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Review article

Product quality assurance in Powder Bed Fusion through the application of ML/AI tools: a critical review

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ABSTRACT

Due to complex physical phenomena, which govern the process of Powder Bed Fusion (PBF), the feasibility and repeatability of the PBF production is often put in question, having as consequence unsatisfactory implementation of PBF at the industrial level. For this reason, many different research approaches have been carried out in terms of improving the governance of the process and its quality indicators. The overall boost of the Machine Learning and Artificial Intelligence (ML/AI) tools in the last decade has brought a significant advantage in this aspect, since these tools enable evaluation of massive amounts of data and extraction of complex relations which are not easily recognizable by the human eye or simple statistical tools. This paper provides an analysis of critical aspects of product quality in PBF, then offers a thorough critical review of the most relevant research efforts in the field of product quality assurance in Metal Additive Manufacturing through the application of ML/AI methods, to finally detect the major gaps, opportunities and future lines.

Key words: *machine learning; artificial intelligence; additive manufacturing;*

1. INTRODUCTION

Powder Bed Fusion (PBF) represents a paradigm of sustainable manufacturing technology. It makes no use of physical tools, it allows simultaneous manufacturing of diverse geometries, it is the most economic manufacturing option for lot-size-one and short series, and it enables reuse of material many times before it needs to be discarded. These characteristics, among others, make PBF very attractive for many industrial sectors, but years after the first products made by PBF have reached the market, the wider implementation of this technology in industry remains challenging. The reasons are multiple - but if we focus on technical reasons only, the most relevant is the premature failure of PBF parts as well as the failure to meet technical specifications such as dimensional stability and tolerances. The complexity of the PBF process and its multi-physics character contribute significantly to this situation. PBF belongs to primary forming processes, but unlike bulk primary forming such as sand casting, die casting or powder metallurgy, PBF consists of millions of consecutive melting-solidification-cooling (MSC) cycles, some of which can go wrong. Even a single inadequate MSC cycle can provoke defects in the manufactured part, such as pores, cracks or delamination, which serve as stress concentrators and are detrimental to the operation of the part. Some of these defects can be solved by post-processing, but some of them cannot. In addition, a continuous inadequate MSC cycle can lead to the accumulation of excessive thermal stresses inside the part, which can cause warpage and loss of tolerances, difficult assembly, but also lead to a premature failure in service.

Many different aspects of PBF have been tackled with ML/AI tools – from topological optimization of lightweight design to the optimization of process parameters. Literature review in that sense would be vast and focusing on all of these aspects in a single review is impossible. Therefore, the focus of this review lies in the

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product quality assurance in PBF. In other words, *how can one manufacture ready-to-print design using standard parameters without critical defects* and *what role can ML/AI play in this*. To answer this question, this paper first offers a scientific approach to the problem of product quality assurance in PBF, then focuses on the review of the state of the art in all of the disclosed approaches, to finally discuss the future application of the developed work.

2. PRODUCT QUALITY ASSURANCE IN PBF

The following **Fig. 1** intends to illustrate the different aspects which have influence on job success in PBF. Post-processing is excluded from this analysis because it does not prevent quality issues, only mitigates their consequences.

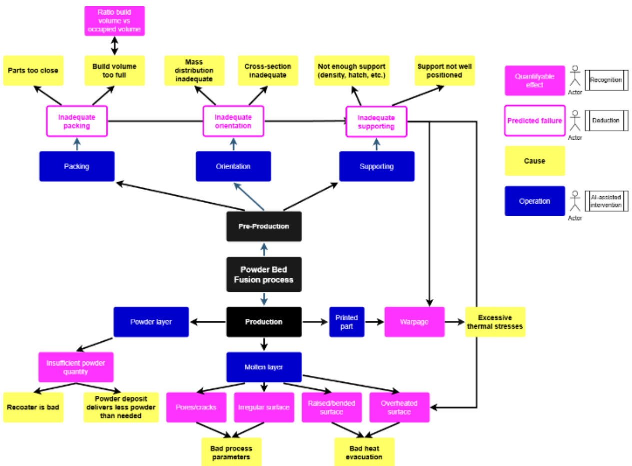

Fig. 1. *An overview and analysis of main causes of build failure in a M-AM. Quantifyable effect – can be measured, Prediction – can be estimated.*

In pre-production, we can relate six principal causes for problems during printing. Four of them are quite clear: *the job can be overloaded*, *the parts can be located too close together*, *the support quantity can be insufficient*, or *the support can be inadequately positioned*. The effects of these causes are logical and easy to understand. Yet, the remaining two causes deserve a bit more explanation. In the literature they are referred to as „orientation-dependent residual stress“ [1], since the orientation of the part generates different lengths and patterns of scanning tracks and lead to anisotropic warpage. We introduce the term „*thermal mass imbalance*“ to refer to an orientation which causes more mass in the upper than in the lower printing layers – that is, longer and more extensive scanning tracks in each layer. When this occurs, the lower geometry can act as bottleneck during the dissipation of excessive heat and lead to the accumulation of thermal stress. A bad thermal mass imbalance is not necessary and sufficient condition for warpage and distortion, but it stresses significantly the need for perfect support to avoid them. In other words, the influence of the support quantity and position can be diminished with a proper thermal mass imbalance. Similar applies to the „geometry-induced thermal gradients“; this term refers to the sudden and abrupt changes in cross-section, but also inadequate width-to-length ratios which lead to warpage. The cause is also a sudden change in the extension and length of the scanning tracks. These are also not necessary and sufficient conditions for warpage and crash but require a relevant intervention of the human in correcting the amount and position of the support structure. In any case, one thing is clear - all of these six causes lead to the accumulation of excessive stresses and warpage, causing deformation and tolerance loss, but sometimes also lead to the recoater crash. **Fig. 2** illustrates this on a simulated (a) and a real (b) example.

a)

b)

