications

Tuning of this algorithm was quite challenging to get a good detection criterion. The method has several parameters that must be properly tuned to get a good criterion. Accuracy of 0.4 was the best obtainable criterion but resulted in the highest number of indications detected thus increasing the number of false positive.

The third monitoring algorithm available, simple indication detector was not able to detect the any defect location for several selection of parameters.

3.2.8 Limitations of the Monitoring Algorithms

The algorithms available in the EOS monitoring requires careful parameters value selection to able to detect process deviations that could lead to defects. Each of these algorithms have at least 8 parameters that needs to be fine-tuned to avoid false detection, which is usually done empirically through series of trial-and-error experiments. This could be laborious, time-consuming, tiring, and the detection capability does improve as more OT images are collected. A more efficient approach for analyzing this OT indications is desired, that would require less amount of parameters tuning and whose detection capability would improve as more OT indications are collected. Machine learning methods could be quite useful in developing detection criterion with minimal parameter tuning.

3.3 Summary

In this chapter, we introduce the monitoring system used for the research. We also discussed the design of experiments, showing the monitoring system capability in detecting the lack of fusion and keyhole defects. We then investigated the sensitivity of the optical tomography indications to variation in process parameters, concluding that there was significant variation depending on the process parameter used, as thus lack-of-fusion signal may vary. We also presented the effectiveness of the statistical monitoring algorithms available in the detection of defects, showing the challenges of careful parameter selection for arriving at successful detection criterion. We desire data-driven methods whose performance increases with increase in recorded dataset and requires no parameter selection for its detection criterion.

4 Optical Tomography and Machine Learning for In-situ Defects Detection in Laser Powder Bed Fusion: A Self-Organizing Map and U-Net Based Approach

4.1 Introduction

As outlined earlier, the statistical approach for linking optical tomography (OT) images with process defects involves substantial parameter tuning, which must be tailored to each set of process parameters. An approach that simplifies the analysis of OT signals, minimizing the need for extensive parameter adjustments and enhancing detection performance with the accumulation of more OT data, is preferable. In this chapter, we introduce a machine learning pipeline designed to boost detection accuracy without the necessity for parameter tuning, offering adaptability to various parameter selections with minimal or no adjustments needed.

4.2 Machine Learning algorithm for detection of lack-of-fusion and keyhole defects phenomena.

In this section, a machine pipeline is established, as depicted in Figure 4-1 that is composed of two primary elements: a self-organizing map (SOM) neural network-based clustering model and a U-Net [56] deep learning model for segmentation. The primary objective is to forecast the presence of lack-of-fusion and keyhole defects within recorded optical tomography (OT) images. The workflow of this pipeline commences with the training of the SOM model to extract defect signatures from the OT images. Subsequently, these detected defect signatures were validated using CT scans. Once validated, these defect signatures serve as the foundation for our dataset, which utilized to train a U-Net neural network. This network's role is to predict porosity in unseen OT images. To augment the accuracy of our defect detection, an additional fully connected neural network into the U-Net model's output was incorporated. This auxiliary network predicts the SOM cluster centroids of the SOM maps generated, ensuring that the predicted SOM clusters closely align with the target SOM clusters.

In the following sections, the SOM clustering analysis and U-Net will be discussed.

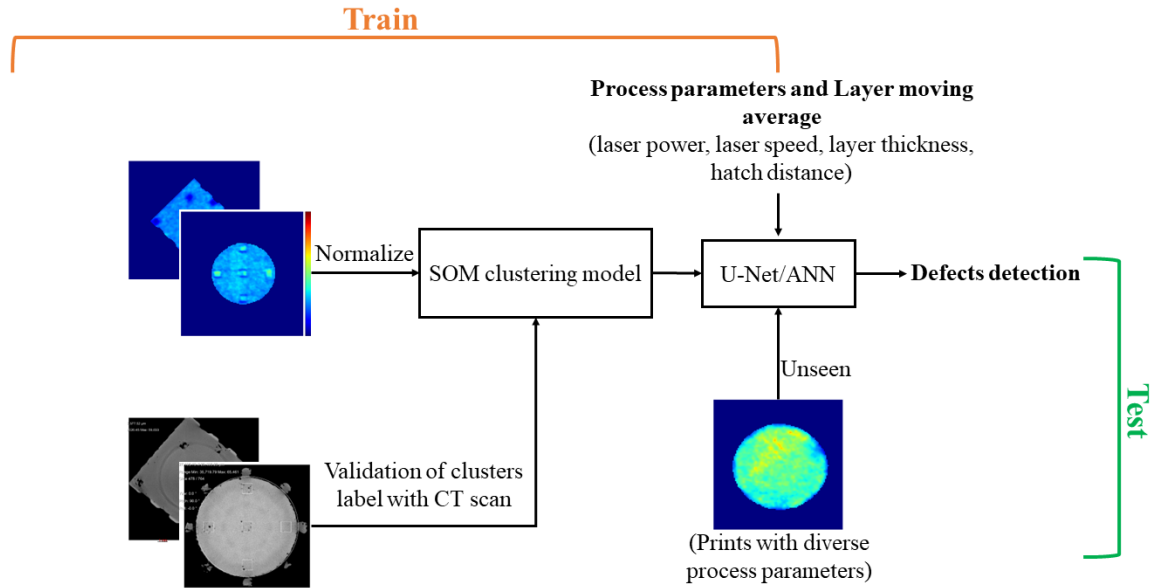


Figure 4-1: Machine-learning pipeline showing combined application of SOM and U-Net algorithms for defect detection.

4.2.1 SOM clustering model

As previously noted, the OT image may exhibit low grey values, referred to as "cold spots," which typically indicate lower energy deposition in the material, leading to lack of fusion defects. Conversely, high grey values, known as "hotspots," may result from high energy input into the material, leading to the formation of keyhole defects. Detecting these unusual grey-value patterns is crucial for improving process quality. One approach to achieving this goal is to empirically set thresholds for the optical thermography (OT) images and visually assess the outcomes by comparing them with CT scans. However, this manual inspection process is labor-intensive and unsuitable for real-time defect detection during manufacturing. Furthermore, adjusting these thresholds becomes necessary whenever there are modifications to the manufacturing process, such as changes in process parameters.

Another strategy entails automatically identifying these distinctive signatures by grouping similar data points together. This approach relies on the assumption that there is a clear demarcation between normal data points and abnormal data points, with the latter being

significantly dissimilar to the former. This assumption appears valid since the nature of OT images dictates that anomalies, whether hot or cold spots, should exhibit marked deviations from the characteristics of normal data points.

One approach within unsupervised machine learning to achieve this goal is clustering. Clustering models aim to automatically group instances that share close relationships into clusters. Several clustering algorithms[82], such as K-Means, Density-Based Spatial Clustering (DBSCAN), and Self-Organizing Maps (SOM), are utilized to assess similarity or measure the distance between instances in feature space, thereby identifying distinct regions.

K-Means operates by initially forming clusters from randomly chosen centroids, which act as the initial cluster centers. These centroids are then iteratively optimized through repetitive iterations. DBSCAN, on the other hand, employs a density-based approach to clustering, grouping points based on their proximity using a distance metric, often the Euclidean distance, and a specified minimum number of points. However, it is important to note that each of these clustering methods can become computationally intensive, particularly when dealing with large datasets, as they demand substantial memory resources.

Conversely, the Self-Organizing Map (SOM) [71], also known as Kohonen maps, represents a specific form of unsupervised learning frequently employed for the purpose of dimensionality reduction and the visualization of high-dimensional data. In this model, a neural network is composed of one input layer and one output layer. The output layer is structured as a two-dimensional grid, with each grid node representing a unit. The input layer is fully connected to the output layer, and the weights of the connections linking the input and output layers are adjusted during the training process. The input space, reduced to a lower dimension, is typically discretized and referred to as a "map" SOM utilizes competitive learning, where a neighborhood function preserves the topological characteristics of the input space, distinguishing it from conventional artificial neural networks that employ error-correction learning.

Given the advantages offered by this algorithm, the decision was made to apply SOM to the OT images. To achieve this, the $n \times n$ image was first reshaped into a 1D vector and concatenated together, as illustrated in Figure 4-2.

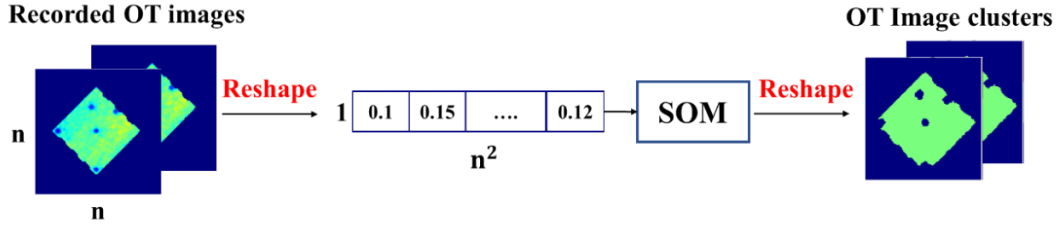


Figure 4-2: Illustration of training of self-organizing maps applied to OT data

Before applying the SOM algorithm, the number of clusters should be carefully defined. To choose the appropriate number of clusters, a technique proposed by a Belgian statistician [83] called the silhouette coefficient was used. The silhouette score measures how similar a data point is to its own cluster compared to other clusters. Its final value ranges from -1 to 1, where a high value indicates that the point is well-matched to its own cluster and far away from neighboring clusters, while a low value indicates that the data point may have been assigned to the wrong cluster. A value of 0 indicates that the point is on or very close to the decision boundary between two neighboring clusters. The silhouette coefficient can be computed by:

$$silhouette\ score = \frac{b - a}{\max(a, b)}$$

Equation 4-1

where a is an average intra-cluster distance (the average distance between each point within a cluster), and b is the average distance to the closet cluster of the data points except for its own clusters.

4.2.1.1 SOM clustering analysis on the original OT images.

Figure 4-3 demonstrates the silhouette analysis conducted on SOM clustering for the original OT images in both the intentional lack of fusion and keyhole defect experiments (specifically, sample EC-2A and sample 1). Each color represents a distinct cluster identified by the SOM clustering algorithm, where clusters group samples with similar characteristics based on the input features. Within Figure 4-3, an inadequate choice of the number of clusters becomes evident, resulting in clusters with silhouette scores falling below the average and significant fluctuations in the silhouette plot's sizes. A visual examination of the plots reveals that either of

the clusters (clusters 4, 6, 7, or 8) would be appropriate for these samples, as their scores are quite similar, hovering around 0.5.

Figure 4-4 showcases the outcome of applying the SOM algorithm to the initial OT image data. To segregate the abnormal data points from the normal ones, we opt to select the upper cluster (depicted in red) for hotspots and the lower cluster for cold spots (displayed in blue). The remaining clusters correspond to the normal data points. To categorize subsequent recorded OT data, a method that involves calculating the Euclidean distance between the data points and the clusters, thereby assigning a label to the points closest to the respective centroids is employed. However, it is important to acknowledge a limitation in this application of SOM. Due to the stochastic nature of the process and potential signal fluctuations within the monitoring system, the centroids of these clusters can experience substantial shifts. To address this issue, a moving average normalization technique was employed, which will be discussed in the following section.

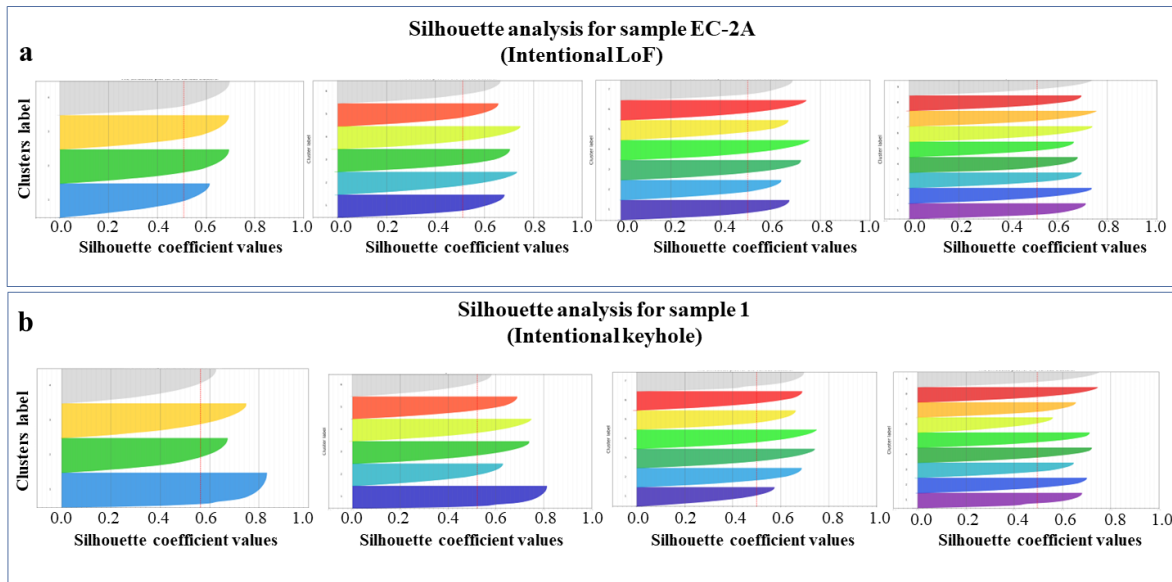


Figure 4-3: Silhouette analysis of SOM clustering algorithm for samples printed with a) intentional lack of fusion (sample EC-2A), b) intentional keyhole (sample 1)

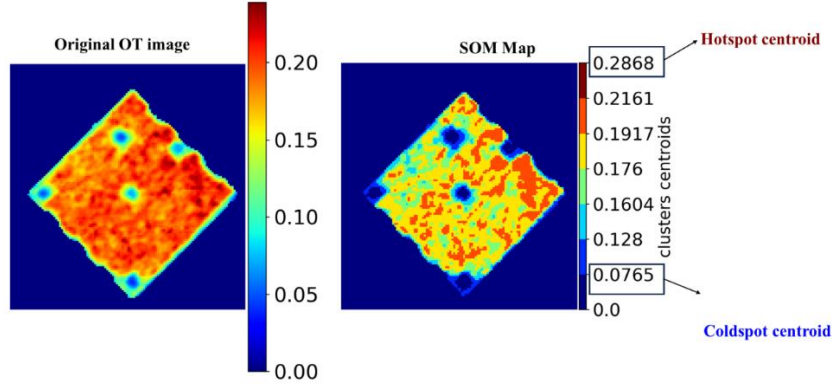


Figure 4-4: Example of SOM applied to original OT image.

4.2.1.2 SOM clustering analysis on normalized OT images.

As previously mentioned, the OT image was normalized by moving average to smooth out fluctuations and make abnormal signatures more pronounced by applying Equation 4-2:

$$I_N^i = \frac{|I_N^i - MGV_{MA_i}|}{2^{16} - 1} \quad \text{Equation 4-2}$$

where I_N^i is the OT image at layer i and MGV_{MA_i} is the moving average grey value for a selected window length prior to layer i . Where:

$$MGV_{MA_i} = \frac{1}{w} \sum_{n=1}^w I_{i-n}^i \quad \text{Equation 4-3}$$

Where w is the number of OT images considered prior to layer i .

In Figure 4-5, we can observe the smoothing impact resulting from the implementation of moving average normalization on the recorded OT data. This process effectively averages out the spikes present within the data, thereby diminishing the probability of signal fluctuations adversely affecting the stability of the SOM cluster centroids. Figure 4-6 (a and c) represents the raw OT images and (b and d) demonstrates normalized OT images after applying moving average with the optimized window size of 5 layers. As shown in the images, the regions of abnormalities are clearly visible after normalization, resulting in relatively easier selection of appropriate number of

clusters, since the abnormal signatures are well separated from the background. It's important to emphasize that the choice of window size for the moving average must be made judiciously since opting for a large value could result in the loss of certain signal information.

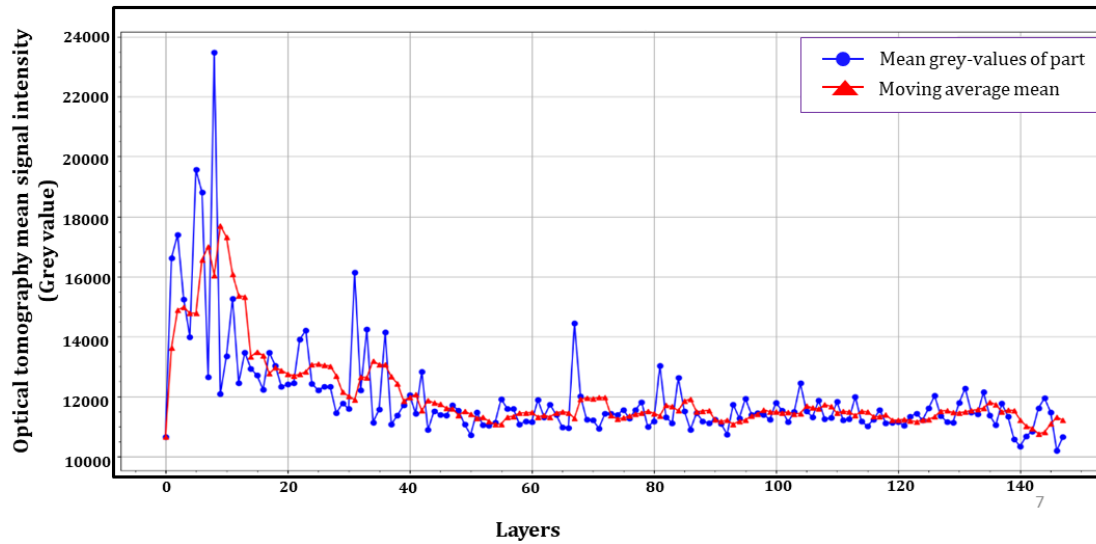


Figure 4-5:Moving average normalization applied on mean OT grey-values.

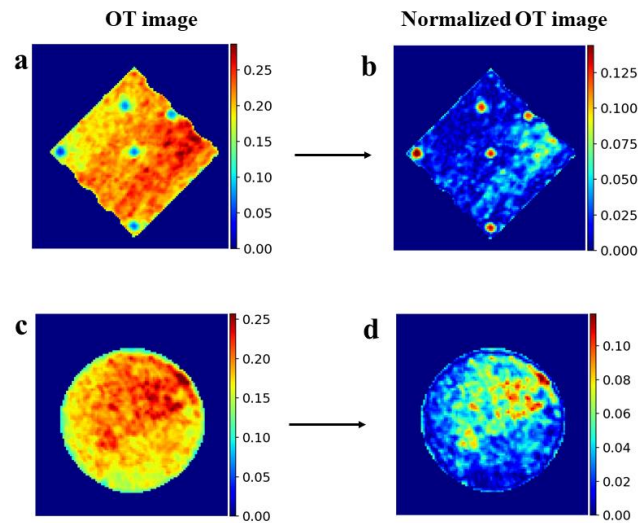


Figure 4-6:raw recorded OT images for sample EC-2A (intentional lack of fusion), b) OT images after normalization for sample EC-2A, c) raw recorded OT images for sample R7 (randomized keyhole), and d) OT images after normalization for sample R7

Figure 4-7 depicts the results of the silhouette analysis conducted on SOM clustering applied to the normalized images in both intentional and randomized defect experiments. Upon visual inspection of the plots, it becomes evident that the silhouette scores, averaging around 0.6, exhibit a slight improvement compared to when SOM is directly applied to the original OT images. This enhancement also significantly contributes to the efficiency of the computational process.

An examination of the plots suggests that either two or three clusters would be suitable, given their similar scores. Notably, the silhouette score for two clusters is marginally superior, even though clusters with scores falling below the average are present in this scenario.

