Evaluation of Design Information Disclosure through Thermal Feature Extraction in Metal based Additive Manufacturing

Mahathir Mohammad Bappy [a], Durant Fullington [a], Linkan Bian [a,b], and Wenmeng Tian [a,b]

[a] *Department of Industrial and System Engineering, Mississippi State University, Mississippi State, MS 39762, United States*

[b] *Center for Advanced Vehicular Systems (CAVS), Mississippi State University, MS 39762, United States*

Abstract

Manufacturing-as-a-Service (MaaS) can accelerate additive manufacturing (AM) process-defect modeling by augmenting training data to all collaborating users via a data sharing network. However, sharing process data may disclose product design information. This paper aims to evaluate design information disclosure of various thermal history-based feature extraction methods for metal-based AM anomaly detection. This is accomplished by evaluating the design information (i.e., printing orientation) retained, and the overall data usability (i.e., anomaly detection) preserved in the extracted features for various state-of-the-art feature extraction methods. The evaluation results indicate that there are urgent needs in privacy preserving data sharing for additive MaaS (AMaaS).

Keywords: Additive Manufacturing, Data Privacy, Data Sharing, Data Utility, Manufacturing as a Service.

1. Introduction

Artificial intelligence (AI) has been recognized as one of the driving forces for the research and development (R&D) in advanced manufacturing. However, a recent symposium highlighted a significant gap of the current lack of industry tools, trust, confidence, and experience with AI technologies in manufacturing. In addition, it is recommended to establish new Public-Private Partnerships (PPPs) to facilitate the collaboration between industry, academia, and government experts [1]. One of the possible paths to establish the PPPs is Manufacturing as a Service (MaaS), a collaborative cloud-based networked manufacturing platform, facilitating capacity and data sharing among geographically diverse users [2]–[6]. Furthermore, additive manufacturing (AM) has demonstrated its unique capacity in manufacturing R&D, and thus should be incorporated into the MaaS, making the expensive AM technologies accessible to small and medium manufacturers (SMMs). The additive MaaS (a.k.a., AMaaS) facilitates users sending designs to the networked machines, where process data collected and leveraged for collaborative AI modeling for quality control purposes, as illustrated in Figure 1. This practice augments data availability for process improvement and quality control that benefits all users, as an augmented training dataset improves the performance of the AI models.

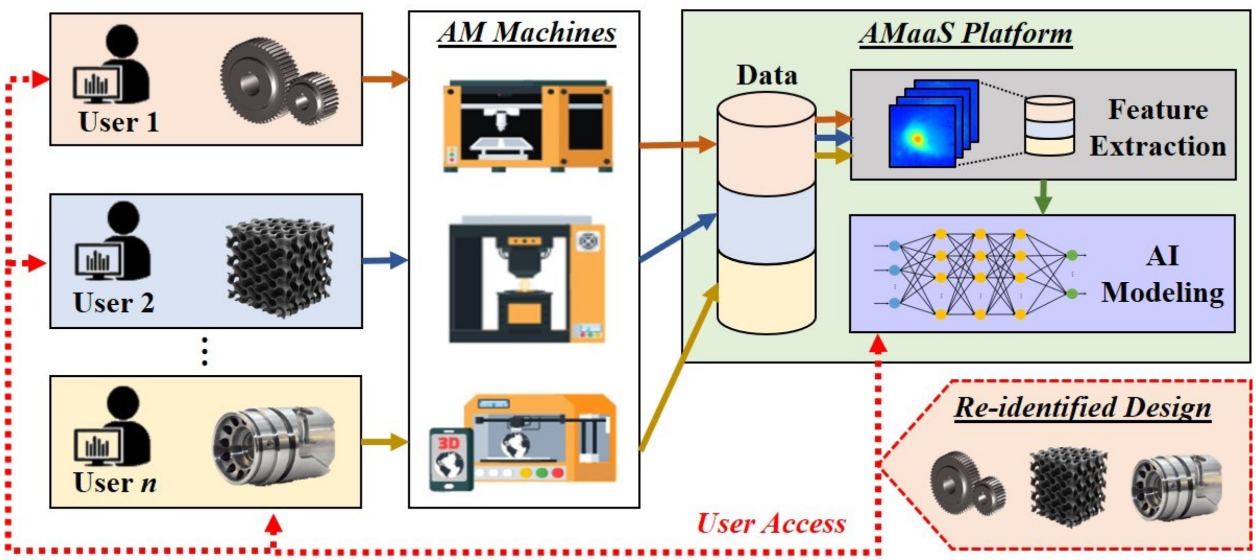

Figure 1: The proposed AMaaS framework and potential design information disclosure through path re-identification.