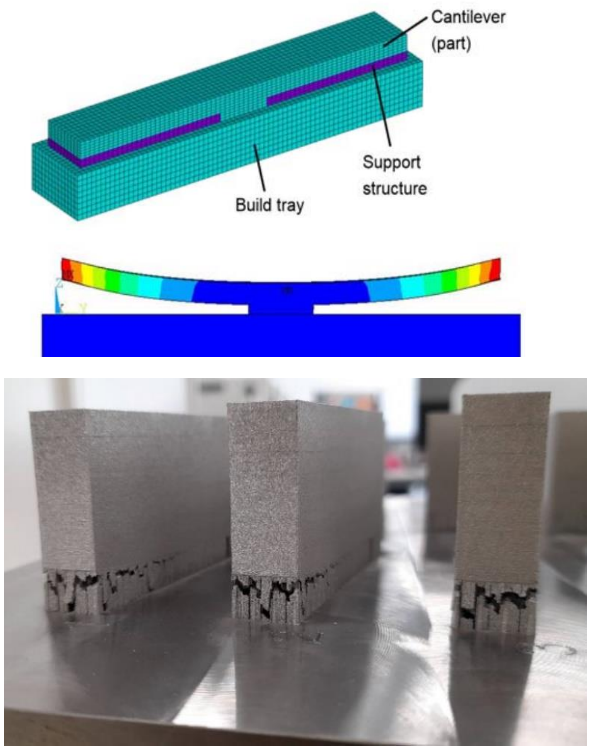

Fig. 2. *a) Simulation result of warpage of a Cantilever (T-structure) after build-up by LBM and the removal of support structures [55]; b) warpage induced by the long and continuous scanning tracks (courtesy of AIDIMME Technology Institute, Valencia).*

Speaking of the production stage, the most relevant direct indicators for the successful print job are powder and melted area, respectively. By melted area, the total surface area of a layer that has been melted by the laser or electron beam is understood. The failure at the powder layer is clear: *bad recoater state* and *failure of the powder delivery system to provide sufficient powder* leads to the insufficient powder amount in each layer. This is detrimental for the powder layer integrity and causes problems during the build. In regard to the melted area, we can detect four main problems – *pores and cracks* on the surface as well as the *irregularity in the melted area* indicate inadequate process parameters (too much or too little energy input), while the *visibly overheated surface and regrowth* – also known as super-elevation or bulging in the literature - are indicators of bad heat dissipation and are almost always linked with the above-mentioned pre-production causes.

The aforementioned possible causes of lack of production quality do not always act as stand-alone features - they are actually strongly interrelated. Nevertheless, by addressing all these causes with a timely response, it is possible to control the production process and minimize the likelihood of manufacturing failures. For this reason, the following sections provide an overview of all the work carried out in the area of ML/AI-endorsed solutions to the aforementioned causes.

3. ML/AI IN PRE-PRODUCTION ORIENTED TO THE AM PRODUCT QUALITY ASSURANCE

Following the structure on Fig. 1 the first part of this review is structured in three subsections: *ML/AI-assisted optimization of the packing and nesting*, *ML/AI-assisted optimization of the build orientation* and *ML/AI-assisted optimization of the support structure*. For each of three aspects, relevant works on how ML/AI can assist will be discussed, focussing predominantly on the assurance of the thermal stability of the print job.

3.1 ML/AI-assisted packing and nesting

The search for optimized packing of a build volume in Powder Bed Fusion is not a novel problem, and it has been referenced since the beginning of the industrial application of AM. Already in the 90s, Ikonen et al [56] have proposed an ML/AI approach consisting in the application of an Genetic Algorithm (GA) to the three-dimensional bin-packing problem in additive manufacturing. The study successfully utilized GA to optimize the orientation and packing of three-dimensional, non-convex parts for the Stereolithography process, with a sight on application in other AM processes. The goal was to solve complex orientation and layout problems for non-convex geometries to ensure they could be packed efficiently within a build volume. Gogath and Pande [2] also used GA to address search and planning problems in production layouts. Their research proposed a system for "Intelligent layout planning" with the aim of enhancing production planning by maximizing the number of parts placed into a single build space. Yao et al. [3] focused on a level-set-based approach for partitioning and packing, developing a methodology for the simultaneous partitioning and packing optimization of printable models. Similar to the prior works, the goal was to optimize the arrangement of model components within the build volume to improve overall printability and space utilization. These research works were followed by several studies, labelled as foundational for production scheduling and planning in AM [4], [5]. These include multi-objective optimization for part-to-printer assignment and Modified Genetic Algorithms (MGA) for single-machine scheduling. These works demonstrate that ML facilitates the execution of planned scheduling and print-on-demand strategies, which contribute to improved time efficiency and a significant reduction in lead-time wastage. GA continued to be of interest, since Zhang et al [6] used it as well for finding sub-optimal solutions to the nesting problem. A new method for the nesting of single-layer parts was developed, determining that GA can provide effective layout solutions within a reasonable amount of computation time. The primary benefits sought were increasing machine utilization, reducing build costs, and improving production efficiency. Another approach was the one of Chergui et al [7], who used AI-enabled software entities designed to manage complex manufacturing tasks with minimal human intervention. The study proposed an integrated approach for AM production scheduling and nesting, seeking the synchronization of the nesting layout with production schedules to improve the overall workflow and throughput of AM systems. Later on, Griffiths et al [8] performed a study utilizing heuristic optimization and search algorithms for multi-part print planning. The research focused on cost-driven bin packing specifically for the Selective Laser Melting (SLM) process. The primary motivation was to reduce total production costs by optimizing both part orientation and the bin-packing arrangement across multiple builds. In recent years, the packing/nesting problem in AM continued to be of interest. Alicastro [9] applied a meta-heuristic Reinforcement Learning (RL) -iterated local search (ILS). This approach integrated GA with a variable neighborhood search, employing Q-learning as a local search mechanism to explore optimal solutions within the neighborhood effectively. The study demonstrated that this hybrid method reached optimal scheduling solutions faster than previous approaches, showing particular effectiveness for large-scale production volumes. The goal was to increase machine utilization and decrease the average costs associated with setup and post-processing operations in the Selective Laser Melting (SLM) process. It specifically accounted not only with the volume but also with the maximum height of the parts in a batch, addressing the influence of the bounding box after orientation. Ying and Lin [10] also used a meta-heuristic RL based on the iterated epsilon-greedy (IEG) algorithm. They also adopted a mixed-integer linear programming (MILP) model to define the two-stage assembly AM machine scheduling problems (AMMSPs) as an optimization task. The IEG algorithm was found to be effective, efficient, and robust in balancing exploration and exploitation to solve complex batch scheduling problems. The primary benefit was the reduction of makespan by optimizing how parts were placed into batches and shortening the waiting time for final product assembly. Sun et al [11] opted for an out-of-order enabled dueling deep Q-Network (O3-DDQN) to approach nesting in AM. This approach formulated dynamic scheduling such as Markov Decision Processes (MDPs), incorporating constraints such as batch processing, random order arrivals, and machine eligibility. The O3-DDQN approach outperformed both state-of-the-art learning methods and classical scheduling rules. The research aimed to minimize total tardiness in dynamic manufacturing environments. Finally, the most recent work is that of Yang et al [12] in which Deep Reinforcement Learning (DRL) methods are applied to multi-laser scanning planning. The DRL methods achieved superior scheduling performance compared to baseline planning methods. The study sought to maximize fabrication efficiency while ensuring the quality of the AM process was maintained through optimized scan assignments.