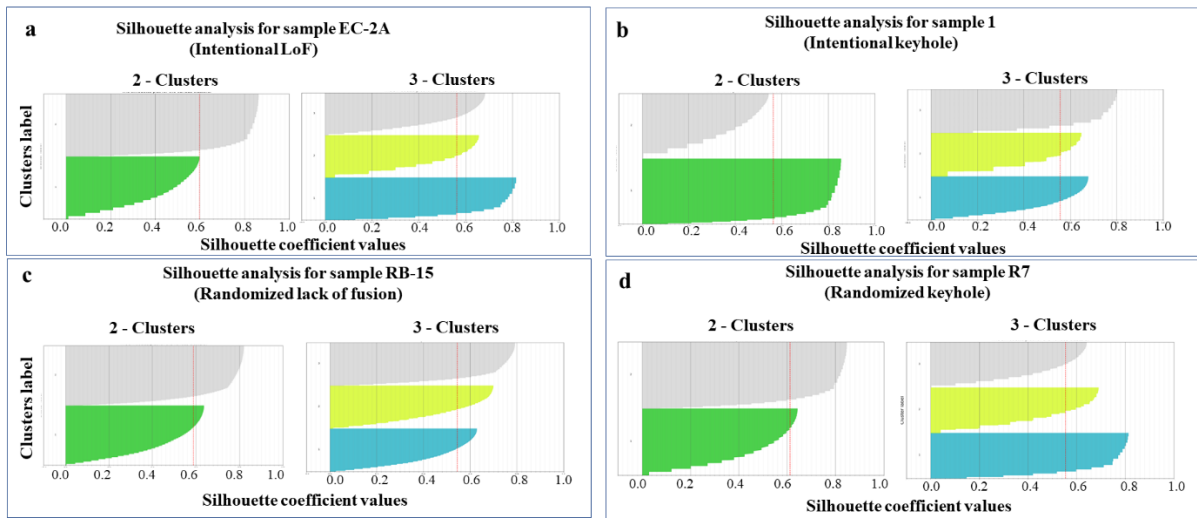


Figure 4-7: Silhouette analysis of SOM clustering algorithm for samples printed with a) intentional lack of fusion (sample EC-2A), b) intentional keyhole (sample 1), c) randomized lack of fusion (RB-15), and d) randomized keyhole (sample R7)

Following numerous experimental trials, a decision was made to opt for a two-cluster approach to segregate the abnormal regions within the recorded OT data. This segmented data will subsequently serve as the training dataset for the U-Net segmentation model, a topic that will be elaborated upon in the forthcoming section.

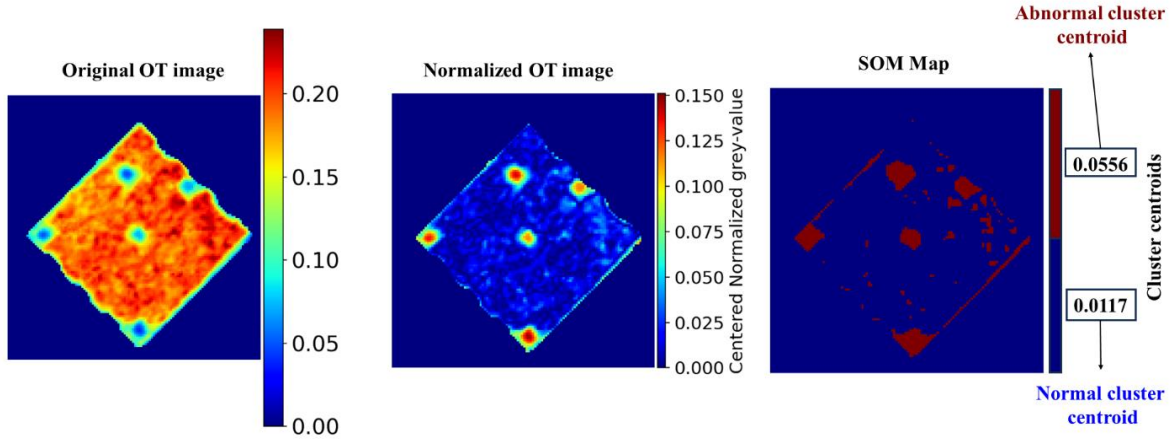


Figure 4-8: Example of SOM applied to normalized OT image.

The architecture of the SOM model is shown in Figure 4-9, it consists of only two neurons for separating the abnormal regions from the OT data.

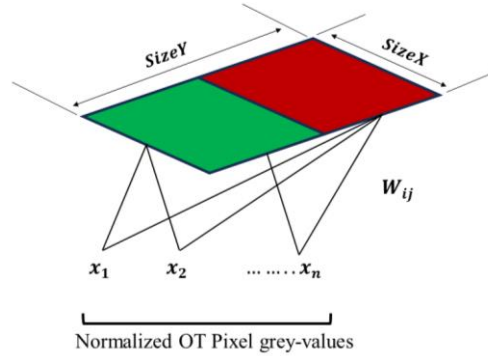


Figure 4-9: SOM Topology for clustering normalized OT image

4.2.1.3 Investigating the stability of the SOM clustering algorithm across process parameter variations

The laser-material interaction is affected by several parameters, including laser power, scan velocity, hatch distance, and layer thickness, which largely influence the amount of energy input in the process given by Equation 3-1 to measure the volumetric energy density (VED) [22]. Thus, understanding the effects of variations in process parameters on the SOM algorithm is crucial in developing effective monitoring algorithms.

To illustrate this point, Figure 4-10 displays the centroids of the two SOM clusters for samples RB-01 to RB-17. In Self-Organizing Map (SOM) clustering, the centroid represents the average position of all data points within a cluster, essentially capturing the cluster's central tendency. These centroids are used to summarize the characteristics of each cluster and provide a simplified representation of the underlying data structure. By analyzing the centroids, we can gain insights into the common features and patterns within each cluster, facilitating a better understanding of the relationships among the samples. These samples were produced using diverse process parameters to evaluate their impact on recorded optical tomography (OT) images. It's important to note that the SOM model was retrained for each individual sample. The numbers on top of the bar plots show the calculated VED for each sample. Notably, we observed significant variations in the cluster centroids across these samples, which can be attributed to the inherent stochastic nature of the process and its sensitivity to variations in parameters. It becomes necessary to retrain the SOM model for each new sample to ensure its effectiveness in detecting anomalies within the process. To overcome this limitation, U-Net/ANN model is adopted, which will be discussed in the upcoming section. This model offers the flexibility to handle a wide range of process parameter variations, thus addressing the challenges posed by the variability in the data.

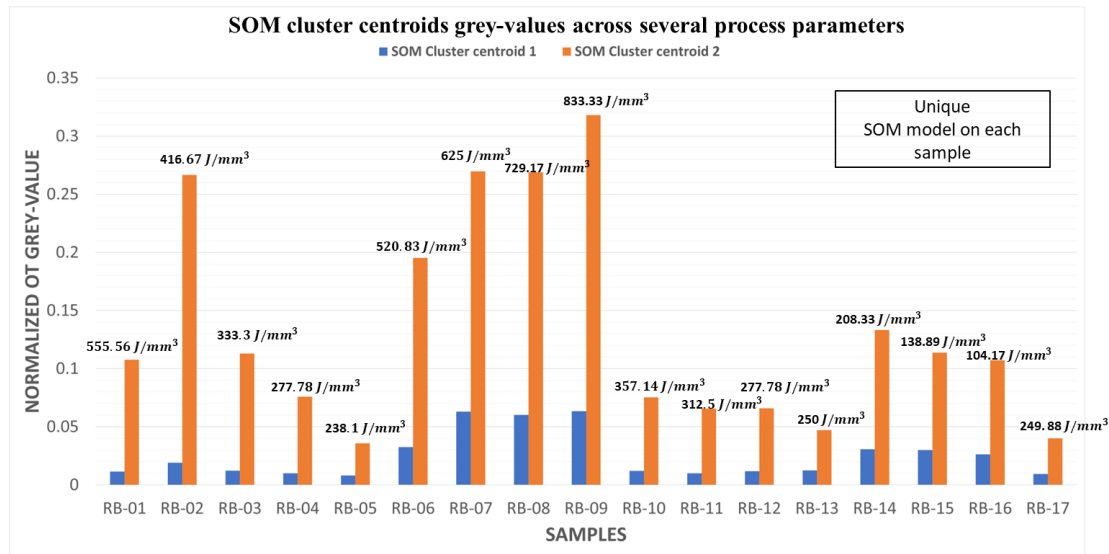


Figure 4-10:SOM clusters centroid for samples RB-01 to RB-17 (Numbers on top bar showing volumetric energy density)

4.2.2 U-Net/ANN semantic segmentation model

As mentioned earlier, due to the inherent variability in the data stemming from the stochastic nature of the process and the objective of achieving real-time defect detection, we utilize the clustered data generated by SOM. This clustered data has undergone validation through CT scans and is employed as the training dataset for a custom U-Net semantic segmentation model. The primary purpose of this model is to forecast cluster centroids based on normalized OT images, effectively distinguishing between normal and abnormal data points. Furthermore, it's important to note that the SOM algorithm demands access to complete layers of OT images spanning the entire printing process to accurately detect defective signatures. However, this necessity is not well-suited for real-time defect detection. Consequently, the segmentation model is introduced to address and overcome this limitation.

The semantic segmentation model represents a variant of the well-known U-Net architecture, initially developed in 2015 by Ronneberger et al. [56]. While the U-Net was originally conceived for biomedical image segmentation, its application has extended into engineering [84] due to its rapid and precise image segmentation capabilities. This model incorporates a fully connected artificial neural network (ANN) [85] alongside the U-Net architecture (as depicted in Figure 4-11). It's a modified version of the original U-Net with fewer parameters to mitigate the risk of overfitting. The model's input consists of image sequences determined by the specified window length, which was used in the calculation of the moving average during image normalization, as discussed in Section 4.2.1.2. The model's output comprises the predicted SOM label, along with the corresponding centroids.

The network encompasses both a contracting path (down-sampling) and an expansive path (up-sampling). The contracting path utilizes a standard convolutional neural network to capture context within the input image. Conversely, the expansive path is dedicated to precise object localization and the refinement of segmentation. The network also incorporates skip connections, which concatenate feature maps from the contracting path with their corresponding counterparts

in the expansive path to preserve fine details within the segmentation. Additional enhancements have been introduced, such as the inclusion of features such as laser power, scan speed, hatch distance, laser thickness, and the moving average of the input image, all processed through two layers of fully connected neural network comprising 64 neurons, aimed at enhancing prediction accuracy. The architecture also encompasses a fully connected ANN consisting of two layers, with 128 and 64 neurons, which are responsible for predicting the centroid clusters within the forecasted SOM map. This inclusion also contributes to regularization during the training process.

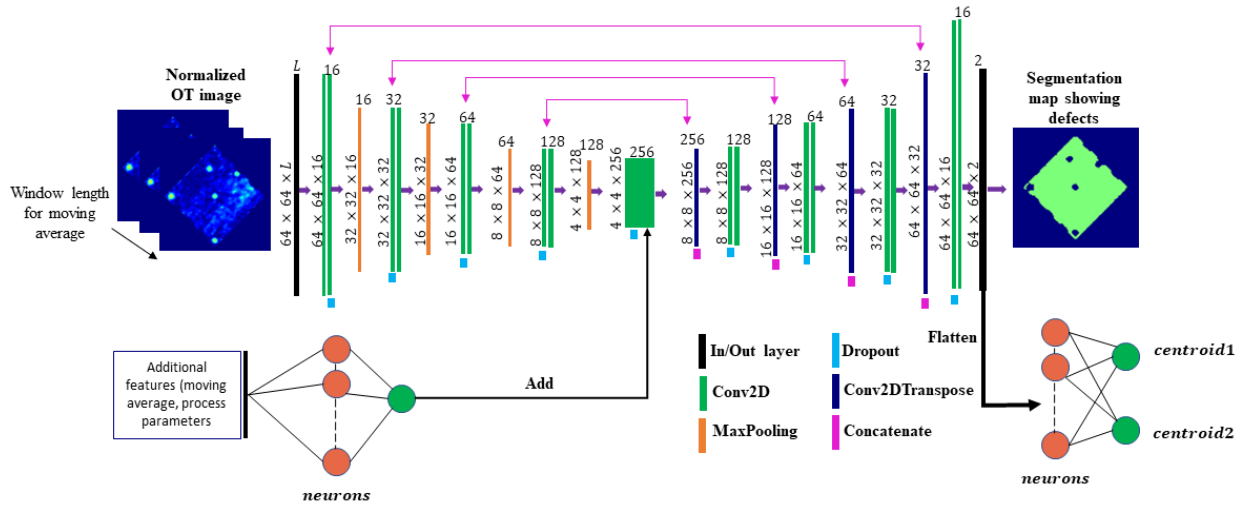


Figure 4-11: The U-Net architecture used for lack of fusion and keyhole porosity prediction (redrawn and adapted from [56])

The model's performance was assessed by employing two key metrics: the Intersection-over-Union (IoU) metric [86] for evaluating the agreement between predicted cluster labels and SOM cluster labels, and the Mean Absolute Error (MAE) for centroid prediction. The IoU metric is a widely used measure in image segmentation tasks due to its effectiveness and simplicity. It quantifies the degree of overlap between the predicted segmented regions and the corresponding ground truth segmented regions within an image. This is achieved by computing the ratio of the intersection of the predicted and ground truth regions to the union of these regions. Essentially, the IoU metric gauges the extent to which the predicted segmentation aligns with the actual segmentation.

The loss function employed for updating the model's weights is a combination of the dice loss [87] and mean square error (MSE). The Adam optimizer was utilized with a learning rate of

0.0001 for adjusting the model's weights. The model underwent training on a workstation featuring an NVIDIA RTX 3070Ti configuration, with a training duration of 100 epochs, a batch size of 64, and early stopping implemented with a patience of 5. Early stopping is applied when the validation IoU score fails to exhibit improvement, serving as a preventive measure against overfitting.

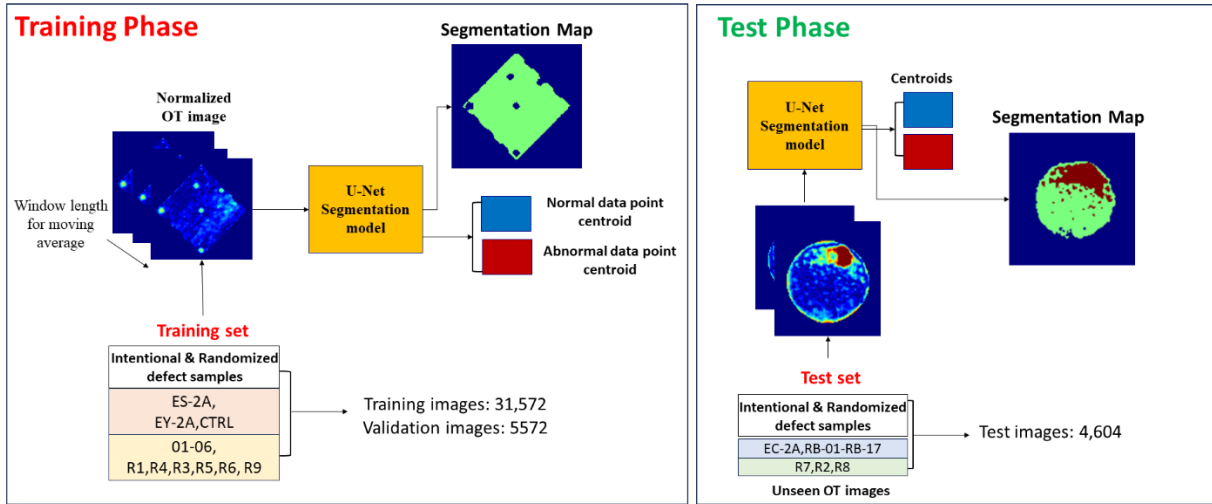


Figure 4-12: Training and testing workflow for model.

Figure 4-12 outlines the training process of the model, where the training and validation datasets exclusively comprise images from intentional and randomized defect experiments, divided into a 0.85 to 0.15 ratio. To align with the model's input size, the images underwent resizing, achieved through zero-padding or center cropping. For testing, a separate set of images was employed, originating from intentional and randomized defect experiments, totaling approximately 4,604 images.

Training the model was challenging, primarily stemming from the highly imbalanced nature of the data. Specifically, over 91% of the data represented the normal class, while the abnormal class accounted for less than 9%. The outcomes of the training, validation, and testing phases are documented in Table 4-1, and the training progress is visualized in Figure 4-13. Notably, the model achieved remarkable scores on both the training dataset (93.99% IoU, 0.03 loss) and the validation dataset (95.86% IoU, 0.02 loss). Furthermore, it demonstrated strong performance on previously unseen images (89.28% score, 0.0716 loss). Of particular significance is the model's outstanding accuracy in predicting the normal class (98.0% score) and the defective class (93.30% score) in comparison to the SOM cluster labels.

However, it is imperative to recognize that while the IoU metric score provides valuable insights, it may not entirely encapsulate the model's overall performance. This is due to the unique generation of SOM labels by different SOM models for various samples, resulting in a low likelihood of the U-Net model making identical predictions. Nevertheless, the trained model's predictions can be demonstrated to closely approximate the SOM cluster centroids for unseen images, as elaborated in the subsequent section.

Table 4-1: Training results for custom U-Net output model in predicting SOM clusters labels.

Architecture	Training Dice loss	Training IoU	Training MSE loss	Validation Dice loss	Validation IoU	Validation MSE loss	Test Dice loss	Test IoU	Test MSE loss	Normal class IoU	Abnormal class IoU
U-Net-Artificial Neural Network	0.0318	0.9399	0.0078	0.0215	0.9586	0.0084	0.0716	0.8928	0.0039	0.98	0.93

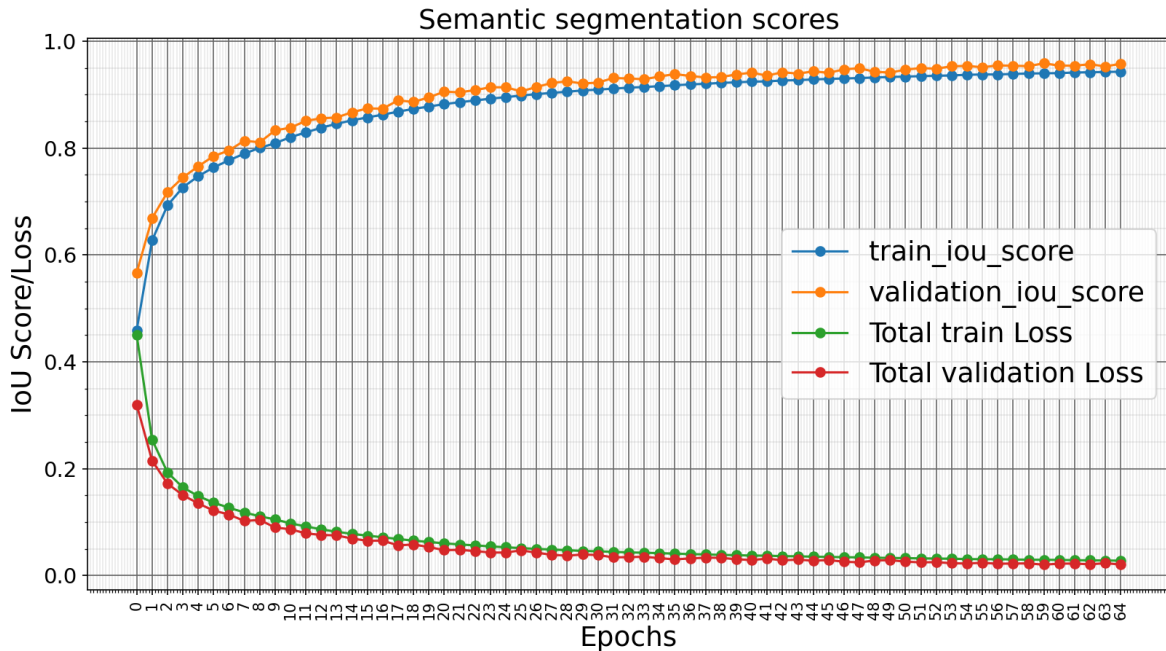


Figure 4-13: Training and validation scores for U-Net/ANN model

4.2.2.1 Comparison of U-Net model robustness in predicting uniquely trained SOM centroids across process parameter variations

As detailed in section 4.2.1.3, due to the inherently stochastic nature of the printing process, it is imperative to retrain the SOM model for every new set of unseen print samples. This necessity led us to adopt the U-Net model. Notably, the trained U-Net model demonstrates a remarkable ability to predict the unique centroids of each SOM cluster for these previously unseen print samples. In Figure 4-14, a visual comparison between the cluster centroids generated by the trained U-Net model and those uniquely trained by the SOM model for a range of samples, specifically RB-01 to RB-17 is shown. These samples were produced using diverse process parameters, allowing us to assess their impact on the recorded optical tomography (OT) images. The results are compelling, as they clearly illustrate the U-Net model's capacity to accurately predict centroids that closely align with those generated by each uniquely trained SOM model. The mean squared error (MSE) score of 0.00119 relative to the SOM centroids reinforces the efficacy of this approach.

