Leveraging Small-scale Datasets for Additive Manufacturing Process Modeling and Part Certification: Current Practice and Remaining Gaps

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Abstract

Additive manufacturing (AM) provides a data-rich environment for collecting a variety of process data. This crucial data can be used to develop effective machine learning (ML) models for anomaly detection and process monitoring. These models are important for users to understand and identify process variations within the AM process, which are directly related to the formation of defects. However, many ML models are data hungry and require copious amounts of data for model training. Because of this, small to medium-sized manufacturers can be at a disadvantage, as collecting, processing, and analyzing large amounts of data can be cost prohibitive, leading to limited sample availability. Despite this limitation, there are several commonly used approaches for improving the usability and effectiveness of small-scale data sets, including feature extraction, data augmentation, and transfer learning approaches. These approaches allow for either dimension reduction of the data through feature extraction, increase in training diversity and size via augmentation techniques, or the transfer and alignment of knowledge from one or more sources of data to improve a target model's performance. This paper aims to explore these three popular techniques for small-scale dataset enhancement, provide insights into their use in AM, and discuss potential limitations and future research directions related to knowledge fusion and advanced learning techniques.

Keywords: Additive manufacturing; data augmentation; feature extraction; machine learning; process monitoring; small-scale data; transfer learning.

1. Introduction

Additive manufacturing (AM) is a rapidly growing and expanding field within a diverse variety of applications and industries. This can be attributed to the collection of benefits it provides, including reduced costs, process waste, as well as enhanced manufacturing flexibility and minimized time to market [1], [2]. In addition, AM technologies have also allowed for the development of unique and complex part geometries, which would have been nearly impossible to create using traditional manufacturing techniques [1], [2], [3]. Due to this large collection of benefits, AM applications have been developed and implemented for a variety of applications in manufacturing [2], [4], [5], medical [6], [7], [8], construction [9], [10], [11], and even for in-space manufacturing [3], [12]. One of the major hurdles for the broader adoption of AM is its part and process certification [13]. There have been a variety of promising research directions focused on defect detection and part certification in AM [2], [14], [15], [16]. Different AM processes provide a data-rich environment that allow AM users to collect various forms of data, as well as leverage that data to make informed decisions regarding the design and quality of the printed part.

From this data-rich environment, AM users can specifically leverage artificial intelligence (AI) to improve part quality and better understand the complexity of AM processes. Within AI, machine learning (ML) has greatly improved process monitoring and defect detection capabilities across a variety of advanced manufacturing techniques [17], [18], [19]. ML has been specifically leveraged to improve a variety of aspects of AM process quality, including part certification, process monitoring, and defect detection [19], [20], [21], [22]. However, despite the benefits and widespread utilization of ML in AM, there are still some challenges when directly applying ML to AM. These limitations are primarily related to the high process uncertainty, lack of consistency across builds, and high part design complexity [23]. These different challenges make it difficult to develop robust and accurate ML-based process monitoring and defect detection frameworks. This can be attributed to the fact that it is difficult to generalize these frameworks across varying AM systems, due to the high variations in machine setups, process parameters, material selection, and environmental factors [23], [24].

In addition to the limitations regarding generalizability, traditional ML frameworks also require a sufficiently large sample size, which can be very expensive to collect. In the AM environment, it is common for practitioners to leverage primarily small-scale datasets due to the prohibitively high cost of collecting, processing, and analyzing larger datasets [25]. **These small-scale datasets are characterized by their limited *sample size*, especially when comparing with the *dimensionality* and *diversity* of data formats.** In fact, it is possible for AM practitioners to collect a variety of different data types simultaneously in this data-rich environment; however, the cost of the AM experiments, as well as the cost of processing and aligning large groups of data, leads to the sample size limitations [26], [27], [28]. This is especially challenging for small-to-medium sized manufacturers (SMMs), who rely more heavily on small-scale datasets to make informed decisions, which can limit their overall capabilities of process modeling and part certification [29].