The benefits of AMaaS are overshadowed by the growing concerns for user data privacy. The AM process data can be leveraged to identify printing path information, which can be used to re-identify part designs [7], [8] (red arrows in Figure 1), ultimately compromising the users' intellectual property (IP) [5]. This brings a serious concern, since different AMaaS users can be potential competitors. Since rapid prototyping is the most popular AM application in new product development [9], any unwarranted access to the IP can be detrimental. In the prospective AMaaS, each user can access the features extracted from the jointly collected process data for their own modeling purposes, which leads to potential unintended design information disclosure. However, there is no study that examine the design information disclosure of the process features extracted from AM process data.

To fill this research gap, this paper aims to evaluate the design information disclosure of the various process features extracted assessing their ability to re-identify instantaneous printing directions. The rest of this paper is structured as follows. Section 2 introduces the proposed procedure for evaluating the level of design information disclosure retained and anomaly detection capacity based on different feature extraction methods in the literature. Section 3 presents the results and discussion, and Section 4 presents the conclusion and future research directions.

2. Proposed Evaluation Procedure of State-of-the-art Feature Extraction Methods

For metal-based AM, there is a strong correlation between thermal history and the presence of faults in the final parts. However, the thermal image data are usually of high volume and dimension, and thus key process features are extracted for anomaly detection [10]. Subsequently, various machine learning approaches can be applied to correlate process features to defect occurrence. provides a summary of different feature extraction and anomaly detection methods for metal-based AM.

Table *1* provides a summary of different feature extraction and anomaly detection methods for metal-based AM.

Table 1: Feature extraction methods for analyzing AM process signals

Extracted Features	Methods for Defect Detection	Citations
Multilinear Principal Component Analysis (MPCA) features	Dual control charting	[11]
Functional Principal Component Analysis (FPCA) based morphological features	Decision Tree (DT); Linear Discriminant Analysis (LDA); Quadratic Discriminant Analysis (QDA); K-Nearest Neighbors (KNN); and Support Vector Machine (SVM)	[12],[13]
Interpolated process characteristics	Self-organizing Map (SOM)	[14]
Principal Component Analysis (PCA) based statistical descriptors	K-means clustering	[15],[16]
Low dimensional features via variational autoencoder	Gaussian Mixture Sparse representation K-Mean clustering	[17]
Melt pool geometric features	DT; LDA; QDA; KNN; and SVM	[12], [18]
Tensor factorization	Bayesian change detection	[19]
Integrated spatio-temporal decomposition and regression	Likelihood ratio test procedure	[20],[21]
Regions of interest of spatters,	SVM, Convolutional Neural Network (CNN)	[22]

plume, and melt pool		
Melt pool image morphology based on SIFT features	Bag of words (BoW); SVM	[23]
Spectral intensity graph	SVM	[24][25]
Multi-dimensional visual features from CT images and in-situ sensing data	SVM	[26]
In-process images	CNN	[27]
K-Means or U-Net autoencoder based image clustering	CNN	[28]
Summary statistics of acoustic emission signals	Logistic regression and Artificial Neural Network (ANN)	[29]
Image local intensity variation and surface texture features	Bayesian classifier	[30],[31]

Figure 2 illustrates the overview of the proposed evaluation. The thermal images are collected from the metal-based AM processes, and various feature extraction methods in the literature have been applied to extract those features. Subsequently, the extracted features are evaluated using three different types of classifiers, i.e., SVM, Ensemble, and Neural Network (NN) classifiers. Two inter-dependent metrics are evaluated.