While most of the prior works focus on intelligent planning, considering the physical and geometrical aspects of the models, seeking for more cost- and time-efficient production planning in AM and PBF, particularly, there is a set of research efforts focusing on predicting thermal effects of packing/nesting in PBF.

Fergani et al [13] utilized an ML algorithm, acting as a digital twin, which was trained on experimentally validated, synthetic data generated from high-fidelity Finite Element Method (FEM) simulations. A developed framework could simulate the full PBF process and predict overheated regions for complex aerospace geometries, such as those made from Inconel 718. The ML model achieved a computation speedup of 107 compared to traditional FEM, allowing for the rapid testing and deployment of alternative scan strategies that successfully avoided overheating critical regions. The primary goal was to ensure thermal stability during the printjob to reduce the high scrap rates and substantial costs associated with thermal defects in metal PBF. Although not particularly focused on nesting, this work allows implicitly to evaluate the thermal effect of packing in PBF. Yi et al. [57] applied Convolutional Neural Networks (CNN) to the same problem, including state-of-the-art models like U-Net and Recurrent residual U-Net, treating the simulation of the temperature field as a semantic segmentation problem. The study established that CNN-based ML can simulate Temperature Gradients (TG) in PBF much faster than solving the partial differential equations (PDEs) used in traditional FEM. This enables rapid evaluation of the thermal history across different component geometries in the pre-processing stage. The primary objective was to enable efficient pre-build planning to evaluate and reduce residual stress and distortion, ensuring that components produced by PBF-LB/M maintain high geometrical accuracy. Like in Fergani's work, the packing/nesting was not an explicit, but an implicit parameter in this study. Similar approach to Yi et al is the one of Ren et al [14] which used a Recurrent Neural Network and Deep Neural Network (RNN-DNN) architecture, specifically incorporating Long Short-Term Memory (LSTM) cells, trained using temperature fields generated from traditional finite element thermal history analysis (synthetic data). The RNN-DNN model achieved an accuracy of more than 95% in predicting the temperature field for various laser scanning paths, so it could be indirectly used to predict the nesting-related thermal accumulation. The authors state that the analysis requires only a few minutes. While Fergani et al. and Yi et al. are notable for using ML to specifically replace high-fidelity FEM for full-part thermal analysis, Ren et al. opt for rapid, high-accuracy thermal history simulation.

3.2 ML/AI-assisted build orientation

Apart from already mentioned works which, together with packing/nesting deal also with build orientation [6], [8], [55]. some other relevant works, specific to the build orientation, should be highlighted. Among the earliest works we find Yang et al [15], who investigated how building positions and orientations impact part shrinkage, using Analysis of Variance (ANOVA) and the Taguchi method to study controllable variables. It established scale factors derived from a linear combination of selected variables to counteract this shrinkage. The primary motivation was to improve dimensional accuracy. The researchers reported an improvement of approximately 24% compared to standard commercial methods. Later Zhang et al [16] employed perceptual models of preference. Their study established models that could accurately predict the preferred 3D printing direction by learning from geometric constraints and user preference data. The primary objective was identifying the ideal print orientation to avoid or minimize support structures on user-preferred features, thereby reducing material waste and post-processing requirements. Interesting is also the work of Brika et al [17], in which a Genetic Algorithm (GA) was used to determine the most effective part placement. The algorithm optimized explicitly the build orientation by simultaneously analyzing multiple conflicting factors, rather than focusing on a single parameter. These factors were mechanical properties, surface roughness, support structure volume, build time, and total cost, which then converged into a single optimized orientation decision. Chowdhury et al [18] integrated Artificial Neural Networks (ANN) with a search-based optimization framework. A system that uses ANN to predict and compensate for geometry deviations caused by thermal-mechanical deformations specifically for different orientations was developed. The goal was to combine orientation optimization with geometric compensation to ensure high-fidelity dimensional accuracy in the final printed part. Another relevant work is the one of Günaydin et al [19], who applied Multi-objective Optimization and stochastic searching techniques to successfully identify the Pareto-optimal orientation for parts by balancing two specific metrics: build time and support volume. The objective was to maximize production efficiency and material conservation in metal powder bed fusion systems. Costa et al [20] developed a hybrid prediction-optimization approach that integrated build-orientation as a primary input parameter alongside five other processing parameters (laser power, speed, etc.). The inclusion of part orientation as a core parameter allowed the ML framework to generate a diverse dataset that successfully modeled the behavior of tilted regions (simulating overhangs at angles from 0 to 90 degrees). The research sought to maximize part density across different part orientations.

This representative selection of works shows that the ML/AI-assessment of the build orientation has been widely researched, mostly from the point of view of support minimization, part quality after build or even to indicate an inadequate design feature. There are works which correlate build orientation and thermal stress accumulation through ML/AI, like the one of Chowdhury et al, but there is still room to investigate especially from the point of view of constellation between part geometry and orientation.