In the subsequent section, connecting these aberrant cluster centroids with the occurrence of fusion-related issues and keyhole defects within the printing process would be discussed.

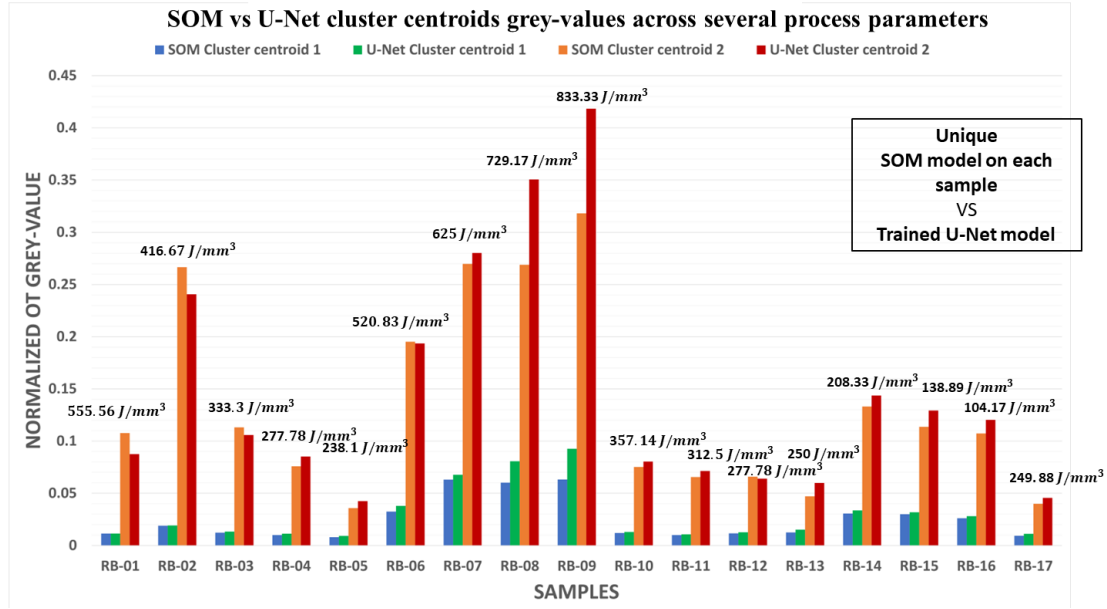


Figure 4-14:SOM vs U-Net clusters centroid for samples RB-01 to RB-17 (Numbers on top bar showing volumetric energy density)

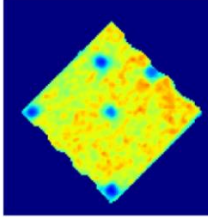
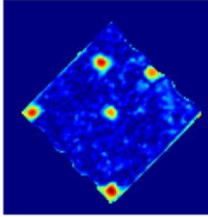
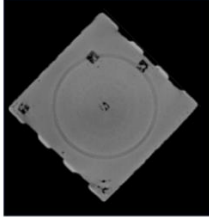
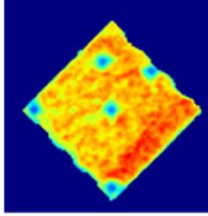
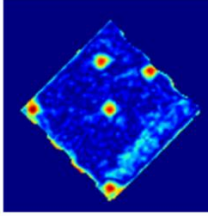
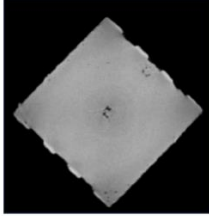
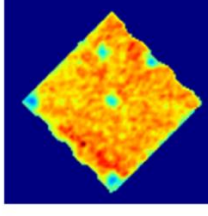
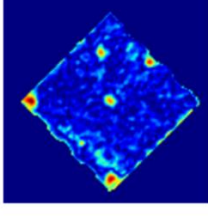
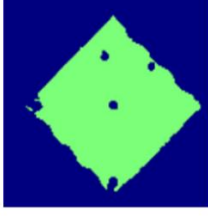
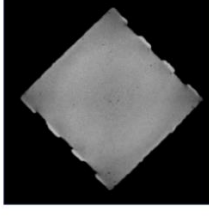
4.3 Results and Discussions

4.3.1 Intentional defect

4.3.1.1 Lack of fusion

As previously indicated, in order to enhance the precision of defect detection within the images, a moving average was employed to standardize the optical tomography image, thereby diminishing signal fluctuations and the requisite number of clusters for defect localization, as elaborated upon in section 4.2.1.2. Subsequently, the standardized images were inputted into the SOM clustering model to recognize signatures of porosity gray values. These SOM cluster labels were then utilized for training a U-Net segmentation model, facilitating the detection of abnormalities in unseen images. In Table 4-2, the comparison results of different steps of prediction using the best-performing model to predict the lack of fusion signatures in sample EC-2A, where cubical size voids of size $200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m}$, $300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m}$, and $400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m}$ were embedded is presented.

Table 4-2: Analyzing OT images by normalization, SOM, and U-Net/ANN for identifying intentional lack of fusion porosity in sample EC-2A, as well as CT-scan slice of corresponding layer

	Representative Image (EC-2A)				
Defect size (μm)	OT image	Normalized OT image	SOM	U-Net	CT-scan
400×400×400					
300×300×300					
200×200×200					

Based on the visualization in Table 4-2, both the SOM and U-Net models were able to effectively distinguish porosity signatures from normal gray values in the image, as confirmed in the CT- scan images (last column).

In the next step, the normalized porosity signal curves for the CT-scan, SOM, and U-Net algorithm will be discussed to evaluate the performance of the developed model across the entire layers of recorded OT images. These curves would assist in observing the porosity levels within each layer and are computed by dividing the pores within a layer with the total part area.

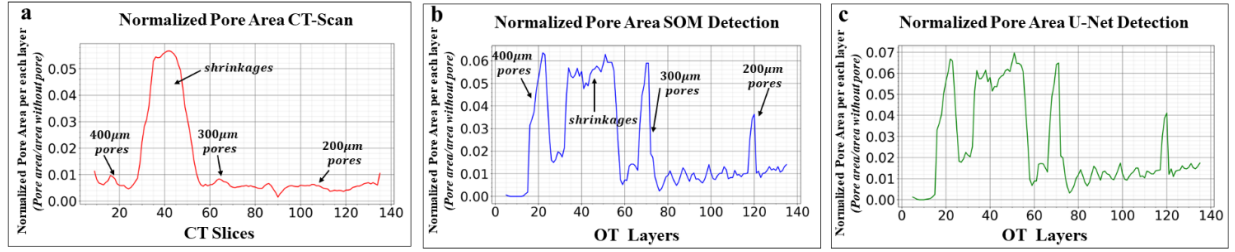


Figure 4-15: Comparison of normalized pore area between a) CT-scan, b) SOM and c) U-Net results for sample EC-2A

In Figure 4-15, the normalized porosity curves for sample EC-2A are depicted, with the y-axis representing the pore area and the x-axis representing sequential layers. Figure 4-15 (a) displays pore levels from each slice of the CT scans for the sample. The presence of fusion pores, caused by embedding $400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m}$ cubically shaped voids, is noticeable from slice 11 to slice 23. Furthermore, the impact of embedding $300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m}$ and $200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m}$ defect sizes can be seen at slices 62 to 72 and slices 114 to 122, respectively. These pores are detectable by both the SOM and U-Net algorithms, as observed in layers 20 to 28 in Figure 4-15 (b) and (c) for the $400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m}$ size defects, layers 69 to 75 for the $300\text{ }\mu\text{m}$ size defects, and layers 120 to 124 for the $200\text{ }\mu\text{m}$ size defects.

In addition, shrinkages were observed at the top and bottom edges of the part, as shown in Figure 4-16, as evidenced by the significant increase in porosity levels from slices 30 to 45 in Figure 4-15 (a). Both models detected this, as seen in the increase in porosity levels in Figure 4-15 (b) and (c) in layers 40 to 60, which supports the effectiveness of the approach.

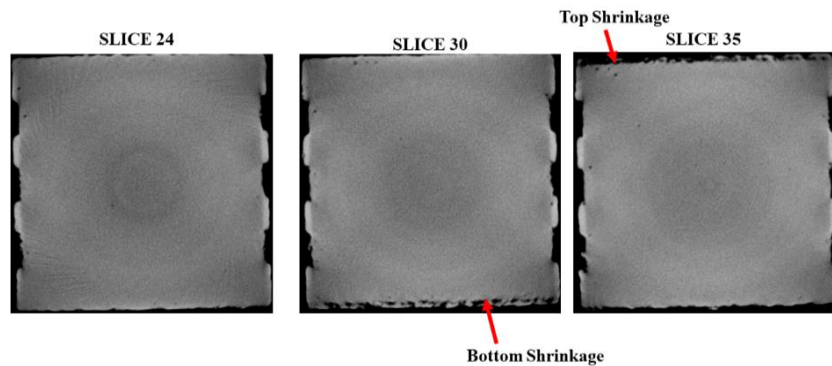


Figure 4-16: Shrinkages in part as observed in the fall in porosity levels curves for the CT scan

It was also observed that larger intentional defects sizes of $400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m}$ have large fusion pore signatures in OT images that persist over 3 to 4 layers, while the relatively smaller intentional defects of $300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m}$ and $200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m}$ have smaller lack of fusion pores that persist for one to two layers. This indicates that the longer the lack of fusion porosity signatures persist, the greater the likelihood of actual pores within the part.

To quantitatively compare the similarity between the curves, Dynamic Time Warping (DTW) [88] was used, which compares two sequences that may have different lengths or shifted in time and is often used in speech recognition, time series and music analysis [89]. This method works by finding the optimal alignment between two sequences such that the accumulated distance between the aligned points is minimized. DTW can handle non-linear distortions in time by allowing the time steps between aligned points to be different in each sequence. This makes DTW a flexible and robust method for comparing sequences that may vary in time or speed. This is relevant since the OT monitoring system can only record images of the current layer, thus previously scanned layers where defects might have formed as captured in CT-scans, would only be visible in subsequent layers of the recorded OT image. The result of DTW is a scalar value that represents the similarity between the two curves compared. The lower the value, the more similar the sequences are according to the distance metric used. Table 4-3 displays the similarity score calculated using DTW [90] with the Euclidean distance between the pore detection by SOM and U-Net, compared to CT-Scans, while Figure 4-17 shows the optimal wrapping paths between the curves, that shows how both sequences are aligned together for the comparison purposes.

Table 4-3: Dynamic time warping similarity score for normalized porosity curves for sample EC-2A (intentional lack of fusion) for CT scans, SOM and U-Net algorithms

Porosity Curves	DTW similarity score
CT-scan and SOM	0.12
CT-scan and U-Net	0.13
SOM and U-Net	0.03

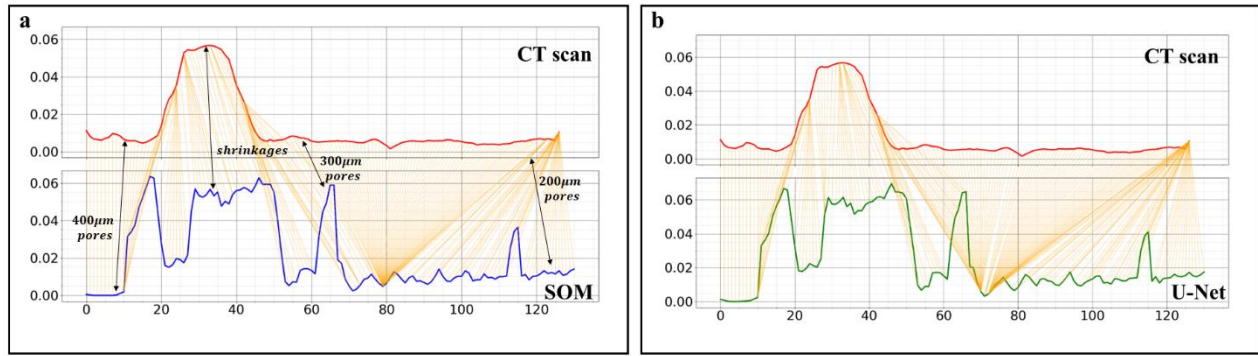


Figure 4-17: Optimal wrapping between CT porosity curves and (a) SOM algorithm (b) U-Net

Based on the result listed in Table 4-3, a strong correlation between the algorithms' defect detection and the actual pores found in the CT-scans was observed with DTW similarity scores of 0.12 and 0.13 for SOM and U-Net, respectively. The best score relative to the CT-scan was obtained using the SOM algorithm. Also, visual inspection of the DTW curves shown in Figure 4-17, shows close matching of the curves in layers 0 to 27 ($400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m} \times 400\text{ }\mu\text{m}$ defect size), layers 30 to 50 (part shrinkage), layers 70 to 75 ($300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m} \times 300\text{ }\mu\text{m}$ defect size), and layers 120 to 124 ($200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m} \times 200\text{ }\mu\text{m}$ defect size) where a noticeable increase in pore area was observed, matching the location of intentional defects in the samples. The similarity score between the pores detected by SOM and U-Net was 0.03, showcasing U-Net's ability to learn from SOM clusters for a broad range of process parameters.

4.3.1.2 Keyhole

The SOM and trained U-Net model were used to predict the keyhole porosity in recorded OT images. Table 4-4 shows an example of using the algorithms to predict keyhole porosity in sample 1 (Table 3-3) for an embedded coupon size of $1000 \times 1000 \times 1000 \mu\text{m}^3$, $500 \times 500 \times 500 \mu\text{m}^3$, and $250 \times 250 \times 250 \mu\text{m}^3$ with reduced laser speed to increase energy density.

As observed in Table 4-4 the method effectively detects keyhole porosity signatures in the image and even recognizes lack-of-fusion zones where the laser beam may not have been present. Additionally, Figure 4-18 compares the normalized porosity curves between the CT scans and pores detected by SOM/U-Net algorithm.

From Figure 4-18 (a), The presence of keyhole pores, caused by increasing the energy input into the embedded coupons of size $1000 \times 1000 \times 1000 \mu\text{m}^3$, is noticeable from slice 145 to slice 217. Furthermore, the impact of embedding $500 \times 500 \times 500 \mu\text{m}^3$ and $250 \times 250 \times 250 \mu\text{m}^3$ defect sizes can be seen at slices 320 to 354 and slices 471 to 494, respectively. These pores are detectable by both the SOM and U-Net algorithms, as observed in layers 175 to 220 in Figure 4-18 (b) and (c) for the $1000 \times 1000 \times 1000 \mu\text{m}^3$ size defects, layers 340 to 360 for the $500 \times 500 \times 500 \mu\text{m}^3$ size defects, and layers 490 to 500 for the $250 \times 250 \times 250 \mu\text{m}^3$ size defects.

Table 4-4: Analyzing OT images by normalization, SOM, and U-Net for identifying intentional keyhole porosity in sample 1 (blue color indicates lack of fusion porosity, red color indicates keyhole porosity, and green color indicates absence of pores), as well as CT-scan slice of corresponding layer

	Representative Image (SAMPLE 1)				
Defect size (μm)	OT image	Normalized OT image	SOM	U-Net	CT-scan
1000×1000×1000					
500×500×500					
250×250×250					

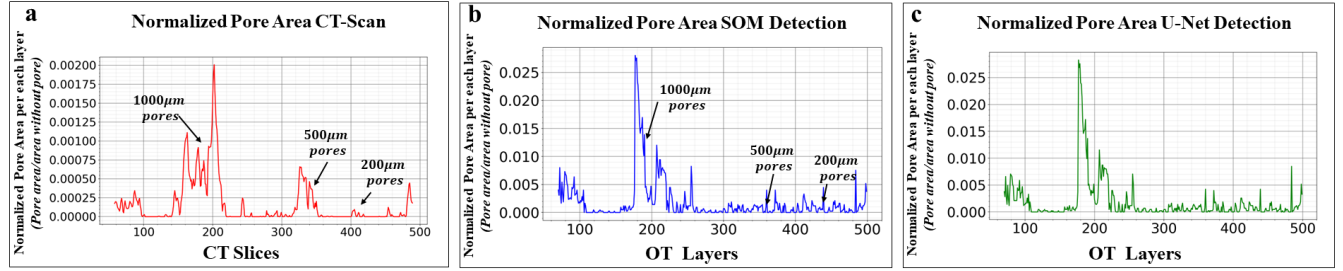


Figure 4-18: Comparison of normalized pore area between a) CT-scan, b) SOM and c) U-Net for sample 1

Similar to Section 4.3.1.1, the DTW score between the above three curves are also shown in Table 4-5 and Figure 4-19 shows the optimal wrapping between the curves to compare how they were matched.