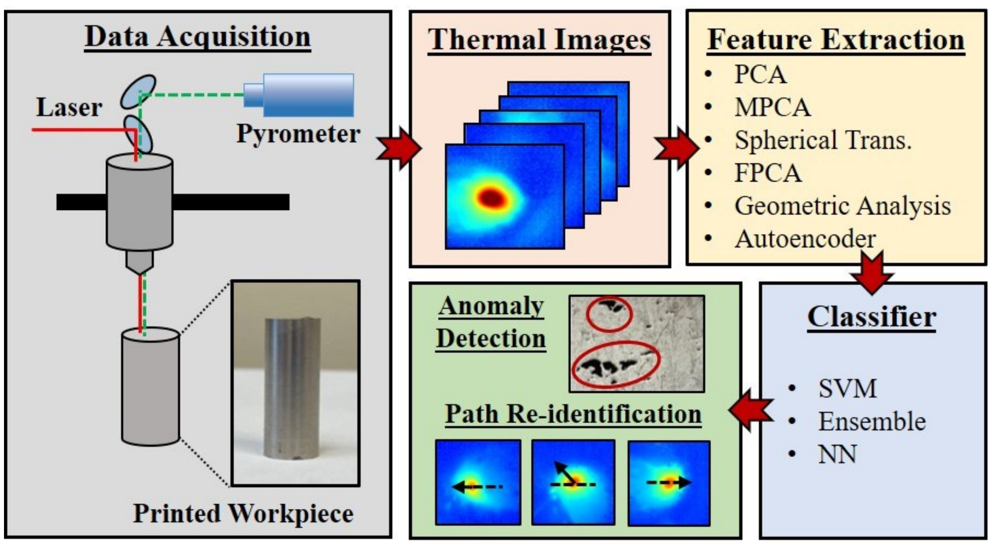

Figure 2: The proposed procedure of evaluating features extracted from thermal images

Metric 1: Design information disclosure (DID) associated with printing path re-identification accuracy is computed as the classification accuracy of print orientation in the context of a multi-class classification of angular labels as below.

$$DID = \text{Accuracy} = \frac{\text{Number of samples with angular labels accurately classified}}{\text{Total number of samples classified}}$$

Metric 2: Utility metric (U) associated with anomaly detection accuracy is calculated as the F1-Score corresponding to the anomaly detection labels, because the percentages of healthy and unhealthy thermal images are usually highly imbalanced [32]. This metric is calculated as below [33], [34],

$$U = \text{F1} - \text{Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$$

where $\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$ and $\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$, and TP and TN represent correct predictions of anomaly and healthy melt pools, and FP and FN represent the incorrect prediction of an anomaly and healthy melt pool, respectively.

It is worth noting that a higher DID indicates significant disclosure of design information, which is unfavorable. On the contrary, a higher U value means the features can accurately detect anomalies, which is most favorable. Therefore, the best process features should demonstrate low DID and high U.

3. Results and Discussion

In the case study, thermal images were collected during the fabrication of two cylindrically shaped specimens (Part 1 and 2), using the OPTOMEC LENS 750 directed energy deposition (DED) system. As visualized in Figure 2, thermal images (with size 480×752) were collected by a co-axial pyrometer camera, where each pixel contains a temperature measurement. The images were cropped into 201×201 to remove irrelevant regions. Furthermore, the printing of Part 1 contains two angular orientations (0°/180°), and the part was examined using X-ray CT to provide defect labels, whereas, Part 2 printing involves three angular orientations (60°/180°/300°) while the fabricated part was not inspected. Based on the data format needed, six feature extraction methods from Table 1 were selected for conducting the DID and U evaluation. Specifically, 2,299 thermal images from Part 1, and 1,296 from Part 2 were utilized for DID evaluation, where image-wise angular labels were calculated using the instantaneous printing orientation in the g-code. In addition, 2,299 images from Part 1 were used to evaluate U.

For both evaluating DID and U values, the dataset was randomly split into 80% training and 20% testing sets. The Bayesian optimization was adopted for parameter tuning. 100 replications were conducted, and both DID and U were evaluated using the mean over 100 replications. The results are summarized in Table 2. Different cell shades were used to color code different feature extraction methods to denote their average performance for both DID and U values. The better the metric is, the lighter the shade used.

In general, it can be observed that there is no feature exacted that can perform well in both DID and U values. For DID, the best performing features are melt pool geometric features, while its U value is only around 77% on average. On the other hand, the VAE features perform the best in U values, whereas its DID metric is quite high as well. It is also noteworthy that there is a potential tradeoff between DID and U values in the feature extracted, where potential improvements in DID may impact the U value of the features. This tradeoff needs to be considered when designing the customized data sharing framework for AM users with different preference of design information protection.

Table 2: DID and U values summary (standard deviations in parentheses).