3.2 ML/AI-assisted support optimization

In the field of automatic support structure optimization, the research on ML/AI application has gone in quite variable directions. The support structure in metal AM, namely PBF, has different considerations. On one hand, it is crucial to support overhangs, but it also is of outmost importance in evacuating the heat from the melting process. However, although being essential, support structure is considered a waste material, contributing to the overall production time and costs. Therefore, many different aspects of support structure such as mass, quantity, position and efficiency have been studied to search for a best possible tradeoff between the least waste and the product quality being assured.
Mirzendehdel and Surech [21] used Topology Optimization (TO) integrated with AM-specific geometric constraints to develop a productive framework that used a Design for Additive Manufacturing (DfAM) filter during each iteration of the optimization process to ensure the design was ready for manufacture. It successfully identified designs that eliminated overhangs greater than 45°, thereby significantly reducing the need for support. They used the level-set based Pareto Topology Optimization (PareTO) method. The main objective was to create lighter and stronger designs while minimizing material usage and reducing the post-processing labor associated with support removal. McComb et al [22] used auto-encoded voxel patterns and Convolutional Neural Networks (CNN) to analyze part geometries, making in that way a system capable of predicting the required mass of support material directly from a 3D CAD model's voxel-based geometry. The idea was to provide designers with a tool for quick manufacturing assessment, allowing them to estimate production costs and material requirements in the early design phase without running full build simulations. Huang et al [23] used a Surfel Convolutional Neural Network (SCNN) for geometric analysis. CNN was trained to detect and identify the exact areas on a part where support structures should be applied. It proved highly effective at determining the optimal distribution of support material for complex geometries in FDM and SLA technologies, with a view of application in PBF as well. The primary motivation was to shorten production time by optimizing support placement, which in turn reduces the volume of support material and the time needed for post-build removal. Vaissier et al [24] employed a Genetic Algorithm (GA) to solve complex layout and optimization problems. Although this work falls into section 3.1., the researchers developed a framework specifically for the optimization of lattice support structures. The GA explored the design space to find lattice configurations that provide maximum stability with minimum material. The study sought to improve the ease of removal and reduce the mass of support structures, which are traditionally difficult to remove when designed as solid blocks.
Concerning the assessment of support structure to avoid overheating and warping, two works stand out. Zhang et al [58] utilized Topology Optimization of support structure focusing on thermal properties. The study developed thermal conductive support structures designed specifically to dissipate heat during the printing process. The focus of this optimization was for supports to act as heat sinks. The main idea was to prevent building failure and cracking caused by excessive residual stress and heat accumulation in metal AM processes. On the other side Nguyen et al [25] introduced a semi-supervised ML approach to detect anomalies like overheating and super-elevation in overhanging and unsupported structures. By capturing layer-wise images and using semantic segmentation, the model identifies where structures with high overhanging angles (in their case, greater than 55°) or unsupported "bridges" begin to fail due to thermal instability. This acts as a quantitative tool to assess if the support structure (or lack thereof) was adequate to maintain part quality. This work also shows a strong correlation between the observation of melted areas and ML-training to detect inadequate support structure.

4. ML/AI IN PRODUCTION ORIENTED TO THE AM PRODUCT QUALITY ASSURANCE

In this section we will discuss the research work in the area of production quality assurance in the production stage. We already discussed the main causes of problems during the print job, namely insufficient powder quantity, bad quality of the melted area and bad heat evacuation. The latter was already addressed in the previous section, at least indirectly, when we labelled the previous research which addresses this issue already in pre-production, commonly using synthetic and historical data to analyze the warpage and deformation before the build job took place. Nevertheless, the work of Nguyen el al [25] shows that often the real data from production is inevitably necessary to train the models. Hence in this section we will address this issue through data collection in production. **Fig. 3** shows the result of the application of Sobel Edge Detector and Deep Learning to categorize layer defects.

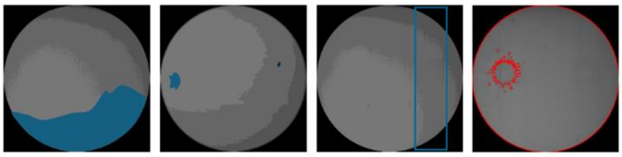

Fig. 3. *From left to right: automatically detected lack of powder, debris, lines made by a damaged recoater and super-elevation (image courtesy of IMH and Samylabs)*