Table 4-5: Dynamic time warping similarity score for normalized porosity curves for sample 1 (intentional keyhole) for CT scans, SOM and U-Net algorithms

Porosity Curves	DTW (similarity score)
CT-scan and SOM	0.07
CT-scan and U-Net	0.07
SOM and U-Net	0.006

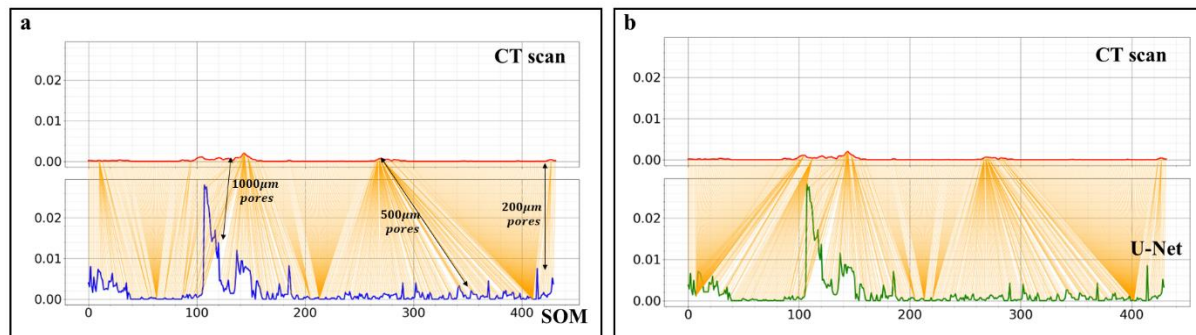


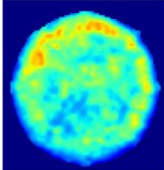
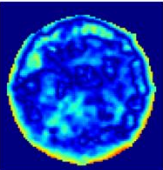
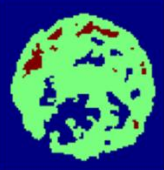
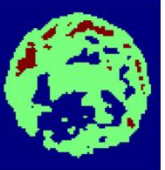
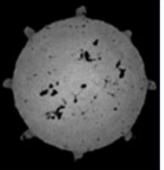
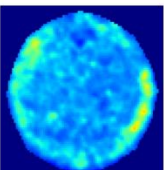
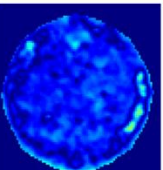
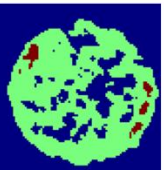
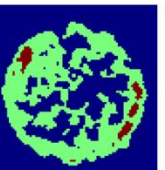
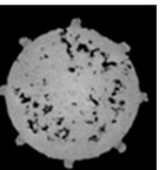
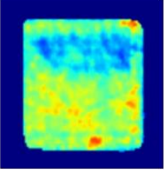
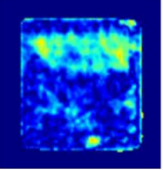
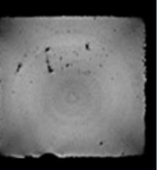
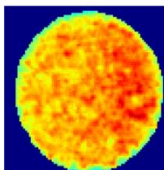
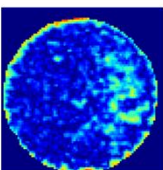
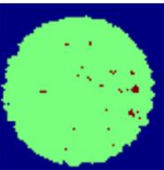
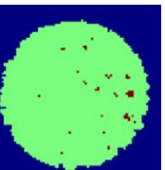
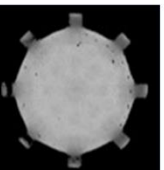
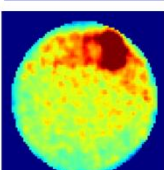
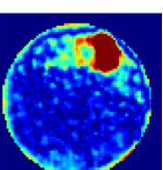
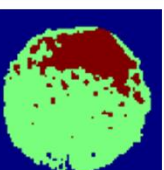
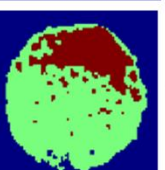
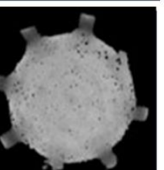
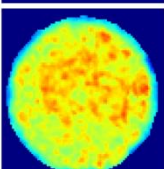
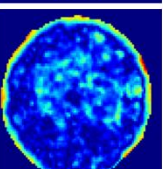
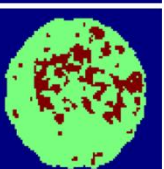
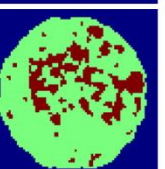
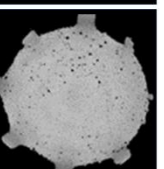
Figure 4-19: Optimal wrapping between normalized CT porosity curves and (a) SOM algorithm (b) U-Net for intentional keyhole (sample 1)

According to Table 4-5, a close relationship was observed between the pores detected by the algorithms and pores present in the CT-scans, with a similarity score of 0.07 for both SOM and U-Net. Also, visual inspection of the DTW curves shown in Figure 4-19, shows close matching of the curves at intentional keyhole defect's locations. The similarity score between the pores detected by SOM and U-Net was 0.006, again showcasing U-Net's ability to learn from SOM clusters for a broad range of process parameters.

4.3.2 Randomized defect

The SOM and U-Net algorithms were tested on recorded optical tomography (OT) images of randomized defects that occurred due to improper process parameters selection, as described in section 3.2.3. Table 4-6 showcases examples of one layer for the recorded images, corresponding CT scans, and porosity detected by the algorithms for Samples RB-15, RB16, RB-17 (randomized lack of fusion) and Samples R2, R7, and R7 (randomized keyhole defects) from Table 3-2 and Table 3-4.

Table 4-6: Analyzing OT images by normalization, SOM, and U-Net for identifying randomized lack of fusion and keyhole porosity (blue color indicates lack of fusion porosity red color indicates keyhole porosity and green color indicates absence of pores), as well as CT-scan slice of corresponding layer.

	Representative Image (Randomized Defects)				
Sample	OT image	Normalized OT image	SOM	U-Net	CT-scan
RB-15					
RB-16					
RB-17					
R2					
R7					
R8					

According to Table 4-6, samples RB-15 and RB-16 displayed a lack of fusion (LoF) due to their relatively large layer thickness of 0.06 mm and 0.08 mm, respectively. This thickness required more energy to melt the powder, which increased the likelihood of LoF defects. On the other hand, the lack of fusion in sample RB-17 could be attributed to various factors, including defocusing of the laser beam, powder spread, or recoater failure. Despite using optimal process parameters, CT scans revealed LoF defects in the direction of gas flow. Additionally, randomized keyhole defects were observed in samples R2, R7, and R8. Reducing the laser speed in sub-sections of R2, R7, and R8 increased the energy density, resulting in the formation of keyhole defects. Although R2 had few keyhole defects due to insufficient energy, R7 and R8 had a significant number of spherical keyhole pores scattered randomly as shown in Table 4-6. Also, Table 4-6 demonstrated that both algorithms effectively detected the pores, with better localization for randomized lack of fusion due to its distinct nature of formation. The randomized keyhole experiment showed increased pore formation in high-temperature layers, similar to the intentional keyhole experiment.

To evaluate the SOM/U-Net models' performance on entire layers of randomized defects, normalized porosity signal curves for the CT-scan, SOM, and U-Net algorithm were analyzed. To avoid repetition, only the porosity curves for sample RB-16 and R7 were presented in Figure 4-20.

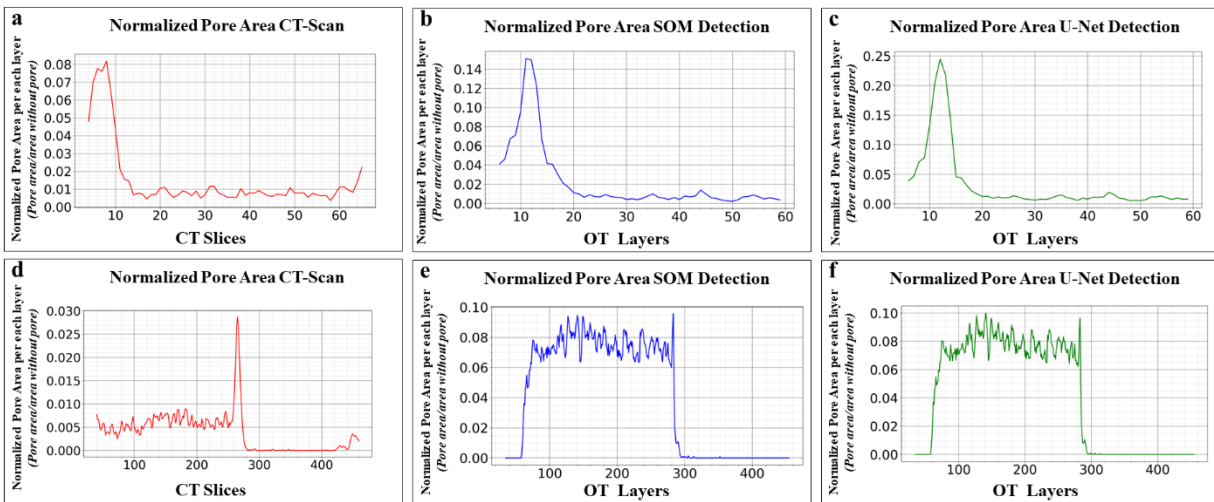


Figure 4-20: Comparison of normalized pore area between a and d) CT-scan, b and e) SOM and c and f) U-Net for randomized porosity respectively for sample RB-16 and sample R7

In Figure 4-20 (a), the pore levels for each slice of the CT scans for sample RB-16 are shown. Large fusion pores caused by the thick layer selection are noticeable from slice 4 to slice 15, as seen in Table 4-6. Additionally, relatively smaller fusion pores are present across all layers, as evidenced by the fluctuations in the CT porosity curves. The SOM and U-Net algorithms can detect these pores, as shown by the closely matching curves in Figure 4-20 (b) and (c), especially for layers 4 to 18 with large fusion pores. The U-Net algorithm performed relatively well in detecting the randomized lack of fusion (RB-16), with a DTW similarity distance score of 0.26 between the porosity curves of CT-scan and U-Net, while the SOM model had a score of 0.11, as presented in Table 4-7.

Table 4-7: Dynamic time warping similarity score for randomized lack of fusion and keyhole pores for CT scans, SOM and U-Net algorithms

Sample	Defect type	CT-scan and SOM	CT-scan and U-Net	SOM and U-Net
RB-15	Randomized lack of fusion	0.24	0.33	0.075
RB-16	Randomized lack of fusion	0.11	0.26	0.13
RB-17	Randomized lack of fusion	0.38	0.41	0.03
Sample 2	Randomized keyhole	0.5	0.52	0.02
Sample 7	Randomized keyhole	0.69	0.73	0.07
Sample 8	Randomized keyhole	0.62	0.63	0.016

Figure 4-20 (d) shows the pore levels for each slice of the CT scans for sample R7. The reduced laser speed of 500mm/s resulted in highly random spherical pores, as shown in Table 4-7, noticeable from the start through to slice 260. Figure 4-20 (e) and Figure 4-20 (f) demonstrated a strong correlation between both curves and the CT curves, especially in layers 160 to almost 290. Although the localization of the keyhole pores was generally low compared to lack of fusion, with DTW similarity scores of 0.69 between CT scans and SOM curves, while the U-Net model had a score of 0.73, highlighting the effectiveness of the model in predicting porosity signatures in

unseen images. The U-Net model also had similar scores as the SOM algorithm for both randomized lack of fusion and keyhole detection in samples RB-15, RB-17, R2, and R8, with a score of 0.33, 0.38, 0.52, and 0.63 between the porosity curves of CT and U-Net, respectively, relative to the SOM algorithm, which had a score of 0.24, 0.41, 0.50, and 0.62, respectively.

These results indicated that both the SOM and U-Net models can detect porosity signatures in recorded OT images. However, further studies are necessary to confirm their performance for various LPBF processes and defect types.

4.4 Summary

In this section, an Optical Tomography (OT) monitoring system in the near-infrared range installed commercially in an EOS M290 LPBF machine is used to collect images during the process. The collected in-situ images were then analyzed by a machine learning framework using a Self-Organizing Map (SOM) and a U-Net model to predict porosity caused by lack of fusion and keyhole. One of the key strengths of this approach is that it does not require a custom dataset to train the model, as the ground truth is obtained automatically without human intervention, reducing the potential for human error. Additionally, the method is robust to changes in process parameters and materials, as the data is normalized using a moving average before extracting abnormalities. It is also computationally efficient as it only requires two clusters to identify defective signatures thus can be applied in real-time using the trained U-Net model for in-situ monitoring. Overall, this study demonstrates the effectiveness of this approach for identifying porosity signatures within recorded OT images from a diverse range of process parameters.

5 Fuzzy- Machine Learning Framework for Porosity Prediction Using Optical Tomography Imaging in Laser Powder-bed Fusion.

5.1 Introduction

As previously shown, fluctuations in pixel intensities in optical tomography images may not always signify defects due to the stochastic nature of the process. The occurrence of colder spots and hotspots in the image generally raises the likelihood of defects in the printed part. This chapter introduces a machine learning pipeline designed to predict the likelihood of defects in parts produced through LPBF which could be helpful to resolve the current challenge. The framework integrates a self-organizing map (SOM), fuzzy logic modeling, and a modified U-Net model.

5.2 Machine Learning framework for predicting the probability of lack-of-fusion and keyhole defects using optical tomography images.

This section presents a machine learning pipeline crafted to estimate the probability of encountering keyhole and lack of fusion defects in the manufacturing process by analyzing OT images. This analysis specifically involves identifying patterns of so-called cold or hot grey values within the images. Based on prior research in the previous chapter [9], the self-organizing map (SOM) clustering algorithm was utilized on OT images to detect these unusual patterns. Initially, images were normalized using a moving average approach to diminish signal fluctuations within the OT images, thereby making abnormal patterns more evident. To circumvent the necessity of retraining the SOM algorithm due to the stochastic nature of the manufacturing process, a hybrid model that combines a neural network with a U-Net architecture was developed to forecast these defect occurrences across various process parameters. An illustration of the results obtained is shown in Figure 5-1.

As indicated in the previous chapters, discrepancies in recorded OT images do not always correlate with actual defects in the finished parts, possibly due to the self-recovering capability of the process or other factors like the noise-to-signal ratio. Consequently, there is a need for a method to predict the likelihood that a detected abnormal pattern in an image will result in real defects within the part. To address this need, a ML pipeline (depicted in Figure 5-3) was established,

encompassing an SOM, a fuzzy-logic reasoning model, and a custom U-Net model for predicting the likelihood of defects in OT images. Initially, the SOM clustering model extracts anomalous signatures from the OT image. The centroids of these features then serve as inputs for the fuzzy-logic model, which utilizes a rule set derived from expert knowledge of the monitoring system to predict defect probabilities. CT scans are used to confirm the predictions made by the fuzzy-logic model. These probability maps are then used to train a U-Net/ANN model to generate probability maps for unseen OT images, aiming to obviate the need for retraining the SOM and fuzzy models with each new print job, considering the randomness of the process and its responsiveness to changes in parameters.

Detailed discussions on the SOM, Fuzzy, and U-Net/ANN models will be provided in the following sections.

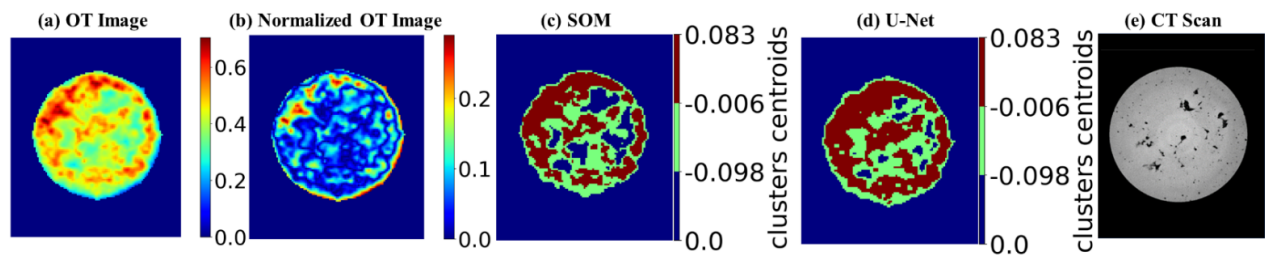


Figure 5-1: Example of SOM/U-Net model for detecting lack of fusion and keyhole phenomena (Blue color-Lack of fusion, Red-Keyhole)-(a) Original OT image (b) Preprocessed image after applying normalization (c) Segmentation map after applying SOM (d) U-Net Segmentation map (e) CT-scan of corresponding slice

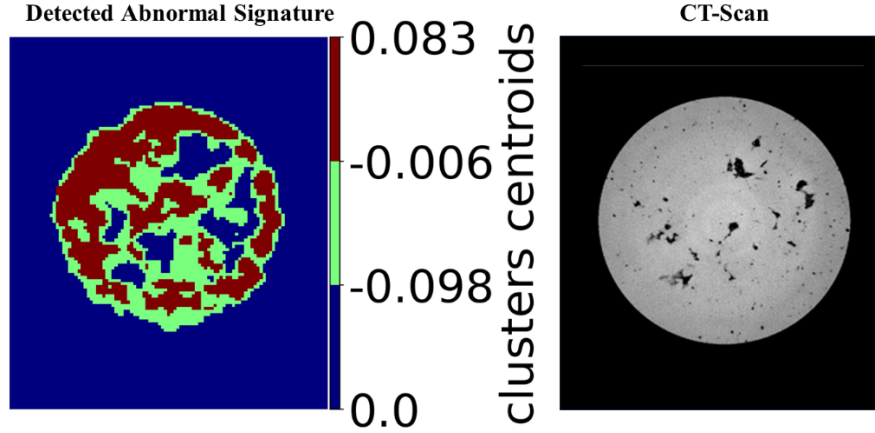


Figure 5-2: Challenge of predicting the probability of defects in actual part from detected abnormal signatures in OT images.

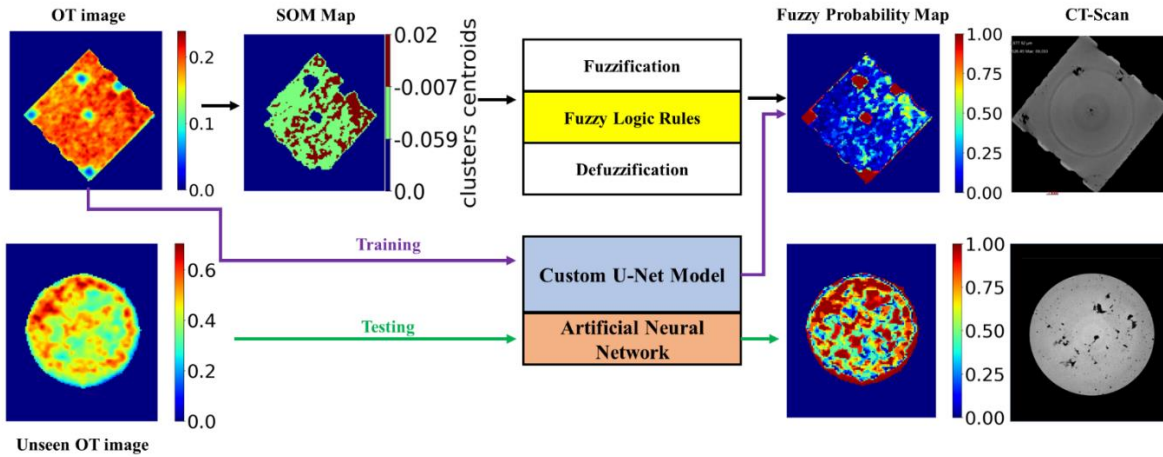


Figure 5-3: Machine-Learning framework for predicting probability of lack of fusion and keyhole defects using in-situ optical tomography images.

5.2.1 SOM clustering model

The Self-Organizing Map (SOM), also referred to as Kohonen maps [71], as previously described is an artificial neural network designed for unsupervised learning. It leverages competitive learning rather than error-correction learning (such as backpropagation with gradient descent), where a neighborhood function ensures the preservation of the topological properties of the input space. This approach facilitates the clustering of similar data points together, effectively organizing them

into clusters within a space of reduced dimensionality. Further insights into the SOM algorithm are available in the cited literature.

For this study, the SOM was utilized to analyze three specific attributes derived from the Optical Tomography (OT) images: the intensity of pixel grey-values, the mean of the image, and its variance. Prior to the SOM algorithm application, the OT data were initially normalized using a moving average method. This step was crucial to diminish signal noise and highlight unusual patterns, as documented by [9].

$$I_N^i = \frac{I_N^i - MGV_{MA_i}}{2^{16} - 1} \quad \text{Equation 5-1}$$

where I_N^i represents the recorded in-situ image at layer i and MGV_{MA_i} denotes the moving average grey value for predetermined window length up to layer i . Herein:

$$MGV_{MA_i} = \frac{1}{w} \sum_{n=1}^w I_{i-n}^i \quad \text{Equation 5-2}$$

where w represents the window length,

Equation 5-1 represents a minor adaptation of the normalization equation used in the previous chapter[9], where the absolute notation has been omitted to differentiate between cold and hot spots in the OT image.