Feature Extraction	***DID* (Smaller is better)**				***U* (Larger is better)**			
	SVM	**Ensemble**	**NN**	**Avg**	**SVM**	**Ensemble**	**NN**	**Avg**
PCA	97.89 (0.55)	97.74 (0.52)	97.38 (0.95)	97.67 (0.73)	85.57 (6.71)	76.20 (9.59)	57.69 (13.42)	73.24 (15.49)
MPCA	98.36 (0.48)	97.43 (0.59)	97.24 (0.87)	97.68 (0.83)	86.68 (6.57)	73.81 (9.10)	57.13 (12.71)	72.54 (15.56)
VAE	96.53 (1.47)	95.88 (1.51)	95.38 (1.44)	95.93 (1.55)	85.32 (10.29)	77.82 (13.19)	87.52 (9.40)	83.55 (11.83)
Spherical	83.61 (1.32)	82.08 (1.47)	79.04 (3.30)	81.60 (2.92)	37.69 (10.22)	51.85 (11.29)	40.57 (12.77)	43.39 (13.00)
FPCA	81.54 (1.34)	80.39 (1.27)	77.84 (3.39)	79.92 (2.95)	40.54 (12.49)	47.63 (11.69)	41.38 (13.03)	43.19 (12.81)
Geometric Features	65.74 (1.67)	64.62 (1.45)	63.54 (2.95)	64.63 (2.31)	75.23 (7.44)	80.39 (7.12)	75.18 (8.6)	76.94 (8.13)

4. Conclusion

In this paper, a new framework is developed for evaluating the design information disclosure and utility of feature extraction methods for AM anomaly detection based on thermal images. Specifically, six state-of-the-art feature extraction methods are compared using three different classification models. Each feature extraction method was evaluated based on its performance in design information disclosure in printing orientation and retaining utility in anomaly detection. From the results, it can be observed that the process feature extraction method plays a key role in both utility and design information disclosure risks. Thus, the proposed framework may serve as a useful tool to evaluate privacy-preserving performance in data sharing mechanisms used in AMaaS. The computational results have highlighted significant gaps and limitations in the state-of-the-art AM feature extraction methods in the context of data sharing on the AMaaS platform.

There are a few potential future research directions. First, the evaluation data set can be further enlarged to include more angular orientation levels in the experiments, which can extend the multi-class classification component for angular levels to an angular regression component. Second, to simultaneously achieve low DID and high U values, AM design de-identification techniques can be established to create a utility-aware, privacy-preserving features extraction to be used in data sharing framework of the AMaaS platform [35]. Third, this evaluation could be further extended by incorporating more machine learning based feature extraction methods.

Acknowledgements

This work was partially sponsored by National Science Foundation CMMI-2046515.

References

[1] S. J. Jim Davis, Stephan Biller, James A. St Pierre, "Towards Resilient Manufacturing Ecosystems Through Artificial Intelligence – Symposium Report, Advanced Manufacturing Series (NIST AMS), National Institute of Standards and Technology, Gaithersburg, MD," *2022*, doi: https://doi.org/10.6028/NIST.AMS.100-47.

[2] Q. Hu, R. Chen, H. Yang, and S. Kumara, "Privacy-preserving data mining for smart manufacturing," *Smart Sustain. Manuf. Syst.*, vol. 4, no. 2, 2020, doi: 10.1520/SSMS20190043.

[3] L. Ren, L. Zhang, L. Wang, F. Tao, and X. Chai, "Cloud manufacturing: key characteristics and applications," *Int. J. Comput. Integr. Manuf.*, vol. 30, no. 6, pp. 501–515, 2017, doi: 10.1080/0951192X.2014.902105.

[4] J. Lee, B. Bagheri, and H. A. Kao, "A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 3, pp. 18–23, 2015, doi: 10.1016/j.mfglet.2014.12.001.

[5] M. Hasan and B. Starly, "Decentralized cloud manufacturing-as-a-service (CMaaS) platform architecture with configurable digital assets," *J. Manuf. Syst.*, vol. 56, no. May, pp. 157–174, 2020, doi: 10.1016/j.jmsy.2020.05.017.

[6] B. Huang, C. Li, C. Yin, and X. Zhao, "Cloud manufacturing service platform for small- and medium-sized enterprises," *Int. J. Adv. Manuf. Technol.*, vol. 65, no. 9–12, pp. 1261–1272, 2013, doi: 10.1007/s00170-012-4255-4.