4.1 ML/AI-assisted powder layer integrity evaluation

Several studies have utilized ML/AI approach to evaluate powder layer integrity—specifically focusing on the spread quality of the powder bed or the identification of anomalies immediately following the recoating process. The earliest found is the one of Kleszczynski et al. [59], which used high-resolution imaging with a 29-megapixel CCD camera to capture process irregularities on the in-situ surfaces of build layers. The system successfully captured surface irregularities in-situ, which were later linked to mechanical part performance in subsequent studies. In this way, the authors developed a system-independent layerwise-imaging system for error detection in PBF-LB. Later on, Zhang et al [60] employed ML algorithms to analyze the physical interactions of powder particles and generate a powder spreading process map. The study demonstrated that automated computer vision algorithms could effectively characterize metal powder feedstocks and evaluate the quality of the spread. They established a data-driven framework for mapping and optimizing the powder spreading process in metal additive manufacturing. It must be said that this study was performed before the job, on a feedstock, but nevertheless contributes to an automatic assessment of the powder spreading capacity equally as well as the inline studies. In similar manner to Kleszczynski, Scime and Beuth [26] used a multi-scale CNN and k-means clustering to analyze high-resolution grayscale images of the powder bed taken after recoating. The algorithm autonomously detected and classified seven types of powder bed anomalies (including recoater hopping, streaking, debris, super-elevation, and incomplete spreading) with 97% accuracy. In this way, the foundations of an autonomous, machine-agnostic system for real-time monitoring and classification of powder spreading errors that could lead to part flaws. Desai and Higgs [27] proposed a feed-forward, backpropagation neural network surrogate model trained on data from discrete element method (DEM) simulations, generating virtual spreads. The model reached at least 96% accuracy in predicting spread layer properties such as surface roughness and porosity based on spreader translation and rotation speeds, with an idea to optimize powder spreader parameters (translation and rotation speed) to ensure high powder layer integrity and throughput. Caggiano et al [60] used a bi-stream Deep CNN to process images captured both after powder deposition and after laser scanning. This bi-stream approach achieved an accuracy of 99.4% in detecting defects by comparing the state of the powder layer before and after processing. The aim was also to implement ML-based image processing for on-line defect recognition in additive manufacturing. In that sense, Bartlett et al [29] predicted microstructural defects by analyzing the quality and uniformity of the spread powder bed captured via digital image correlation (DIC), employing a Naïve-Bayes classification algorithm. In this way, they correlated the initial powder bed quality with the occurrence of microstructural defects in the final part. Feng et al [30] on their side applied ML classification and regression models to multi-layer in-situ optical tomography (OT) images captured via a CMOS camera. The study found that analyzing multiple consecutive layers (rather than a single layer) was necessary to precisely predict local porosity, mainly lack of fusion and keyhole. A special innovation was the capacity of this approach to identify "self-healing" phenomena where subsequent layers eliminate previous defects and, thus, predict local porosity through in-process monitoring. Later on, Westphal and Seitz [31] made an interesting contribution, using supervised CNNs, including pre-trained VGG16 and Xception models. By achieving high F1 score in classifying recordings of the powder bed as "good" or "defective", the authors automated detection of defects and visualization using computer vision. Although developed for selective laser sintering (SLS) of polymers, this study can be extrapolated to PBF of metals as well. CNNs were a useful tool in the work of Ansari et al [32], who used them to classify powder bed images, demonstrating exceptional performance with accuracies up to 99% in identifying surface deformation problems, being able to establish a real-time approach to classify surface deformation problems during LPBF processing using layer-wise images as input. On the other side, Fischer et al [33] applied Deep Transfer Learning models to successfully monitor the quality of the powder bed using high-resolution imagery and leveraged knowledge from other image recognition tasks. The main achievement was to implement a robust quality monitoring system for the powder bed that requires less machine-specific training data, which obviously widens the impact of their work. Furthermore, Nguyen et al [25] introduced a semi-supervised ML approach using semantic segmentation to classify surface appearances in layerwise optical images. This model successfully identified areas of lack-of-fusion and overheating. It also detected super-elevation—where elevated sintered areas are not covered by powder during recoating—by identifying laser-scanned features in "post-recoat" images. This work is quite relevant since it actually correlates powder layer and melted area imaging in a single approach. Another interesting approach was by Ero et al [34]. They integrated a Self-Organizing Map (SOM), a fuzzy logic scheme, and a tailored U-Net architecture for the analysis of in-situ optical tomography (OT) data. The integration of fuzzy logic allowed the application of expert knowledge to interpret variations in thermal emissions (identifying cold spots as lack of fusion and hot spots as keyhole defects), with model reporting probabilities of defect arising ranging from 0.375 to 0.819. Therefore, the authors created a more nuanced and interpretable ML model for estimating defect likelihood, instead of a „yes“ or „no“ principle, which allows quality assurance professionals to adjust probability thresholds based on custom rules. Last but not the least, Zhao et al [35] introduced an indirect approach projecting 3D point cloud data into 2D height maps and applying the DeepLabV3+ semantic segmentation model. They outperformed direct point cloud models (PointNet, PCT) in segmenting small defects and reduced inference time to 11ms, enabling closed-loop remediation (recoating) during printing. Real-time detection and feedback control of powder bed defects (stacking, craters, insufficient spreading) using binocular vision and 3D data was achieved.

This section shows that a predominant approach is based on computer vision and ML/DL algorithms (particularly CNNs) applied to high-resolution images taken in situ following the recoating process. All these studies share the common objective of automating the early detection and classification of anomalies or defects in the powder layer in order to correlate them with the final quality of the printed part. It is important to highlight that most aim to develop agnostic systems—independent of the machine used—that operate in real time or through layer-by-layer monitoring. Recent innovations are focused on multi-layer analysis to detect squaring-off phenomena, semi-supervised models and 3D mapping to enable closed-loop corrections during manufacturing.

4.2 ML/AI-assisted melted area integrity evaluation

There is a substantial amount of research work focused on ML/AI evaluation of melted area integrity through inline data collection. Unlike in the evaluation of powder layer, where the optical imaging predominate as the source of data collection, here the studies utilize thermal detection sensors such as thermal cameras, pyrometers, and photodiodes – although high-speed CMOS cameras are not excluded - to monitor the melted area directly or indirectly (through the observation of the melt pool). By the variation of thermal footprint defects like pores, keyholes, or issues resulting from improper heat evaluation are recognized.

The analysis can start from Ye et al [36], who developed a Deep Belief Network (DBN) and applied it directly to raw multisource data (including acoustic signals often paired with melt pool signatures) to analyze the process proneness to generate defects. DBN proved superior at learning structure from raw, unlabelled data compared to traditional Support Vector Machines (SVMs), identifying process regimes like balling and overheating. In this way they detect internal defects such as cracks and porosity in L-PBF by leveraging the inherent patterns in in-situ signals without extensive manual feature engineering. Smoqi et al [37] approached the problem with k-Nearest Neighbor (kNN) and 2D-CNN algorithms, in order to analyze images from an off-axis imaging pyrometer. The kNN algorithm reached a maximum F1-score of 0.95 for porosity prediction. The study used so-called „physics-informed melt pool signatures“, including melt pool length and temperature distribution, to improve accuracy. The main goal was to monitor and predict porosity levels by extracting physically intuitive features from the molten zone. Li et al [38] used supervised ML, including Deep Belief Networks (DBN) and Deep Transfer Learning (DTL), to process high-resolution coaxial high-speed VIS camera images. Similar to [36] a DBN model, which achieved an accuracy of 99.59% in classifying different porosity modes based on melt pool features, is used. This work showed that multi-sensor fusion (combining optical, photodiode, and acoustic signals) outperformed single-sensor approaches for quality classification. The goal was to achieve intelligent, in-situ classification of porosity levels and part quality (low, medium, high) based on melt pool morphology and radiation intensity. In similar direction went Ren et al [39], having generated a pretrained ResNet-18 architecture and used it to analyze wavelet-transformed frequency images derived from melt pool intensity data. Their approach achieved perfect accuracy for binary porosity detection in single-track experiments using a NIR camera at 200 kHz, aiming to obtain the real-time detection of keyhole pore generation through high-speed molten pool monitoring.