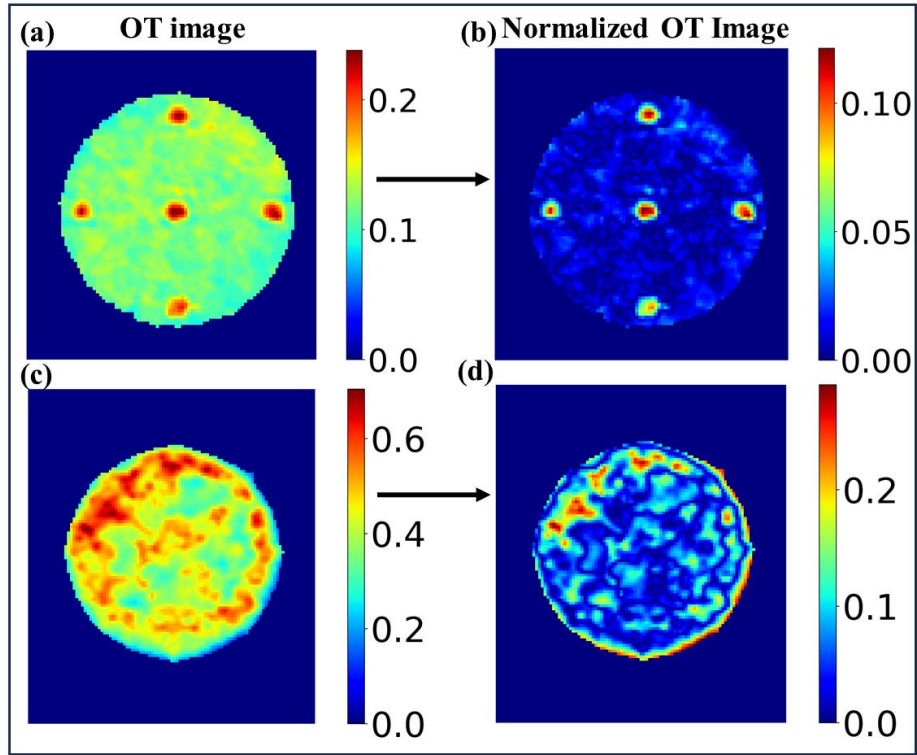


Figure 5-4: Visualization of normalization applied on optical tomography images: (a & c) Original OT image (b & d) Normalized OT image

Figure 5-4 (a and c) display the initial OT images, whereas Figure 5-4 (b and d) present the images after normalization, demonstrating a significant improvement in the visibility of anomalous areas. It is important to note that choosing the appropriate window size for the moving average is critical, as a too large size could obscure certain signal details. A larger window size can reveal longer-term effects like overheating, which may lead to keyhole defects, whereas a smaller window size can highlight shorter-term effects such as smoke interactions and lack of fusion defects.

As mentioned before, the SOM algorithm was utilized to analyze three specific features from the OT images: pixel grey-value intensity, the average of the image, and its variance. To detect both keyhole and lack of fusion defects, window sizes of 10 and 20 were used, as shown in Figure 5-5. Initially, the original OT image was normalized with the smaller window size to enhance the visibility of lack of fusion defects. The lowest cluster centroid, found using the SOM algorithm with the shorter window, was used to identify cold spot areas (colored dark blue). Similarly, the original OT image was normalized with a larger window size to highlight keyhole defects. The

highest cluster centroid, obtained from the longer window size, was used to detect hotspot areas (colored red).

Figure 5-6 illustrates how these cluster centroids correspond with areas where seeded pores are clearly visible in the CT scans. These cluster centroids will form the basis for the discussion on fuzzy modeling in the following section.

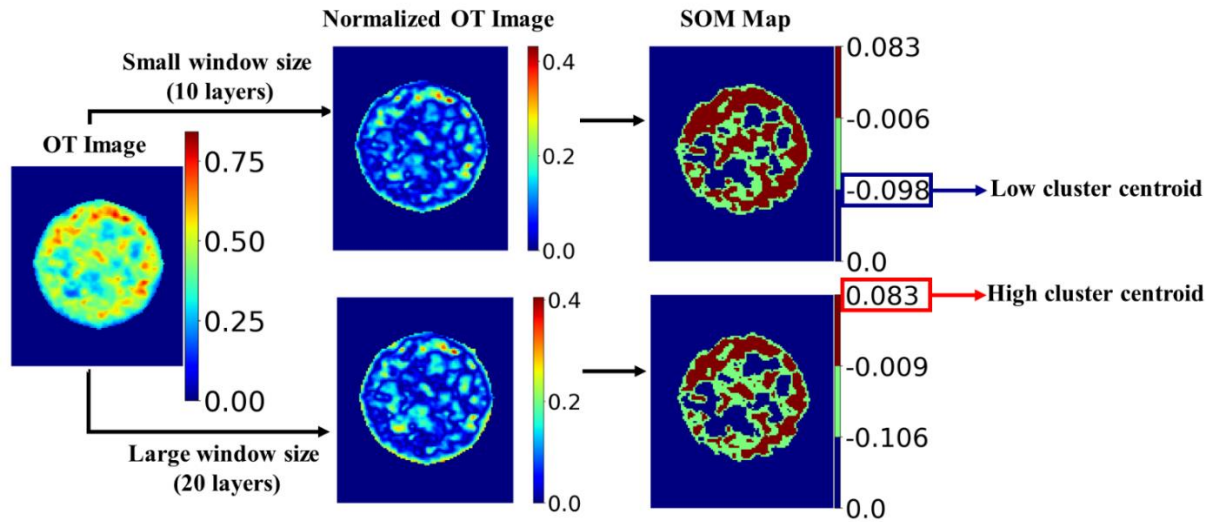


Figure 5-5: Example of applying multiple window size for normalizing OT image to show both short- and long-term effects within the process.

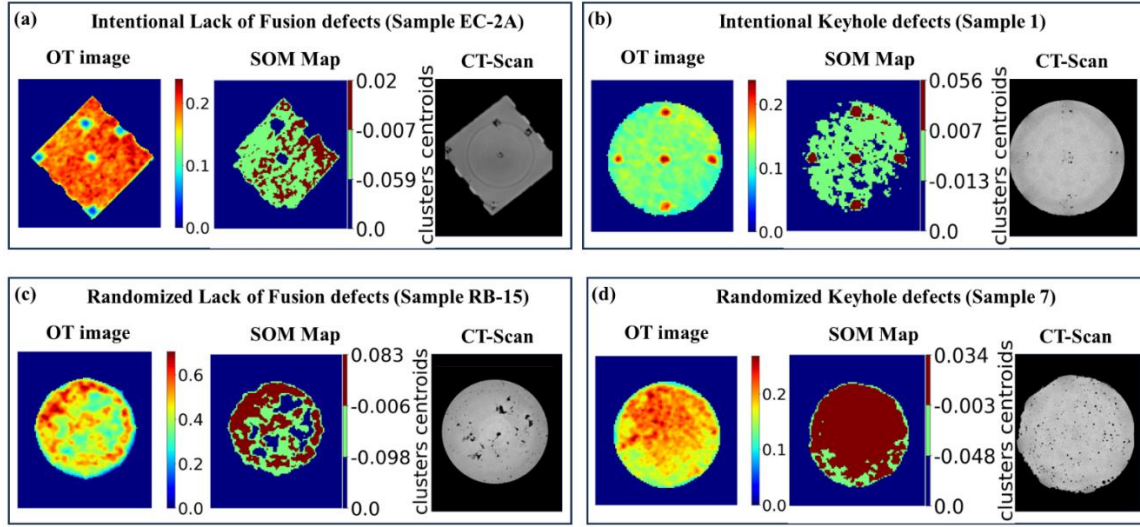


Figure 5-6: SOM applied on normalized pixels of OT image with corresponding CT-scans (a) Intentional Lof (b) Intentional keyhole (c) Randomized Lof (d) Randomized keyhole

5.2.2 Fuzzy-Logic Modelling

To estimate the likelihood of predicted defects in the produced part using centroids from the clustered features (pixel intensity, mean, and variance of OT images) discussed in section 5.2.1, the fuzzy logic modeling technique was employed. Fuzzy logic [91] provides a mathematical structure for dealing with imprecise or vague information, facilitating knowledge based (process-aware) reasoning under uncertainty. Unlike conventional binary logic that adheres to strict true/false outcomes, fuzzy logic introduces the concept of partial truth where, for example, a pixel from an OT image might be deemed somewhat defective. Within this framework, input variables are ascribed membership functions that gauge their degree of association with a particular set, known as fuzzy sets. These sets enable a smooth transition between being a member and not being a member of a set, eliminating abrupt cutoffs. This characteristic of fuzzy logic makes it adept at handling and reasoning with ambiguous or uncertain data, such as characterizing very high or very low OT image means and grey values.

Fuzzy logic employs a collection of rules, typically based on expert knowledge, to map these input variables to output values, which quantify the probability of certain outcomes. These rules utilize linguistic variables—terms or phrases that describe input or output values in terms understandable to humans. For example, the input variable might be "grey value" with linguistic

values like "low," "normal," and "high" assigned to it. The logic is then applied through a series of if-then statements, such as "if the grey value is low, then the likelihood of a lack of fusion defect is high."

Fuzzy logic finds application across diverse domains such as control systems, artificial intelligence, decision-making, and the healthcare industry [92]. It encompasses multiple phases, as outlined in [93]:

- **Problem Formulation:** This initial phase involves defining the problem and identifying both input and output variables. Inputs are the factors affecting the outcome, and can be either quantitative or qualitative, while the output represents the system's response and can also vary in nature.
- **Fuzzification:** At this stage, input variables are mapped onto fuzzy sets. A fuzzy set is characterized by values that possess varying degrees of membership, ranging from 0 to 1. Membership functions assign each value a membership degree based on its resemblance to the fuzzy set. Various forms of membership functions exist, including triangular, trapezoidal, Gaussian, bell-shaped, and sigmoidal.
- **Rule Generation:** This involves creating rules that link input variables to the output. Typically framed as if-then statements, such as "if temperature is high and humidity is low, then the likelihood of outcome X increases." These rules can be derived from expert insights or generated via machine learning techniques.
- **Inference:** Using the established rules, this phase deduces outcomes or makes decisions about the output based on the inputs. Fuzzy logic employs fuzzy reasoning to evaluate each rule's membership degree given the input variables.
- **Defuzzification:** This step converts fuzzy output variables into precise values. Methods for defuzzification include centroid, maximum membership, and weighted average.
- **Validation:** The final phase tests the model against real-world scenarios to evaluate its precision and effectiveness. Depending on the validation outcomes, the model might be further refined or adjusted.

Figure 5-7 illustrates the schematic of the fuzzy modeling process employed for estimating the likelihood of defects in the printed component. The subsequent sections will explore each of these

stages in detail, discussing their importance in forecasting defect probabilities in the fabricated item.

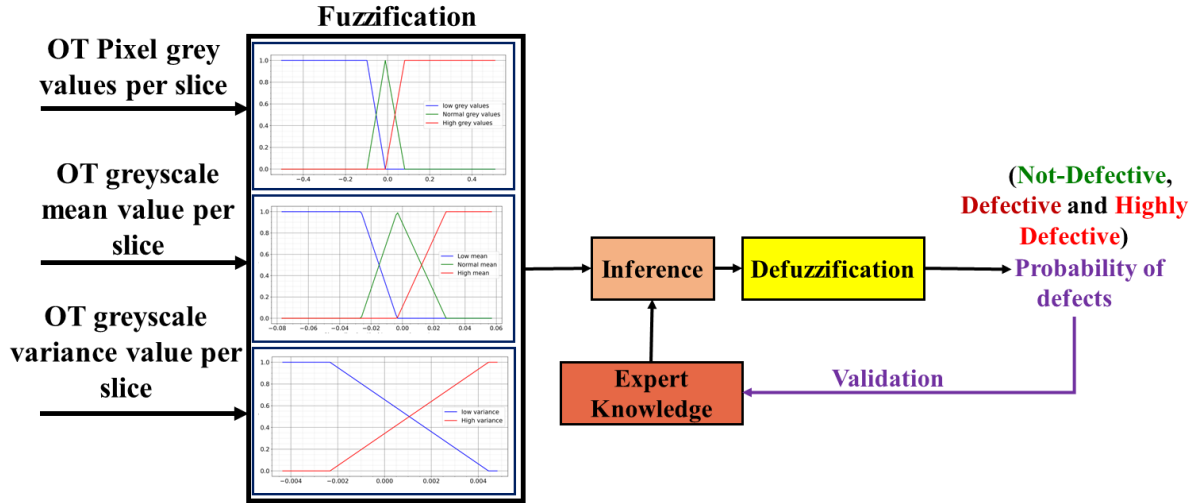


Figure 5-7: Block diagram of fuzzy modelling for probability of defects in printed parts

5.2.2.1 Problem formulation

The unpredictability inherent in LPBF presents substantial challenges in creating effective algorithms for defect prediction in 3D-printed objects based on OT data. Defects appearing in one layer might self-heal in the layers that follow, leading to potential inaccuracies in predicting defects. Implementing fuzzy logic modeling appears promising for assessing the probability of defect occurrences. However, the effectiveness of fuzzy logic critically depends on accurately defining the inputs, rules and membership function, which involves specifying the problem's boundaries and pinpointing the relevant variables that describe the system being analyzed. A crucial step in the problem formulation is the identification of input variables, which are factors that affect the system's behavior, and output variables, which represent the anticipated outcomes. For this fuzzy model, the input variables chosen were the pixel grey value of the OT image, alongside the OT greyscale mean and variance per layer since variations in these attributes are often indicative of pore formation within the printed parts.

5.2.2.2 Fuzzification

The subsequent phase in the process involves fuzzifying the selected input variables by defining their ranges with specific membership functions. Initially, this step requires identifying appropriate linguistic variables that accurately capture the nuances of the problem domain. Given the characteristics of the OT data, the input variables were categorized as 'low,' 'normal,' and 'high'. An instance might include a scenario with high pixel intensity grey value, a normal overall OT greyscale mean, and a low variance. Consequently, the linguistic variables 'LOW,' 'NORMAL,' and 'HIGH' were selected to represent these input attributes. The next task is translating these linguistic input variables into fuzzy sets, which signifies the level of association of each input variable with its respective linguistic descriptor. This transformation employs carefully chosen membership functions to facilitate this process.

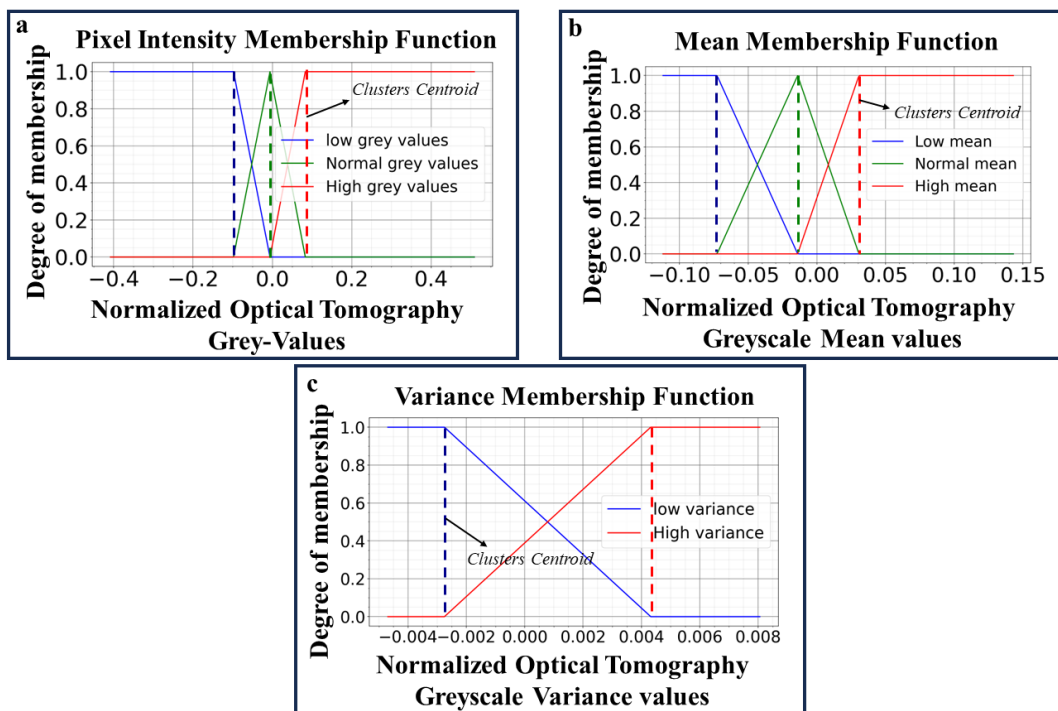


Figure 5-8: Membership function for the OT features (a) pixel intensity, (b) OT greyscale mean, and(c) OT greyscale variance

Figure 5-8 illustrates the membership functions designated for the input variables, adopting trapezoidal functions for 'LOW' and 'HIGH' values, and a triangular function for the 'NORMAL'

range. The centroids obtained from the SOM algorithm informed the foundation of these membership functions' boundaries. Figure 5-8(a) and (b) display the membership functions for OT pixel values and OT greyscale mean, respectively, where the blue function denotes low values, green indicates normal values, and red signifies high values. In Figure 5-8(c), the focus is narrowed to membership functions for low and high values to simplify the rule set. This approach concentrates on instances exhibiting low variance in the OT image, typically desired except in certain cases, and high variance, often suggesting melting process instability potentially leading to defects in the final product. Moreover, given the LPBF process random nature, the analysis includes the frequency of persistence of keyhole and lack of fusion defect classes (denoted by red and dark blue) across a number of layers within a specified window. Insights from experts on the OT monitoring system suggest that not all abnormal OT signatures necessarily point to defects unless they recur over several layers. To quantify this observation, Equation 5-3 was used to calculate the proportion of layers showing persistent defective clusters relative to the total layer count examined. Figure 5-9 exemplifies the application of Equation 5-3 in determining membership values for a pixel's grey value in OT images, for sample RB-14, clearly distinguishing areas with a high likelihood of porosity (where voids were intentionally created) indicated by values nearing 1, from areas less likely to have porosity, marked by values approaching 0.

$$M_{repeat} = \frac{N_{lof\&keyhole}}{\text{Number of layers considered}} \quad \text{Equation 5-3}$$

where $N_{lof\&keyhole}$ is the number of times abnormal clusters persist within the layers considered.

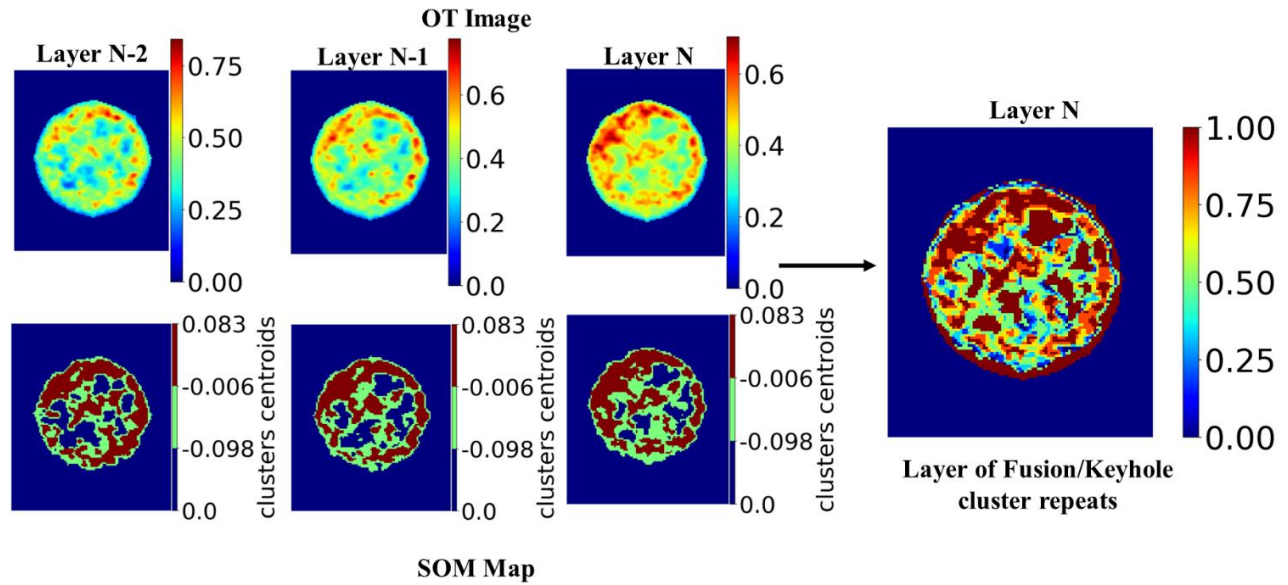


Figure 5-9: Illustration of fuzzification of the number of layers abnormal cluster persists.