[7] M. N. Islam, Y. Tu, M. I. Hossen, S. Guo, and X. Hei, "A Survey on Limitation, Security and Privacy Issues on Additive Manufacturing," Mar. 2021, [Online]. Available:

http://arxiv.org/abs/2103.06400
[8] M. Yampolskiy, T. R. Andel, J. T. McDonald, W. B. Glisson, and A. Yasinsac, "Intellectual property protection in Additive Layer Manufacturing: Requirements for secure outsourcing," *ACM Int. Conf. Proceeding Ser.*, vol. 12-Decembe, 2014, doi: 10.1145/2689702.2689709.
[9] K. V. Wong and A. Hernandez, "A Review of Additive Manufacturing," *ISRN Mech. Eng.*, vol. 2012, pp. 1–10, 2012, doi: 10.5402/2012/208760.
[10] M. N. Esfahani, M. M. Bappy, L. Bian, and W. Tian, "In-situ layer-wise certification for direct laser deposition processes based on thermal image series analysis," *J. Manuf. Process.*, vol. 75, no. July 2021, pp. 895–902, 2022, doi: 10.1016/j.jmapro.2021.12.041.
[11] M. Khanzadeh, W. Tian, A. Yadollahi, H. R. Doude, M. A. Tschopp, and L. Bian, "Dual process monitoring of metal-based additive manufacturing using tensor decomposition of thermal image streams," *Addit. Manuf.*, vol. 23, no. August, pp. 443–456, 2018, doi: 10.1016/j.addma.2018.08.014.
[12] M. Khanzadeh, S. Chowdhury, M. Marufuzzaman, M. A. Tschopp, and L. Bian, "Porosity prediction: Supervised-learning of thermal history for direct laser deposition," *J. Manuf. Syst.*, vol. 47, no. April, pp. 69–82, 2018, doi: 10.1016/j.jmsy.2018.04.001.
[13] L. Meng *et al.*, "Machine Learning in Additive Manufacturing: A Review," *Jom*, vol. 72, no. 6, pp. 2363–2377, 2020, doi: 10.1007/s11837-020-04155-y.
[14] M. Khanzadeh, S. Chowdhury, M. A. Tschopp, H. R. Doude, M. Marufuzzaman, and L. Bian, "In-situ monitoring of melt pool images for porosity prediction in directed energy deposition processes," *IISE Trans.*, vol. 51, no. 5, pp. 437–455, 2019, doi: 10.1080/24725854.2017.1417656.
[15] M. Grasso, V. Laguzza, Q. Semeraro, and B. M. Colosimo, "In-Process Monitoring of Selective Laser Melting: Spatial Detection of Defects Via Image Data Analysis," *J. Manuf. Sci. Eng. Trans. ASME*, vol. 139, no. 5, 2017, doi: 10.1115/1.4034715.
[16] C. Wang, X. P. Tan, S. B. Tor, and C. S. Lim, "Machine learning in additive manufacturing: State-of-the-art and perspectives," *Addit. Manuf.*, vol. 36, no. January, p. 101538, 2020, doi: 10.1016/j.addma.2020.101538.
[17] Z. Xiyue, I. Aidin, K. Mojtaba, I. Farhad, and B. Linkan, "Automated Anomaly Detection of Laser-Based Additive Manufacturing Using Melt Pool Sparse Representation and Unsupervised Learning," in *Solid Freeform Fabrication 2021: Proceedings of the 32nd Annual International Solid Freeform Fabrication Symposium – An Additive Manufacturing, ConferenceAt: University of Texas - Austin, 2-4 August*, 2021, pp. 376–387. doi: org/10.26153/tsw/17561.
[18] A. J. Pinkerton and L. Li, "Modelling the geometry of a moving laser melt pool and deposition track via energy and mass balances," *J. Phys. D. Appl. Phys.*, vol. 37, no. 14, pp. 1885–1895, 2004, doi: 10.1088/0022-3727/37/14/003.
[19] L. J. Segura, T. Wang, C. Zhou, and H. Sun, "Online droplet anomaly detection from streaming videos in inkjet printing," *Addit. Manuf.*, vol. 38, no. December 2020, p. 101835, 2021, doi: 10.1016/j.addma.2020.101835.
[20] H. Yan, M. Grasso, K. Paynabar, and B. M. Colosimo, "Real-time Detection of Clustered Events in Video-imaging data with Applications to Additive Manufacturing," pp. 1–40, 2020, [Online]. Available: http://arxiv.org/abs/2004.10977
[21] H. Yang, S. Zhang, Y. Lu, P. Witherell, and S. Kumara, "Spatiotemporal Monitoring of Melt-Pool Variations in Metal-Based Additive Manufacturing," *IEEE Robot. Autom. Lett.*, vol. 7, no. 3, pp. 8249–8256, 2022, doi: 10.1109/LRA.2022.3187540.
[22] Y. Zhang, H. G. Soon, D. Ye, J. Y. H. Fuh, and K. Zhu, "Powder-Bed Fusion Process Monitoring by Machine Vision with Hybrid Convolutional Neural Networks," *IEEE Trans. Ind. Informatics*, vol. 16, no. 9, pp. 5769–5779, 2020, doi: 10.1109/TII.2019.2956078.
[23] L. Scime and J. Beuth, "Using machine learning to identify in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process," *Addit. Manuf.*, vol. 25, no. October 2018, pp. 151–165, 2019, doi: 10.1016/j.addma.2018.11.010.
[24] W. Ren, Z. Zhang, Y. Lu, G. Wen, and J. Mazumder, "In-Situ Monitoring of Laser Additive