Furthermore, the work in which CNNs were used are abundant. Lee et al [40] employed CNN, this time 3D-CNN, to process spatially-integrated melt pool intensity data from on-axis photodiodes. The data was mapped into a regular 3D grid via interpolation. The model successfully predicted the location, type (lack-of-fusion vs keyhole), and severity of porosity. The predictions showed strong correlation with X-ray Computed Tomography (X-CT) ground truth across a wide range of density values. Here it was innovative to have overcome the limitations of single-layer analysis by providing volumetric and temporal context to supervised models for more accurate porosity prediction. Mao et al [41] generated a framework also using 2D-CNN and 2D-ConvLSTM architectures was introduced to monitor a coaxial Planck thermometry system. The CNN model achieved an F1-score of 0.82 for defect detection in the current layer. Crucially, the ConvLSTM was able to predict future porosity formation in the subsequent layer by analyzing surrounding pixel data and previous thermal history. In that way a prognostic tool that not only detects existing defects but also anticipates future melted area integrity issues was achieved. Pak et al [42] close this selection of works using CNNs, which here was converted into a deep learning framework for porosity quantification and Video Vision Transformers (ViT) for defect localization. The model utilized in-situ thermal images to build a real-time porosity map. It achieved an accuracy of $R^2 = 0.57$ for quantification and an average IoU of 0.32 for localizing porosity within the build. It was possible to quantify and localize hidden internal porosity in stainless steel LPBF parts by correlating in-situ thermal signatures with ex-situ micro-CT data.

Regression feature-based models have also been employed in melted area integrity evaluation. Oster et al [43] compared feature-based models (Random Forest, Gradient Boosting Trees, etc.) with a novel raw data-based model called IMSEQR (Image Sequence-based Regressor). The Random Forest (RF) model outperformed others in predicting systematic local trends for both forced and random flaws, including lack-of-fusion and keyhole porosity. The study identified that spatiotemporal cooling features (Time Over Threshold) are critical for predicting keyhole porosity. This study showed the potential of in-situ SWIR thermography for local porosity level prediction in multi-layer HAYNES 282 parts using localized "clusters" for high spatial resolution. Mahato et al [44] also used various regression models (including XGBoost), which were applied to features engineered from in-situ pyrometer time-series data using tools like TS-Fresh. The research concluded that binary classification (categorizing layers as "low" vs "high" porosity) is significantly easier and more accurate than performing regression to predict exact porosity percentages. The pyrometer data effectively captured the interaction between melt pool temperature and pore formation. In this way it was possible to provide "predictive control" by using melt pool temperature fluctuations to predict the porosity percentage of individual layers in real-time, allowing operators to potentially re-melt anomalous zones.

Power et al [45] compared the unsupervised STRAY (Search and TRace AnomalY) algorithm and a semi-supervised 1D autoencoder (1-DAE). These models processed real-time 1D time-series data from on-axis photodiode sensors capturing near-infrared and ultraviolet emissions from the melt pool. The 1-DAE model achieved a high predictive accuracy with an F1 score of 0.94. It proved highly efficient for industrial implementation, with a post-training inference time of only 1.92 ms. The STRAY algorithm offered a faster implementation time (0.49 ms) but lower maximum accuracy (0.92). The authors managed to develop a real-time, low-cost anomaly detection system for identifying processing defects (such as lack of fusion or overheating) during the fabrication of complex Ti-6Al-4V lattice structures. This work is highlighted for its realistic direct application in industry.

If we focus on ML/AI approaches which concentrate on the evaluation of the melted area only, thermal or tomographic, several works should be highlighted. Gobert et al [46] used supervised machine learning, specifically a Support Vector Machine (SVM) classifier, to process high-resolution layerwise visible-light and infrared (IR) images, and to demonstrate in-situ defect detection accuracies greater than 80%. It showed that assessing features through multiple build layers is critical for accurately identifying discontinuities. The goal was to develop an inexpensive, system-independent approach for detecting discontinuities in metallic powder bed fusion (PBF) parts as they are built layer-by-layer. Baumgartl et al [47] employed a CNN architecture with depthwise-separable convolutions trained on off-axis thermographic images, achieving recognition of defects such as delamination and splatter with an accuracy of 96.80%. The architecture is lightweight, making it suitable for real-time operation on standard hardware. Estalaki et el [48] used Random Forests and other supervised ML models to analyze features (maximum radiance and time above melting threshold) extracted from in-situ short-wave infrared (SWIR) thermographic data. The models achieved F1 scores above 0.96 for predicting the state of voxels (defective or normal). The analysis revealed that the thermal history of voxels above the current layer is more influential for defect prediction than those beneath it and was capable of predicting micropore defects in LPBF stainless steel on a voxel-by-voxel basis using thermal history. Feng et al [49] employed various models, including CNNs and Multi-Layer Perceptrons (MLP), to process in-situ optical tomography (OT) images, which provide a 3D reconstruction of the layer-by-layer heat distribution. The model accurately predicted local porosity by analyzing multiple consecutive layers (10–15 layers), accounting for the "self-healing" effect where subsequent laser passes can remelt and correct defects in previous layers. Akmel et al [61] compared Multinomial Logistic Regression (MLR), ANN, and CNN models trained on optical tomography IR images. They found out that the CNN classifier achieved 100% accuracy in classifying manufactured layers as either standard or defective (specifically distinguishing between lack of fusion and keyhole porosity). More recently Bonato et al [50] used image convolution and CNNs on data acquired from off-axis long-exposure optical monitoring. This ML approach achieved 90% accuracy for predicting spatter-related lack-of-fusion defects. It successfully predicted defects by analyzing only two consecutive layers after detecting an initial spatter signature. Finally, Hoffmann et al [51] used a Gradient Boosting Decision Tree algorithm (LightGBM) trained on features extracted from transient temperature profiles captured via infrared thermography. The peak temperature of the molten area was identified as the highest predictor for porosity. The study found that including thermal signals from adjacent and subsurface voxels (interlayer effects) significantly improved prediction accuracy.