5.2.2.3 Rule Generation

The subsequent stage in the modeling process involves the creation of knowledge-based rules, leveraging expert insights regarding the monitoring system, for the fuzzified input variables discussed in section 5.2.2.2. These rules were formulated through a blend of expert knowledge about the monitoring system and the use of an unsupervised machine learning algorithm for anomaly detection, the Isolation Forest [94]. This algorithm excels at pinpointing outliers or anomalies within a dataset by identifying data points that are rare and significantly distinct from the majority, thus rendering them "isolated" in the feature space, such as porosity signatures amid the OT data collection. Introduced by Liu et al. in 2008, the Isolation Forest algorithm is adept at highlighting such anomalies. Figure 5-10 outlines the procedure wherein this algorithm, coupled with expert system knowledge, was utilized to derive the rules presented in Table 5-1. Initially, abnormal combinations of fuzzified features are detected using the Isolation Forest algorithm. Subsequently, expert knowledge of the monitoring system, supplemented by CT scans of the part, are employed to formulate the rules. For example, Rule 1 in Table 5-1 illustrates a case where a particular pixel in the OT image shows a combination of low grey value (LGV), low mean (LM),

and low variance (LV). This specific combination indicates a recorded OT layer characterized by low energy density, which may predispose the layer to lack of fusion defects.

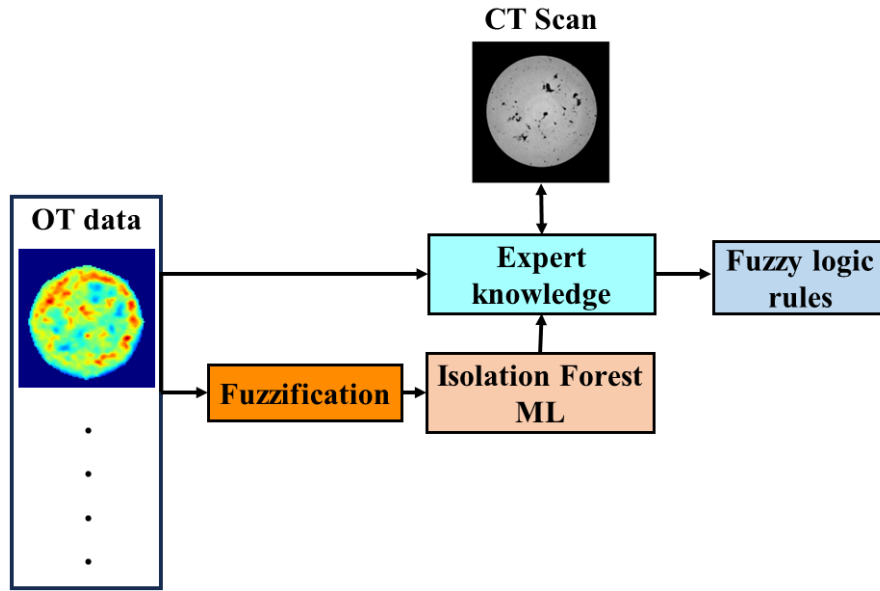
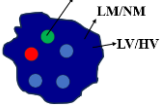
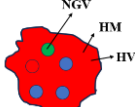
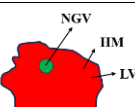
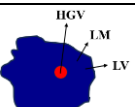
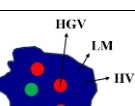
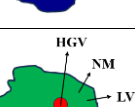
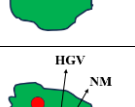
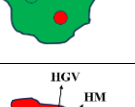


Figure 5-10: Fuzzy rules generation workflow

Table 5-1: Fuzzy rule set from expert knowledge (LGV-Low grey value, NGV-Normal grey value, HGV-High grey value, LM-Low mean, NM-normal mean, HM-high mean, LV-Low variance, HV-High variance)

S/N	LGV	NGV	HGV	LM	NM	HM	LV	HV	Illustration	Type of defect	Conclusion
1	True	False	False	True	False	False	True	False		Lack of fusion	Highly Defective
2	True	False	False	True	False	False	False	True		Lack of fusion	Highly Defective
3	True	False	False	False	True	False	True/False	True/False		Lack of fusion	Defective
4	True	False	False	False	False	True	True/False	True/False		Lack of fusion	Highly Defective

5	False	True	False	True/ False	True/ False	False	True/ False	True/ False		None	Not Defective
6	False	True	False	False	False	True	False	True		Lack of fusion	Highly Defective
7	False	True	False	False	False	True	True	False		Lack of fusion	Defective
8	False	False	True	True	False	False	True	False		Keyhole	Defective
9	False	False	True	True	False	False	False	True		Keyhole	Highly Defective
10	False	False	True	False	True	False	True	False		Keyhole	Defective
11	False	False	True	False	True	False	False	True		Keyhole	Highly Defective
12	False	False	True	False	False	True	True/ False	True/ False		Keyhole	Highly Defective

5.2.2.4 Inference & Defuzzification

This stage involves using the rules to make predictions or decisions about the probability of defects given the fuzzified input variables. Inference and defuzzification was carried out using Equation 5-4 and Equation 5-5.

$$Inference = W_p P_{mf} + W_m M_{mf} + W_v V_{mf} \quad \text{Equation 5-4}$$

where P_{mf} is the pixel membership value, M_{mf} is the mean membership value, and V_{mf} is the variance membership value. W_p , W_m and W_v are the weights that determine the importance of each

of the features to predicting the outcome. The output of Equation 5-4 was normalized using Equation 5-5 into the ranges of 0-0.33 for “Not Defective”, 0.33-0.66 for “Defective”, and 0.66-1 for “Highly Defective”

$$Probability\ of\ defects = Inference * (t_{max} - t_{min}) + t_{min} \quad \text{Equation 5-5}$$

where t_{max} and t_{min} is the upper and lower limit of the probability range for each defect category.

Figure 5-11 illustrates the defect probability maps created for various samples, encompassing both intentionally induced and randomly occurring keyhole and lack of fusion defects. The images clearly demonstrate that regions marked by higher probability values correspond closely to the actual locations of porosity, as verified through CT scan analyses.

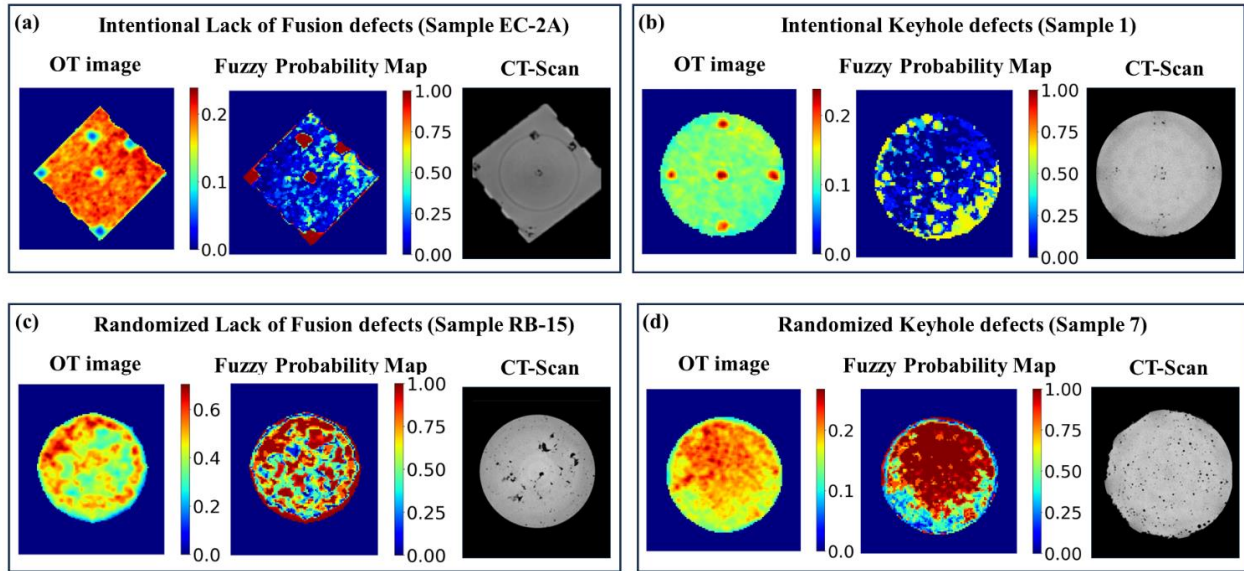


Figure 5-11: Fuzzy modeling applied on OT image with corresponding CT-scans (a) Intentional Lof, (b) Intentional keyhole (c) Randomized LoF, and (d) Randomized Keyhole samples.

5.3 U-Net/Artificial Neural Network-Based Semantic Segmentation Framework

Undertaking the described procedures becomes essential when analyzing a new batch of in-situ data, given the LPBF process's inherent variability and the monitoring system's sensitivity to changes in parameters. Nonetheless, applying these steps for real-time defect detection poses a significant challenge due to the algorithm's need to process the entirety of in-situ data, rendering the task time-intensive. In a prior investigation in the previous chapter [9], a strategy was put forward to overcome this obstacle by devising a hybrid model that merges a modified U-Net framework with an artificial neural network (ANN). This model, trained on data validated by SOM clusters, showcased the capability to forecast cluster centroids under diverse process parameter settings. This study adopts a similar approach, leveraging the probability maps generated in preceding steps to tackle this limitation. The validated probability maps, as confirmed through CT scans, were used to train an integrated model combining a modified U-Net [56] structure with an ANN [85], as depicted in Figure 5-12. This model refines the approach used in previous chapter [9], incorporating an extra output layer designed to predict the fuzzy probability maps. It processes image sequences as input, determined by the selected window length during the moving average calculation for image normalization, as discussed in section 5.2.1. Additionally, it assimilates extra inputs like scan speed, laser power, hatch distance, and layer thickness, alongside the moving average of the input image, to elevate prediction accuracy. The model outputs include the predicted SOM map, the identified centroids, and the fuzzy probability map. Further details about the model can be found in the listed reference [9].

To ascertain the model's efficacy, the Intersection-over-Union (IoU) metric [86] was employed to gauge the closeness between predicted and target labels. Furthermore, the Mean Square Error (MSE) metric was utilized to determine the precision of the fuzzy probability map and SOM centroid predictions. The model was trained over 200 epochs, with a batch size of 128 and employing the Adam optimizer set to a learning rate of 0.0001. The training regimen combined dice loss [87] and MSE for optimization. These processes were conducted on a workstation equipped with an NVIDIA RTX 3070Ti GPU.

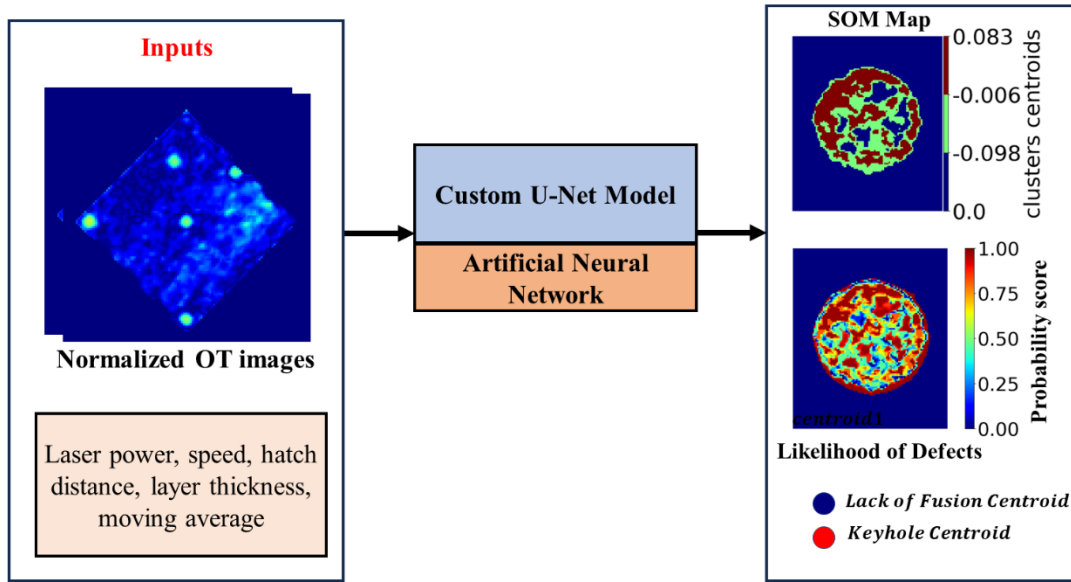


Figure 5-12: The U-Net framework used for predicting the likelihood of keyhole lack of fusion and porosity.

The model underwent training with a total of 37,144 images derived from experiments involving both intentional and random defects, split into 31,572 images for training and 5,572 for validation. To accommodate the model's input requirements, resizing methods such as zero-padding or center cropping were employed. The trained model was subsequently evaluated using 4,604 previously unseen images from both sets of experiments.

The results from the training cycle are detailed in Table 5-2 and Table 5-3, showcasing the predictions for the SOM and fuzzy probability maps, respectively. Figure 5-13 and Figure 5-14 illustrate the training progress, capturing the predictions for both the SOM cluster maps and the fuzzy probability labels. The model displayed excellent accuracy in predicting the SOM cluster maps and the fuzzy probability labels across the training and validation datasets, as indicated in the tables. Additionally, it demonstrated strong performance on the testing dataset comprising new images, achieving a 95.2% Intersection-over-Union (IoU) score and a 0.0042 Mean Square Error (MSE) score. Remarkably, the model accurately predicted the normal class (97.3% accuracy), the lack of fusion class (95.87% accuracy), and the keyhole class (92.48% accuracy).

It is critical to note that while the chosen metric scores provide some information, they may not fully capture the model's true performance. This limitation arises from the variability in

generating Self-Organizing Map (SOM) and Fuzzy probability labels across different samples and SOM models, which may decrease the likelihood of the model producing same predictions. Despite this limitation, it's noteworthy that the predictions from the trained model closely match the centroids of the SOM cluster for new images, reaffirming the findings from the previous study [9].

Table 5-2: Training scores for developed model in SOM clusters map and centroid predictions.

Metric	Training	Validation	Test
Dice loss	0.0278	0.0272	0.0806
IoU	0.9464	0.9487	0.952
MSE loss	9.63e-4	0.0011	0.0057

Table 5-3: Training scores for developed model in predicting fuzzy probability maps.

Metric	Training	Validation	Test
MSE loss	0.0061	0.0054	0.0042

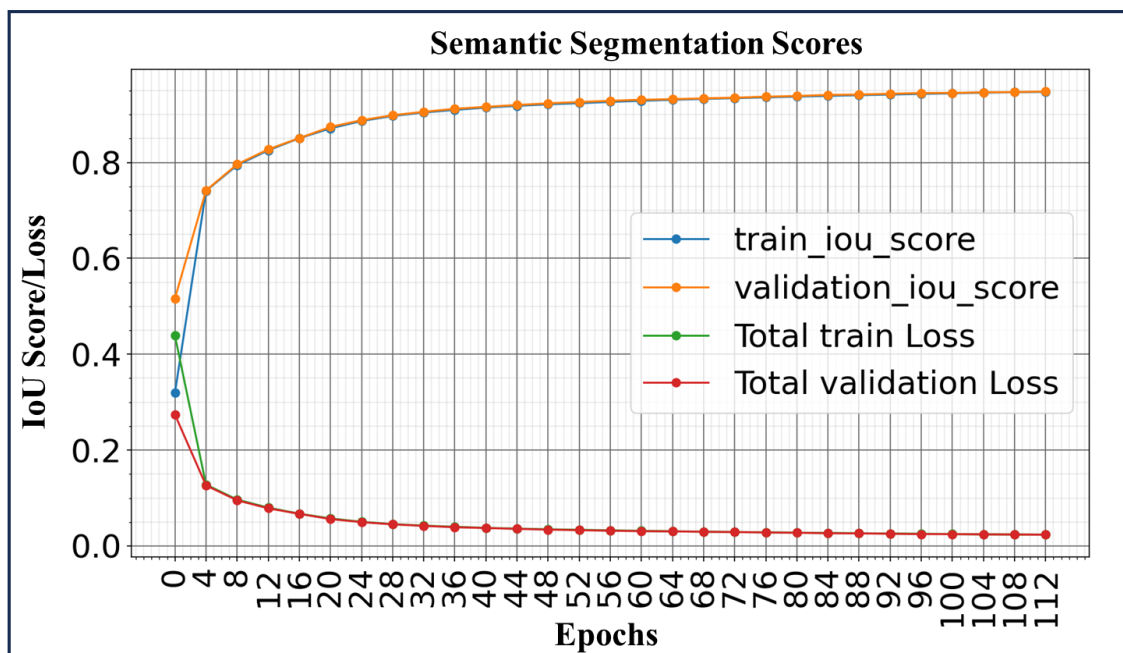


Figure 5-13: Evaluation Metrics for SOM Predictions Using the U-Net/ANN Model: Training and Validation Performance.

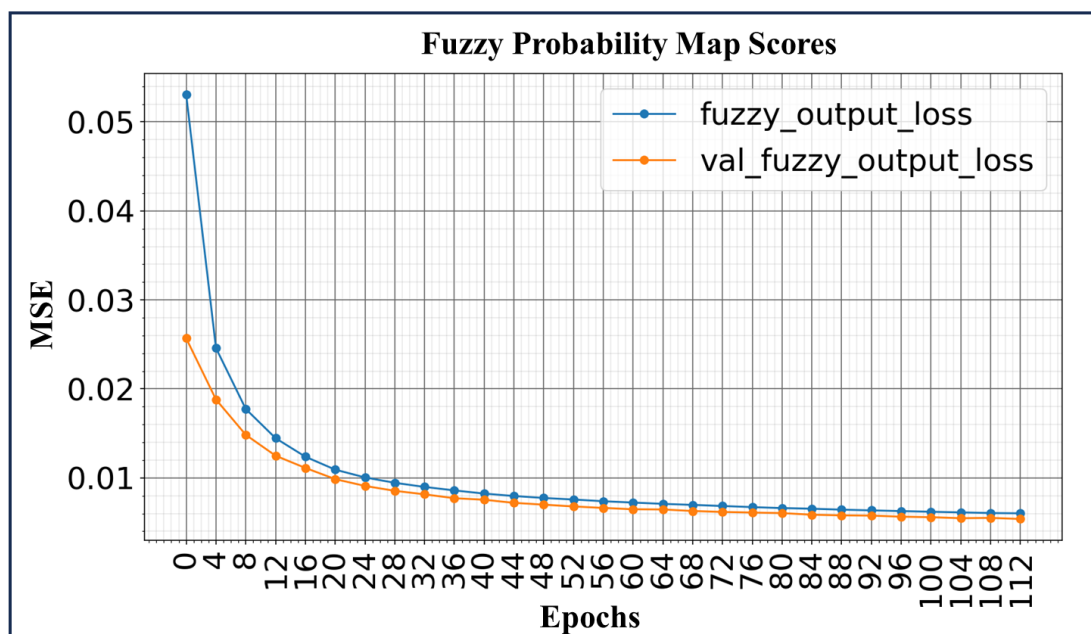


Figure 5-14: Training and validation scores for fuzzy probability map prediction for U-Net/ANN model.