Manufacturing for Al7075 Alloy Using Emission Spectroscopy and Plume Imaging," *IEEE Access*, vol. 9, pp. 61671–61679, 2021, doi: 10.1109/ACCESS.2021.3074703.
[25] F. W. Baumann, A. Sekulla, M. Hassler, B. Himpel, and M. Pfeil, "Trends of machine learning in additive manufacturing," *Int. J. Rapid Manuf.*, vol. 7, no. 4, p. 310, 2018, doi: 10.1504/ijrapidm.2018.10016883.
[26] C. Gobert, E. W. Reutzel, J. Petrich, A. R. Nassar, and S. Phoha, "Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging.," *Addit. Manuf.*, vol. 21, no. April, pp. 517–528, 2018, doi: 10.1016/j.addma.2018.04.005.
[27] A. Caggiano, J. Zhang, V. Alfieri, F. Caiazzo, R. Gao, and R. Teti, "Machine learning-based image processing for on-line defect recognition in additive manufacturing," *CIRP Ann.*, vol. 68, no. 1, pp. 451–454, 2019, doi: 10.1016/j.cirp.2019.03.021.
[28] M. M. Sato *et al.*, "Anomaly Detection of Laser Powder Bed Fusion Melt Pool Images Using Combined Unsupervised and Supervised Learning Methods," 2022, vol. Volume 2: doi: 10.1115/DETC2022-88313.
[29] H. Gaja and F. Liou, "Defect classification of laser metal deposition using logistic regression and artificial neural networks for pattern recognition," *Int. J. Adv. Manuf. Technol.*, vol. 94, no. 1–4, pp. 315–326, 2018, doi: 10.1007/s00170-017-0878-9.
[30] M. Aminzadeh and T. R. Kurfess, "Online quality inspection using Bayesian classification in powder-bed additive manufacturing from high-resolution visual camera images," *J. Intell. Manuf.*, vol. 30, no. 6, pp. 2505–2523, 2019, doi: 10.1007/s10845-018-1412-0.
[31] P. Razvi, S. S., Feng, S., Narayanan, A., Lee, Y. T. T., & Witherell, "A review of machine learning applications in additive manufacturing.," in *In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 59179, p. V001T02A040). American Society of Mechanical Engineers.*, 2019.
[32] G. Menardi and N. Torelli, *Training and assessing classification rules with imbalanced data*, vol. 28, no. 1. 2014. doi: 10.1007/s10618-012-0295-5.
[33] S. H. Seifi, W. Tian, H. Doude, M. A. Tschopp, and L. Bian, "Layer-Wise Modeling and Anomaly Detection for Laser-Based Additive Manufacturing," *J. Manuf. Sci. Eng. Trans. ASME*, vol. 141, no. 8, pp. 1–12, 2019, doi: 10.1115/1.4043898.
[34] M. M. Bappy, C. Liu, L. Bian, and W. Tian, "Morphological Dynamics-Based Anomaly Detection Towards In Situ Layer-Wise Certification for Directed Energy Deposition Processes," *J. Manuf. Sci. Eng.*, vol. 144, no. 11, pp. 1–11, 2022, doi: 10.1115/1.4054805.
[35] W. T. Durant Fullington, Linkan Bian, "Design De-identification of Thermal History for Collaborative Process-defect Modeling of Directed Energy Deposition Processes," *J. Manuf. Sci. Eng.*, pp. 1–40, 2022, doi: 10.1115/1.4056488.