An overall analysis shows that the in-situ monitoring of the melted area relies mostly on optical sensors (VIS/IR cameras, thermography and photodiodes) to capture thermal and morphological signatures. The predominant and most successful approach is Convolutional Neural Networks (CNNs) due to their accuracy of over 95% in classifying porosity, keyholes and lack of fusion. Most of the authors agree that analyzing data from a single layer is insufficient, so they integrate the thermal history and spatiotemporal context of multiple layers to predict defects. Specific highlights include physical simulations (DEM), analysis of the ‘self-healing’ phenomenon using optical tomography, which includes the analysis of 10–15 consecutive layers and the use of ultra-fast models (1D auto-encoders with 1.92 ms inference), which are crucial for industrial environments. Finally, the most disruptive innovation involves the use of sequential networks (GRUs) that enable transfer learning between different materials (such as from steel to superalloy), drastically mitigating interlayer heat accumulation.

4.3 ML/AI-assisted thermal deformation evaluation

The treatment of regrowth of the melted area is categorized in the literature both as a specific thermal management issue requiring dedicated analysis and as part of a generic classification of melted area defects.

It is important to define first how the literature sources categorize these heat-driven issues – they are using several technical terms: Z-growth and dross describe the excess material and regrowth typically found in overhanging regions. This occurs when the laser plunges the melt pool into unmelted powder due to poor heat evacuation, causing particles to adhere to the part. Super-elevation is a dedicated classification for raised edges that result from thermal stress. Nguyen et al [25] identify super elevation as a specific anomaly where overheated areas of sintered powder rise above the surrounding layer. The authors note that this typically occurs in overhanging structures where the low thermal conductivity of the underlying unfused powder prevents efficient heat evacuation. Their semi-supervised ML model is specifically trained to detect these overheated and super-elevated regions by comparing images captured after laser scanning and after powder recoating. Finally, there are terms of overburning and bulging, seen as manifestations of localized heat accumulation. Wang et al. [63] classify distortion and bulging as „final part defects“ that are distinct from in-process transient phenomena like spattering. shows an AI-generated illustration of these defects.

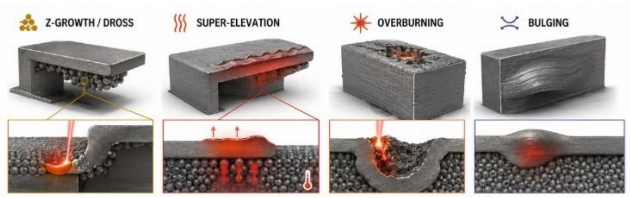

Figure 4. *AI-generated illustration of dross, super-elevation, overburning and bulging.*

Hence, the regrowth as a general term is often treated as part of a generic classification of melted area defects, and treated as such. Nevertheless, there are some specific works in this sense. Apart from the aforementioned works of Nguyen and Wang, respectively, in Fergani's work [13] there is a specific focus on the prediction of local overheated regions caused by sub-optimal laser paths and short scanning vectors. It defines these zones as areas where the melt pool becomes too wide, leading to an accumulation of material that causes recoater collisions in subsequent layers. The study uses simulation-trained ML to proactively correct exposure strategies to avoid this specific effect. Another specific issue, which doesn't have to do neither with the geometry of the part nor with the support structure is the thermal accumulation at contours [53]. Ogoke et al highlight how thermal energy accumulates near boundaries or when the laser reverses direction, which can lead to localized overheating and employs Deep Reinforcement Learning to discover control policies that specifically reduce power in these areas to stabilize the melted area and prevent overheating-induced defects. Specific analysis of bent edges and curling was a subject of study [61] but in the context of polymer PBF.

Last but not least, one of the most recent effort found in the literature is the one of Gao et al [54]. Here the authors established a Gated Recurrent Unit (GRU) neural network model. They defined sequence features of interlayer infrared radiation intensity (IIRI) to predict thermal signatures for subsequent layers based on data from previous layers. This allowed for a material transfer application where a model trained on 316L alloy was successfully applied to DZ125 super alloy. The GRU model achieved highly precise prediction results with a coefficient of determination of 0.964. Components fabricated using this ML-driven dynamic parameter adjustment showed a significant increase in relative density (from 91.6% to 98.5%) and a reduction in surface roughness. Most notably, the residual stress on the top surface was reduced from 169.21 MPa to 102.37 MPa. Therefore, the primary objective - to predict the interlayer heat accumulation (IHA), which typically leads to the mitigation of uneven temperature distribution, "overburning" at component edges, and high thermal stresses that cause warping or distortion – was successfully achieved on both materials.

4. CONCLUSIONS AND FUTURE WORK

The following Table tries to wrap up the most interesting aspects of the reviewed works.

Table 1 - *Overview of the research works described in this paper.*

ML/AI method/technique employed	Particularly relevant achievement
Inadequate packing/nesting: *Efficiency in build volume use and prediction of thermal instability in complex nesting layouts.*	
Ikonen 1997, **Zhang 2018**, GA (Genetic Algorithm); **Alicastro 2021**, RL-ILS (Reinforcement Learning); **Ying 2023**, RL (Reinforcement Learning); **Sun 2024**, O3-DDQN (Dueling Deep Q-Network); **Yi 2022**, CNN (Neural Networks).	**Alicastro 2021:** Integrated GA with Q-learning to reach optimal scheduling solutions faster for large-scale production. **Sun 2024:** Outperformed state-of-the-art methods in minimizing tardiness in dynamic environments. **Yi 2022:** Simulated temperature fields 10^7 times faster than traditional FEM.
Inadequate orientation: *Improving dimensional accuracy and mechanical properties while minimizing support volume.*	
Yang 2002, ANOVA/Taguchi method (Statistical models); **Zhang 2015**, Perceptual preference models; **Brika 2017**, GOA (Genetic Optimization Algorithm); **Chowdhury 2018**, ANN (Neural Networks); **Günaydin 2022**, Multi-objective Optimization.	**Yang 2002:** Achieved a 24% improvement in shrinkage compensation compared to standard commercial methods. **Brika 2017:** Simultaneously analyzed conflicting factors like surface roughness, build time, and total cost to find the optimal orientation.
Inadequate support: *Elimination of overhangs as material waste and improving heat evacuation through the support.*	
Mirzendehdel 2016, PareTO (Topology Optimization); **McComb 2018**, CNN (Neural Networks); **Huang 2019**, SCNN (Surfel Convolutional Neural Network); **Vaissier 2019**, GA (Genetic Algorithm); **Zhang 2019**, Topology Optimization (Thermal).	**Mirzendehdel 2016:** Successfully identified designs that eliminated overhangs greater than 45°, significantly reducing support material. **Zhang 2019:** Developed thermal conductive supports designed specifically to act as heat sinks to prevent cracking.
Bad powder quality: *Inline detection and classification of anomalies such as streaking, debris, or incomplete coating.*	
Scime 2018, Multi-scale CNN/k-means (Neural Networks); **Desai 2019**, FF-BPNN (Feed-forward Neural	**Scime 2018:** Autonomously detected and classified seven types of powder bed anomalies with 97%