5.4 Results and Discussions

5.5 Predicting probability of defect occurrence using the developed model

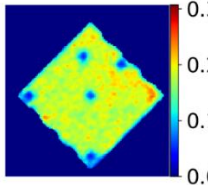
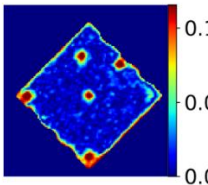
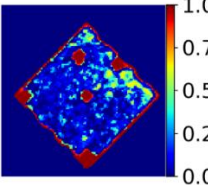
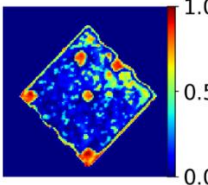
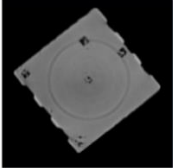
This section details and confirms the efficacy of the devised model in forecasting the likelihood of both lack of fusion and keyhole porosities during the manufacturing process.

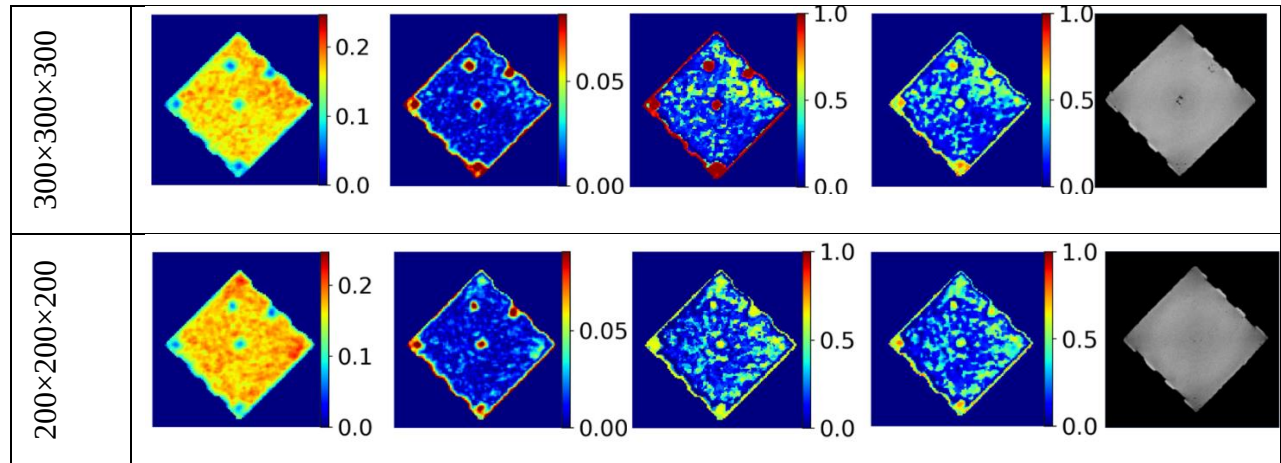
5.5.1 Intentional defect

5.5.1.1 Lack of fusion

As highlighted earlier, the emergence of lack-of-fusion defects is commonly linked to the inadequate delivery of energy during the melting process. To simulate this flaw, deliberate voids were strategically incorporated into the sample, a technique previously employed in [9], [51], [72], [95]. This process results in the laser imparting less energy to the material in subsequent layers above these intentional voids. Such instances manifest as cold spots in OT images, signifying diminished energy absorption by the material and thus, are characterized by lower pixel grey values in the OT imagery. Table 5-4 offers a side-by-side evaluation of the prediction outcomes at different phases, employing the formulated model to forecast lack of fusion defects in the sample EC-2A. The deliberate voids introduced were cubic in shape with sizes of $200\ \mu m^3$, $300\ \mu m^3$ and $400\ \mu m^3$, respectively.

Table 5-4: Visualization of fuzzy probability maps produced for deliberate lack of fusion pores in sample EC-2A, accompanied by a slice of the CT-scan of the relevant layer.

Defect size (μm)	Representative Image (Sample EC-2A)				
	OT image	Normalized OT image	Fuzzy Target Map	U-Net Predicted Fuzzy Map	CT-scan
400×400×400					



Based on the visualizations, it is evident that the developed model was able to accurately forecast the occurrence of fusion pores at sites of intentional defects, registering average probability scores of approximately 0.819 and 0.710 for the fuzzy logic model and the trained U-Net model respectively for the defect size of 400 μm , as detailed in Table 5-5. These scores fall within the range indicative of a highly defective classification (0.66-1). Conversely, smaller defects measuring 300 μm and 200 μm displayed lower probability scores, approximately 0.53 (0.5 for the U-Net model) and 0.375 (0.376 for the U-Net model) respectively, aligning with the defective category (0.33-0.66).

Table 5-5: Probability scores for deliberate lack of fusion defects in sample (EC-2A)

Defect size	Average Target Probability score	Average U-Net Predicted Probability score
400 μm	0.819	0.710
300 μm	0.527	0.500
200 μm	0.375	0.376

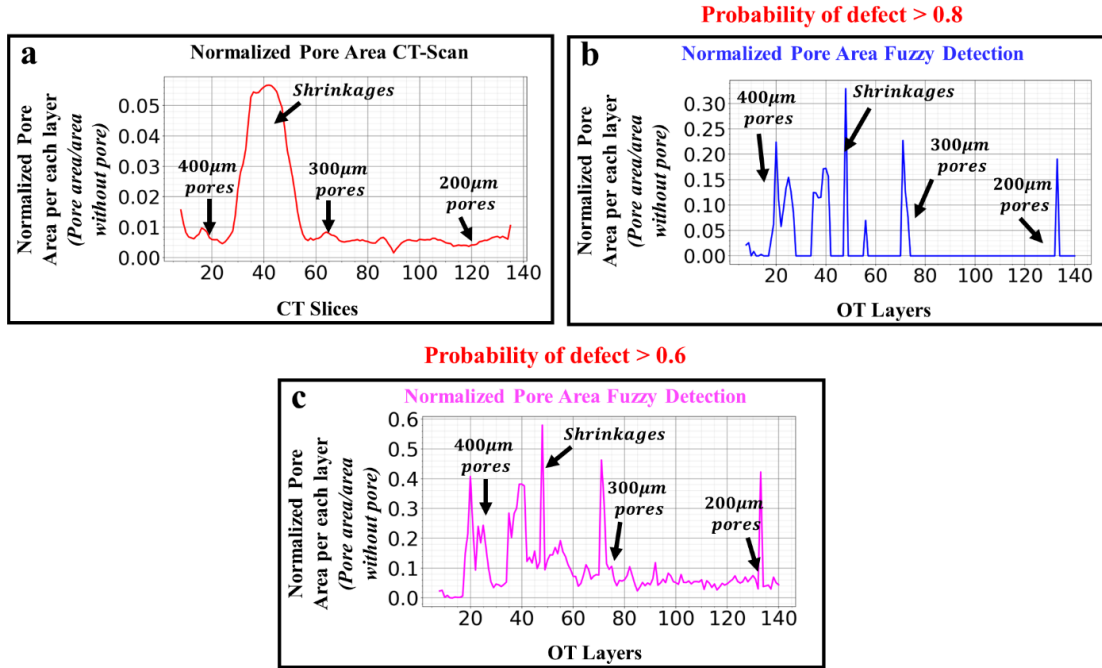


Figure 5-15: Normalized porosity curves for deliberate lack of fusion defects in sample EC-2A, showcasing a) CT-scan results, b) probability of defects exceeding 0.8, and c) probability of defects exceeding 0.6.

The normalized porosity signal curves, derived from both CT-scan data and the developed algorithm, are depicted in Figure 5-15. These curves serve as a tool to evaluate the method accuracy throughout the layer-wise manufacturing process [9]. The calculation of these values involves the ratio of the pore areas within a layer to the total area of the part. Specifically, Figure 5-15a illustrates the porosity levels from each CT scan slice for sample EC-2A (intentionally created lack of fusion sample). Furthermore, Figure 5-15b and 20c display the porosity levels identified by the developed model with probabilities exceeding 80% and 60%, respectively.

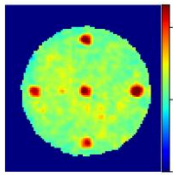
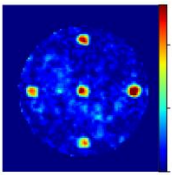
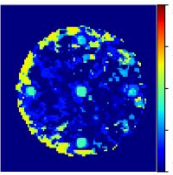
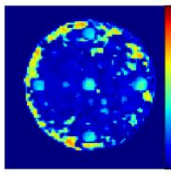
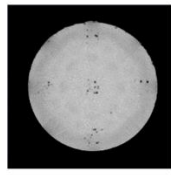
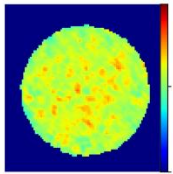
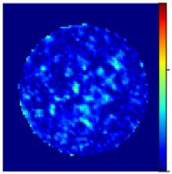
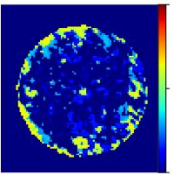
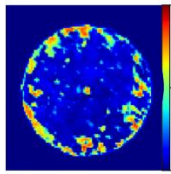
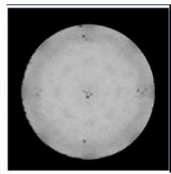
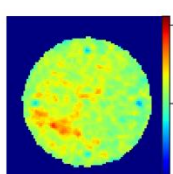
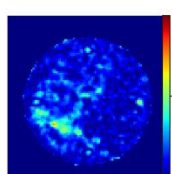
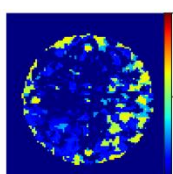
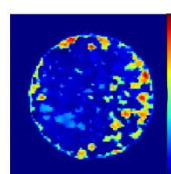
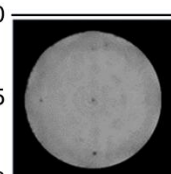
In Figure 5-15a, for sample EC-2A, the porosity identified in slices 11 to 23, slices 62 to 72, and slices 114 to 122 corresponds to the intentional introduction of cubic defects with dimensions of 400 μm , 300 μm , and 200 μm , respectively. The algorithm successfully detects the increase in porosity curves associated with these defects when analyzing pores identified with at least an 80% probability, as seen in Figure 5-15b. This detection is consistent even when the threshold is lowered to a 60% probability (Figure 5-15c), though with greater signal fluctuation indicating potential defects in other layers due to the lower probability threshold set. Additionally, a notable rise in

porosity levels from slices 30 to 45 in Figure 5-15a, caused by part shrinkage [9], was also captured by the developed method, as evident in layers 45 to about 60 in Figure 5-15b and 20c.

5.5.1.2 Keyhole

Keyhole defects are formed when an excessively high level of energy is delivered to the powder bed during the printing process. To replicate this type of defect, cubic inserts of varying sizes were embedded within the samples, followed by a reducing the laser speed to increase the energy input at those specific locations, causing artificial keyhole pores. Table 5-6 illustrates the use of the framework to forecast this type of porosity in sample 1.

Table 5-6: Visualization of fuzzy probability maps produced for deliberate keyhole pores in sample 1, accompanied by a CT-scan slice of the relevant layer.

	Representative Image (Sample 1)				
Defect size (μm)	OT image	Normalized OT image	Fuzzy Target Map	U-Net Predicted Fuzzy Map	CT-scan
1000×1000×1000					
500×500×500					
250×250×250					

As illustrated in Table 5-6, the methodology effectively detects these keyhole pores within the images, yielding an average probability score of approximately 0.48 and 0.47 for the fuzzy logic model and the trained U-Net model respectively, for the defect size of 1000 μm , as detailed in Table 5-7. These scores fall within the range identified as the defective class (0.33-0.66), highlighted by the relatively small pores at the locations of the defects. Defects of smaller dimensions, such as 500 μm and 250 μm , demonstrated probability scores of around 0.62 (0.56 for the trained U-Net model) and 0.39 (0.38 for the trained U-Net model) respectively, aligning them within the same defective classification.

Table 5-7: Average probability scores for Intentional keyhole zones sample (1)

Defect size	Average Target Probability score	Average U-Net Predicted Probability score
1000 μm	0.478	0.471
500 μm	0.616	0.561
250 μm	0.391	0.382

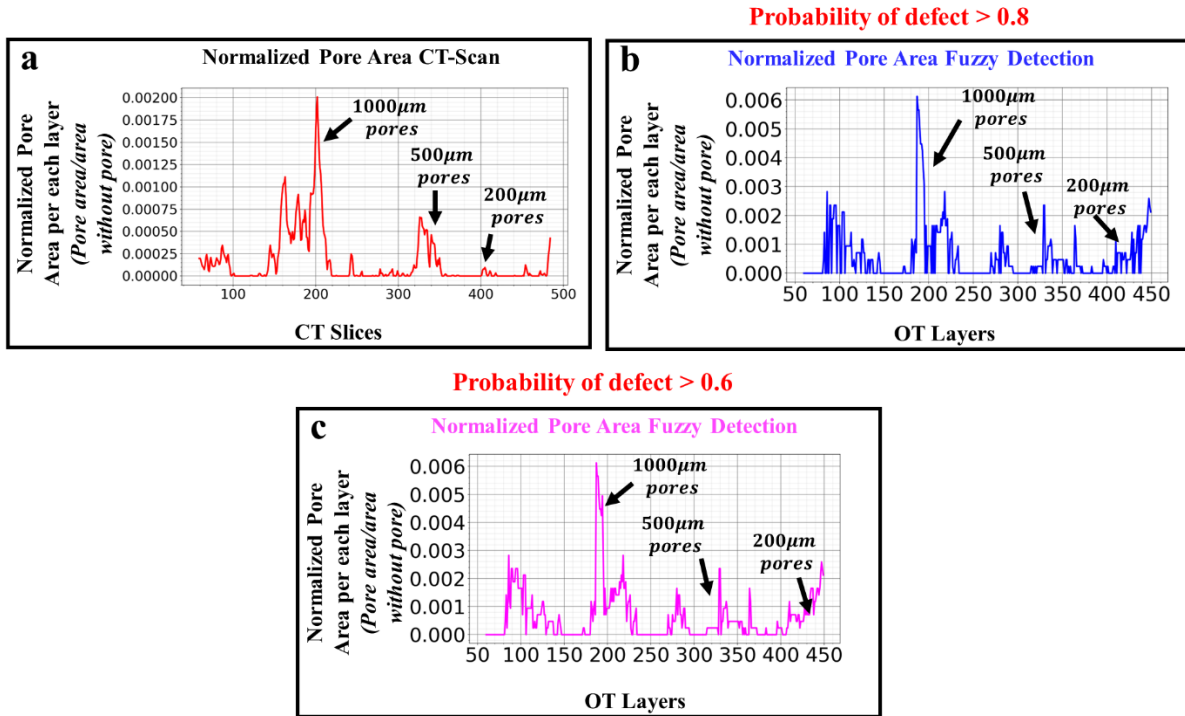


Figure 5-16: Normalized porosity curves for deliberate lack of fusion defects in sample 1, showcasing a) CT-scan results, b) probability of defects exceeding 0.8, and c) probability of defects exceeding 0.6.

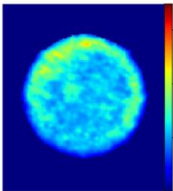
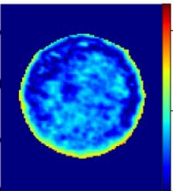
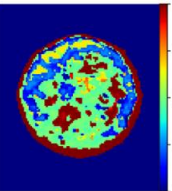
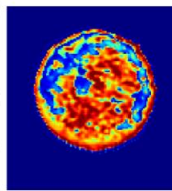
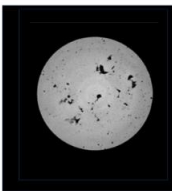
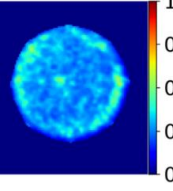
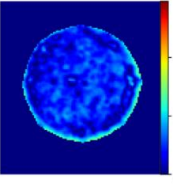
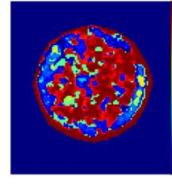
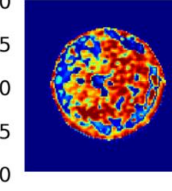
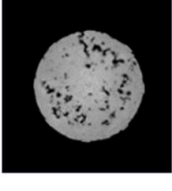
The curves derived from both CT-scan data and the developed algorithm is shown in Figure 5-16. From, Figure 5-16a illustrate the porosity levels from the CT scans for sample 1 (Intentional keyhole sample) .In addition, Figure 5-16b and Figure 5-16c depict the porosity levels detected by the developed method with probability values exceeding 80% and 60%, respectively.

In Figure 5-16a, slice 145 to slice 217, 320 to 354 and 471 to 494 are pores caused by the keyhole pores, resulting from heightened energy density at those defects locations, measuring defects of sizes 1000 μ m, 500 μ m, and 250 μ m respectively. While considering all the pores detected by the algorithm with at least a 0.8 probability, the rise in the porosity curves associated with introducing these defects are all detected by the algorithm.

5.5.2 Randomized defect

The efficacy of the devised algorithm was evaluated on images with defects arising from improper process parameter choices, as detailed in section 3.2.3. Table 5-8 provides a selection of examples from individual layers captured in the images, paired with their respective CT scans and the detected probabilities of porosity by the algorithms. These instances are taken from Samples RB-15, RB-16, RB-17, which exhibit random lack of fusion pores, and Samples R2, R7, and R8, showcasing random keyhole pores. In Samples RB-15/RB-16, the observed lack of fusion defects was linked to the choice of a thicker layer thickness (0.06 mm and 0.08 mm, respectively), necessitating a greater energy input for adequately melting the powder and hence elevating the risk of defect formation. In contrast, the defects in Sample RB-17 were caused by a combination of issues, including deviations in laser focus, inconsistencies in powder spread, and problems with the recoater mechanism. For Samples R2, R7, and R8, keyhole defects were because of localized reductions in laser speed in certain regions in the sample, which consequently increases the energy input in those areas.

Table 5-8: Visualization of fuzzy probability maps produced for naturally induced keyhole and lack of fusion porosity, accompanied by a CT-scan slice of the relevant layer.