Network); **Caggiano 2019**, Bi-stream Deep CNN (Neural Networks); **Fischer 2022**, Deep Transfer Learning; **Zhao 2025**, DeepLabV3+ (Semantic Segmentation).	accuracy. **Zhao 2025:** Reduced inference time to 11ms using binocular vision and 3D data, enabling real-time closed-loop remediation.
Bad melted area quality: *In-situ detection, classification, and quantification of porosity, cracks, and lack-of-fusion defects.*	
Ye 2018, DBN (Deep Belief Network); **Li 2022**, DBN and DTL (Transfer Learning); **Lee 2023**, 3D-CNN (Neural Networks); **Mao 2023**, 2D-CNN and ConvLSTM (Sequential Networks); **Oster 2024**, Random Forest (Regression models).	**Lee 2023:** Provided volumetric and temporal context for more accurate porosity prediction, overcoming single-layer limitations. **Mao 2023:** Developed a prognostic tool that anticipates future integrity issues by analyzing thermal history. **Akmel 2023:** Achieved 100% accuracy in classifying standard vs defective layers.
Bad heat evacuation: *Mitigation of defects caused by localized heat accumulation between layers.*	
Nguyen 2023, Semi-supervised ML; **Fergani 2020**, ML-based Digital Twin; **Ogoke 2021**, Deep Reinforcement Learning (DRL); **Gao 2025**, GRU (Gated Recurrent Unit).	**Ogoke 2021:** Discovered control policies to reduce laser power near boundaries and stabilize the molten layer. **Gao 2025:** Successfully applied "material transfer", using a model trained on steel for a superalloy, reducing residual stress by 40%.

Based on the frequency of use and explicit statements within the related source, Convolutional Neural Networks (CNNs) in several variants are identified as *the most relevant and predominantly employed ML/AI technique for product quality assurance in Powder Bed Fusion*. The sources highlight the relevance of CNNs for many aspects: from evaluating the powder layer, based on computer vision and CNNs applied to high-resolution in-situ images, to molten layer integrity, since the CNNs achieve over 95% accuracy in classifying various defects like porosity, keyholes, and lack of fusion. Also, CNNs are versatile and used in nearly every cause that we discussed: to simulate temperature fields and predict required support material or identify optimal support placement in pre-production as well as in production for real-time monitoring of both the powder bed (detecting spreading anomalies) and the molten layer (identifying surface and internal defects). While other techniques, like Genetic Algorithms (GA) for optimization tasks in pre-production and Reinforcement Learning (RL) for scheduling and real-time control, are gaining relevance, CNNs remain the most widely cited tool for the core task of automated defect detection and classification.

Speaking of the future work, a joint implementation of these research efforts and findings – *maybe even in combination with the deployemnt of LLM as the Quality Assurance orchestrators* – seems to be an adequate step forward. As an illustration, a possible combination of the aforementioned research works, which would ensure the defect-free print job and guarantee the product quality assurance, is summarized in the following diagram.

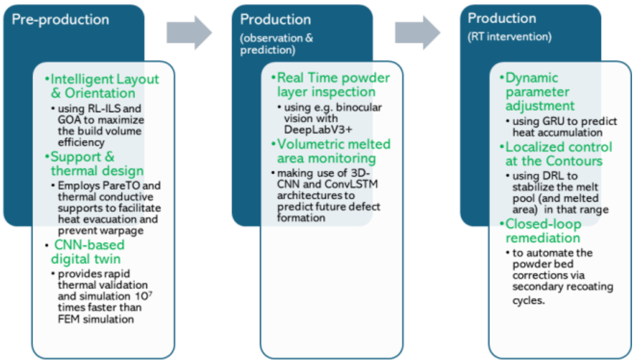

Figure 5. *A proposition of joint deployment of the different ML/AI tools developed in the SoA for total part quality assurance in PBF production.*

This visual diagram is organized into the three critical phases of the manufacturing lifecycle:

1. Pre-production, or predictive optimization, in which tools like RL-ILS (e.g. [9]) and Genetic Optimization (e.g. [17]) for layout planning, and CNN-based Digital Twins for thermal simulation (e.g. [13]) are deployed together.
2. Production, which includes a twofold solutions:
   - 2.1 High-Fidelity Monitoring, showcasing 3D-CNNs and semantic segmentation models (e.g. [40] or [41]) used to monitor both the powder bed and the molten layer in real-time.
   - 2.2 Real-Time Intervention or Autonomous Control, which would be visualizing the use of Gated Recurrent Units (GRU) ([54]) and Deep Reinforcement Learning (e.g. [53]) to dynamically adjust process parameters and mitigate heat-related defects like overburning, as well as a feedback loop to automatically recoat the defective powder layer (e.g. [35])

The aforementioned concept would need to undergo a deeper analysis of the implementability of data collection sources and HW tools, as well as a joint operability of different software environments, needed for each individual tool. However, the application of a digital architecture with underlying ML/AI tools operating in a combined manner is most likely the only path to finally remove the stigma of uncertainty when the product quality assurance of AM parts comes into question.

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