	Representative Image (Randomized Defects)					
Sample	OT image	Normalized OT image	Fuzzy Target Map	U-Net Predicted Fuzzy Map	CT-scan	
RB-15						
RB-16						

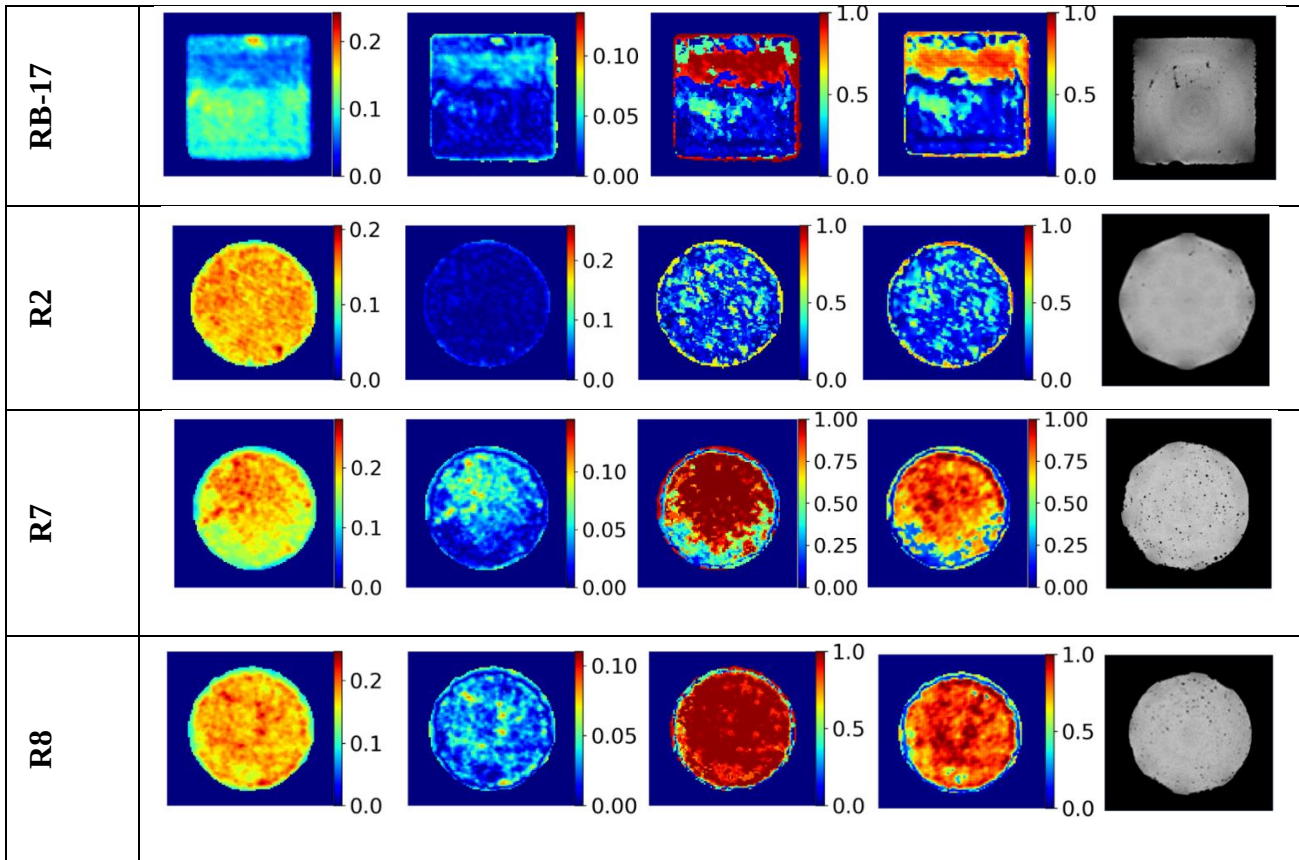


Table 5-8 highlights the effectiveness of the algorithms in pinpointing specific patterns of porosity within the images. The assessment of the model's capability to detect randomized defects across entire layers involved the examination of normalized porosity signal curves derived from both CT scans and the algorithm's outputs. Figure 5-17 and Figure 5-18 focus on showcasing the porosity curves for samples RB-15 and R7, respectively, based on different defect probability thresholds. For brevity, only these would be presented.

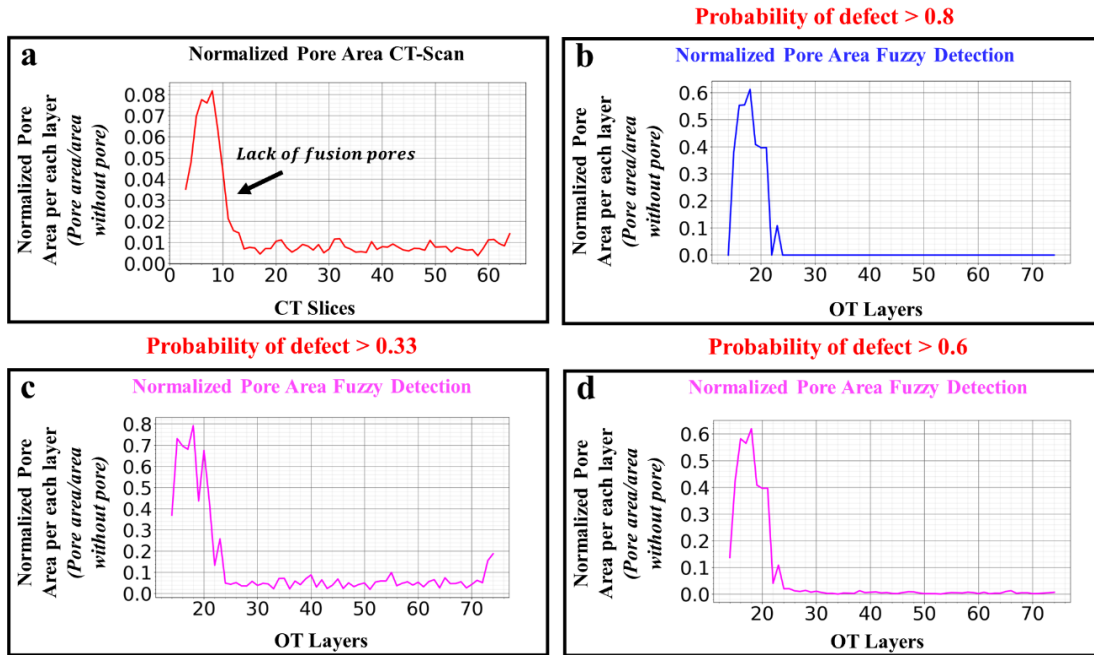


Figure 5-17: Normalized porosity curves for randomized defects a) CT-scan, b) probability of defects greater than 0.8 and c) probability of defects greater than 0.6 d) probability of defects greater than 0.33 for RB-15.

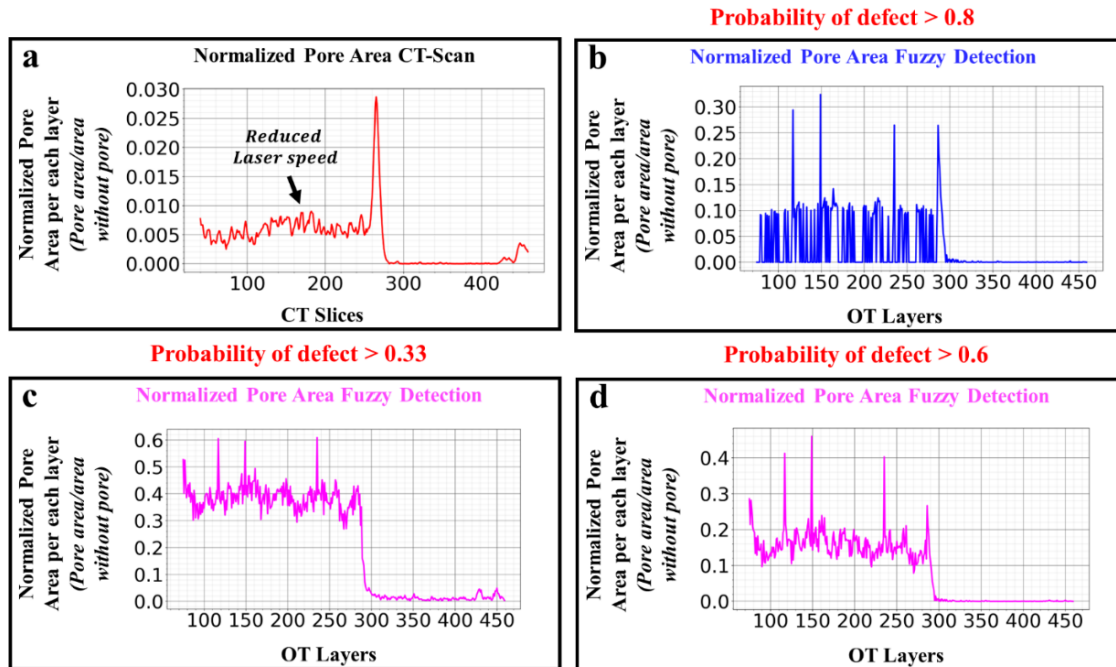


Figure 5-18: Normalized porosity curves for randomized defects a) CT-scan, b) probability of defects greater than 0.8 and c) probability of defects greater than 0.6 d) probability of defects greater than 0.33 for Sample 7

In Figure 5-17(a), the fluctuation in porosity levels through various slices of the CT scans for sample RB-15 is detailed. The selection of a thicker layer thickness led to the formation of substantial fusion pores between slices 4 and 15, as identified in Table 5-8. Moreover, smaller fusion pores are consistently observed across all layers, resulting in variable porosity signals in the CT data. The algorithm's ability to discern these pores is highlighted by the well-matched curves in Figure 5-17(b), (c), and (d), especially in layers 4 to 18 where large fusion pores are predominant. With a defect probability threshold of 0.8, the algorithm pinpoints the larger fusion pores, while smaller pores remain undetected. Adjusting to a lower probability threshold allows for the identification of these smaller pores.

Similarly, Figure 5-18(a) displays porosity levels across CT scan slices for sample R7, where the application of a reduced laser speed of 500 mm/s led to the creation of notably irregular spherical pores, identifiable from approximately slice 50 to slice 300, as mentioned in Table 5-8. The subsequent Figure 5-18(b), (c), and (d) reveal a marked congruence between the algorithm-

generated curves and the CT data, notably in layers 50 to almost 290, underscoring the method's precision in identifying defects.

5.5.3 Predicting probability of defects in a complex geometry

The effectiveness of the devised method was tested on images produced from the fabrication of a complex component with intricate internal lattice structures, as introduced in Section 3.2.3 and depicted in Figure 3-4. The goal was to assess the algorithm's capability to differentiate between typical phenomena associated with geometric configurations and genuine defects. The outcomes presented in Figure 5-19 indicate the detection of relatively minor pores under standard printing parameters, which were linked to overheating phenomenon, as confirmed by the small spherical pores observed in the CT scans. The novel integrated algorithm proficiently recognized the overheating, assigning a defect probability score around 0.6, categorizing it within the defective range. Due to the CT scans' limited resolution, it was impractical to display the normalized porosity signal curves for these samples.

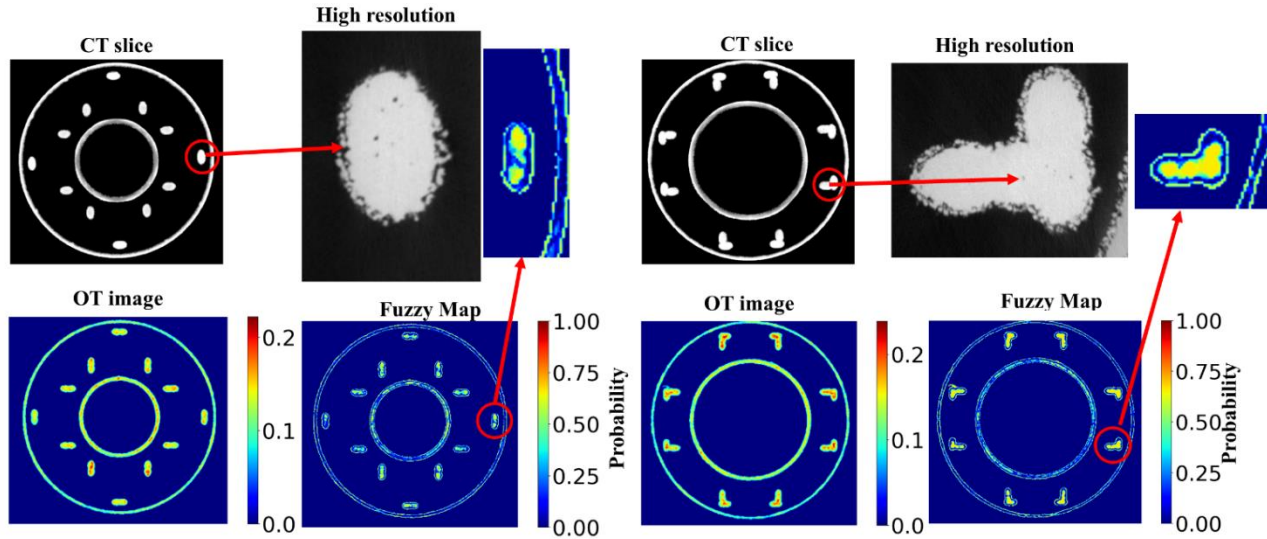


Figure 5-19: Example of OT image with corresponding CT slice for complex Geometry.

5.6 Summary

In this chapter, ML framework combining a Self-Organizing Map (SOM), Fuzzy modeling, and a U-Net model was used to predict the likelihood of porosity due to inadequate fusion and keyhole formation under varying processing conditions. The ML framework successfully predicted keyhole and lack of fusion defects assigning average porosity scores from 0.375 to 0.819 for deliberate lack of fusion and from 0.391 to 0.616 for intentional keyhole defects, according to defect sizes. Moreover, the model exhibited strong performance in detecting random occurrences of these defects, as evidenced by the alignment of normalized porosity curves derived from CT scans with those predicted by the algorithm. A key feature of this technique is that it eliminates the requirement for a custom dataset for training the U-Net model, as it automatically gathers the necessary ground truth data without needing manual input, thus reducing the chance of human error. Moreover, this approach is designed to be robust against changes in processing conditions and material types, as it normalizes data via a moving average prior to the identification of any discrepancies. This methodology presents significant benefits, notably its adaptability, which permits quality assurance professionals to define detection probability thresholds tailored to precise quality standards. Additionally, these engineers can apply their knowledge of the monitoring system using fuzzy rules, thereby improving part qualification.

6 Conclusions and Future Work

6.1 Conclusions

In this research, we utilized an Optical Tomography (OT) system, operational in the near-infrared spectrum, that is commercially integrated into an EOS M290 LPBF machine for image acquisition during process-PBF. The in-situ images captured were analyzed using a machine learning framework that incorporates a Self-Organizing Map (SOM), Fuzzy Logic, and a U-Net architecture to assess the probability of porosity due to lack of fusion and keyhole phenomena. To validate the effectiveness of our model, five experimental batches featuring both deliberate and random defects were produced, analyzed, and cross-referenced with CT scans. Furthermore, we examined normalized porosity trends to establish a relationship between the CT scans and our analytical algorithms. A significant advantage of our method is its ability to generate its own training data, eliminating the need for manually curated datasets and thus minimizing human error. This technique proves to be adaptable to variations in process parameters and materials by normalizing the data through a moving average before pinpointing anomalies. This approach is not only computationally efficient requiring just two clusters for identifying defects, but also viable for real-time application using the trained U-Net model for in-situ monitoring. Overall, our findings validate the capability of this innovative approach in detecting porosity signatures across a wide array of process conditions.

The following conclusions can be drawn from the research:

- The changes in process parameters resulted in significant variations in the magnitude of recorded optical tomography grey-values. As a result, porosity signatures may vary greatly, which makes it challenging to deploy developed algorithms across a wide range of process parameter selections, materials, and machine configurations.
- Process parameters that could lead to recorded higher optical tomography image grey-value include higher laser power, low laser speed, smaller layer thickness and decreased hatch distance. In contrast, lower laser power, larger layer thickness, faster laser speed, and increased hatch distance lead to lower optical tomography image grey-value readings.

Also, other parameters such as the hatching method, stripe width, and stripe overlap could still significantly impact the signal magnitude.

- The process deviations identified in optical tomography images do not necessarily lead to the detection of defects in the fabricated parts due to the self-healing nature of the LPBF process or other reasons like noise to signal ratio. To accurately predict pores formation in a layer, the OT images from current and subsequent layers need to be considered (e.g, 2 to 4 layers for lack of fusion porosity and over 5 layers for the keyhole porosity).
- The thresholding-based algorithm available within the monitoring setup was the most effective for detecting lack-of-fusion signature with an accuracy of about 0.65 with intentional defect sizes 200 μm , 300 μm and 400 μm all detectable by the algorithm. However, this detection accuracy is mainly dependent on careful parameter selection.
- The U-Net model architecture performed excellently well in predicting SOM clusters for previously unseen images. The former model achieved a test score of 89.3% and a defect class score of 93%, Nonetheless, additional experimentation is required to further enhance the model's performance.
- Both the SOM and U-Net algorithms exhibited a robust correlation with the pores identified in the CT-scans, as evidenced by their normalized porosity curves. These curves showed a low dynamic wrapping distance similarity score in comparison to the CT curves. Furthermore, the U-Net/ANN model architecture exhibited similar performance compared to the SOM algorithm in detecting both randomized lack of fusion and keyhole defects in the printed component, thus supporting the efficacy of these methods.
- The fuzzy machine learning framework successfully predicted the probability of keyhole and lack of fusion defects assigning average porosity scores from 0.375 to 0.819 for deliberate lack of fusion and from 0.391 to 0.616 for intentional keyhole defects, according to defect sizes. Moreover, the model exhibited strong performance in detecting random occurrences of these defects, as evidenced by the alignment of normalized porosity curves derived from CT scans with those predicted by the algorithm.
- A key feature of these machine learning technique is that it eliminates the requirement for a custom dataset for training the U-Net model, as it automatically gathers the necessary ground truth data without needing manual input, thus reducing the chance of human error. Moreover, this approach is designed to be robust against changes in processing conditions

and material types, as it normalizes data via a moving average prior to the identification of any discrepancies.

- This methodology also presents significant benefits, notably its adaptability, which permits quality assurance professionals to define detection probability thresholds tailored to precise quality standards. Additionally, these engineers can apply their knowledge of the monitoring system using fuzzy rules, thereby improving part qualification.

6.2 Recommendations and Future Work

The research described in this dissertation has focused on the development of data-driven detection algorithms using in-situ optical tomography images from the process. The following are some recommendations to further extend this research:

1. Advanced Image Processing Algorithms:

- **Development and integration of AI and machine learning algorithms:** Focus on the creation of advanced algorithms that can automatically analyze and interpret tomographic images to detect defects. Deep learning models, particularly Convolutional Neural Networks (CNNs), can be trained to recognize complex defect patterns and improve over time with more data.
- **Real-time defect detection:** Explore the feasibility of implementing real-time image processing and defect detection during the LPBF process. This would allow for immediate corrections and significantly reduce the number of defective parts produced.

2. High-Resolution Imaging Techniques:

Investigate the use of high-resolution optical tomography techniques to detect microscale defects that are currently challenging to identify. Enhancements in hardware, such as the use of higher resolution cameras and advanced optics, combined with sophisticated image reconstruction algorithms, could lead to significant improvements in defect detection capabilities.

3. **Integration of Multimodal Imaging Systems:** Combine optical tomography with other non-destructive evaluation (NDE) methods, such as ultrasound, X-ray computed tomography (CT), or eddy current testing, to create a multimodal imaging system. This approach could provide complementary information and offer a more comprehensive understanding of the defects, including their nature, size, and location.
4. **In-situ Monitoring and Control:** Explore the integration of optical tomography for in-situ monitoring within the LPBF process. Research how this technology can be used not only for defect detection but also for process optimization, such as adjusting laser power, speed, and strategy to correct potential defects on the fly.
5. **Quantitative Analysis and Characterization:** Develop methodologies for quantitative analysis of defects detected by optical tomography. This includes quantifying defect sizes, densities, and distributions, and relating these characteristics to the mechanical properties of the manufactured parts. Understanding these relationships is crucial for establishing acceptable defect thresholds for different applications.
6. **Expanded Dataset for Machine Learning Models:** Utilizing a larger and more varied dataset for training machine learning models can improve their ability to generalize across different machine setups, materials, and process parameters. This can be implemented by conducting several experiments to investigate other process defects such as surface roughness, dimensional accuracy, and recoater failures.
7. **Material and Process Parameter Studies:** Conduct systematic studies on how different materials (metals, alloys, ceramics) and LPBF process parameters (laser power, scan speed, layer thickness) affect the formation of defects. This can help in optimizing process parameters for minimizing defects and improving part quality.

- 8. Standards and Benchmarking:** Work towards the development of industry standards for optical tomography in LPBF applications. Creating benchmark tests and validation procedures for optical tomography systems will help in standardizing defect detection methodologies and ensure reliability across different platforms and applications.

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