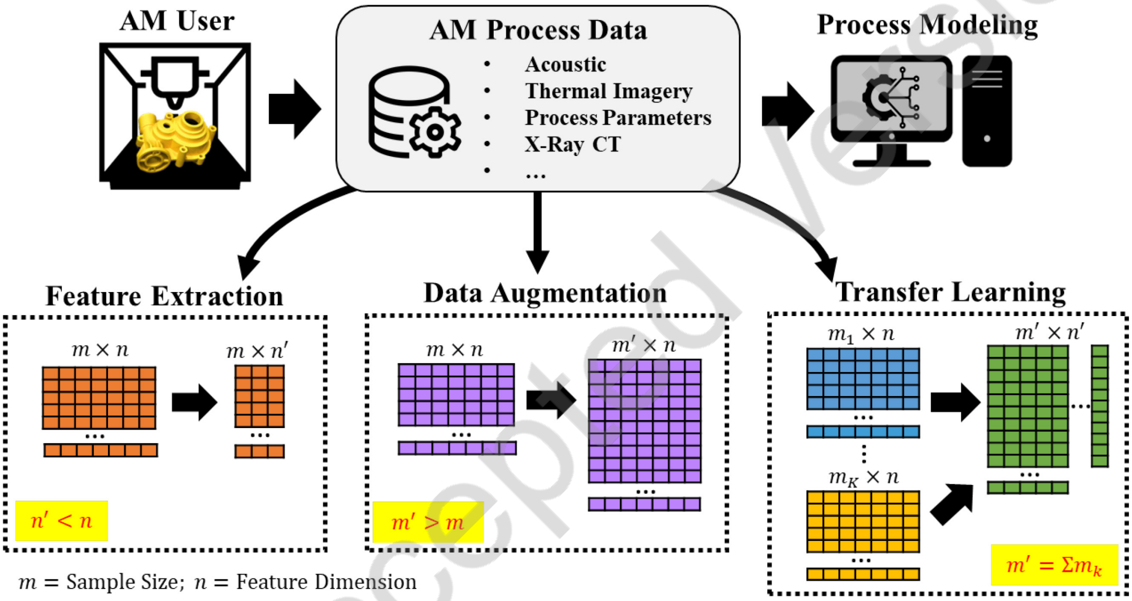

Figure 1: Overview of small-scale AM data enhancement framework for improved process modeling capabilities and how they impact the training data for ML training.

Three main approaches can be leveraged to enhance the usability of small-scale datasets for AM process modeling and part certification, as illustrated in Figure 1. These include (1) ***feature extraction***, (2) ***data augmentation***, and (3) ***transfer learning***. Firstly, ***feature extraction*** methods enhance the capabilities of small-scale datasets by identifying key, low-dimensional attributes that are informative of the process condition or defect occurrences [30], [31]. These techniques include transform-based and statistical-based methods, which allow AM users to use their existing data more efficiently and effectively. In addition, ***data augmentation*** techniques have also shown promising benefits for improving the usability of small-scale datasets [32], [33]. These techniques focus on enhancing the existing data availability by increasing and augmenting the training data, without the need to collect new data. This can provide data hungry ML models with more diverse data to train with, helping to facilitate the development of more robust models [34]. Common data augmentation techniques include data manipulation techniques, such as cropping, flipping, noise injection, and other common methods used in computer vision [35], oversampling techniques such as the SMOTE algorithm [36], and generative modeling methods, such as generative adversarial networks and diffusion generative models [32], [34]. Finally, ***transfer learning*** (TL) can be leveraged to enhance data availability by transferring knowledge from one or more domains to another related domain [37], [38], [39]. This includes the ability to transfer key features, individual samples, or even model parameters to better leverage knowledge from a collection of smaller training sets [40]. This can lead to improved model robustness and generalizability, which has shown great benefits to small-scale dataset modeling [41], [42].

The rest of this paper is organized as follows: Section 2 will introduce and discuss feature extraction techniques and their application and benefit for small datasets in AM. Section 3 will introduce data augmentation techniques, and Section 4 will discuss transfer learning. Section 5 will address some key limitations and future research directions and Section 6 will conclude the work.

2. Feature Extraction Methods and Their AM Applications

2.1. Overview of Feature Extraction Methods

Feature extraction is a fundamental technique in ML that involves transforming raw data into a reduced, meaningful set of features. These features represent essential information from the original data, enabling more efficient analysis and improved performance of ML algorithms [43]. Feature extraction serves several critical purposes in data analytics and ML: (1) it reduces the dimensionality, making the data more manageable and reducing computational complexity [44]; (2) extracting relevant features enhances the performance of machine learning models [45]; (3) extracted features are often more interpretable than raw data, enabling a deeper understanding of the underlying patterns [46]. There are a variety of different feature extraction techniques, covering a wide range of applications; however, we can group them into two main categories:

- ***Statistical features*** include measures like mean, variance, skewness, and kurtosis, providing insights into the central tendency, spread, and shape of the data distribution. These features are widely used in various applications for their simplicity and effectiveness [47].

- ***Transform-based features*** include methods such as wavelet transformation, principal component analysis (PCA), and manifold learning, which enable a compact representation of data in a transformed space, reducing dimensionality and highlighting relevant patterns [48]. There are several other specialized techniques designed for specific data types and applications. Some of these methods that can be considered in AM applications include frequency domain features [49], [50], time-domain features [51], [52], geometric features [53], [54], [55], texture features [56] and many others.

These tailored methods cater to diverse datasets, ensuring a comprehensive approach to extracting valuable information. Ultimately, the continuous evolution of these techniques enriches the field of feature extraction, as well as advancing the realm of data analytics and machine learning.

Table 1: Overview of feature extraction for dimension reduction in AM

Data Type	Feature Extraction Methods	Modeling Algorithms	References
Image Data	Principal component-based feature extraction techniques (PCA, vPCA, MPCA, etc.)	K-means clustering	[57],[58]
		Dual control charting and monitoring statistics	[55], [59]
		Decision tree (DT); linear/quadratic discriminant analysis (LDA/ QDA); k-nearest neighbors (KNN); support vector machines (SVM)	[20], [60], [61]
	Interpolated process characterization	Self-organizing map (SOM)	[62]
	Variational autoencoder (VAE)	Gaussian mixture sparse representation; K-means clustering	[63]
	Geometric features	DT; LDA; QDA; KNN; and SVM	[61], [64]
	Tensor factorization	Bayesian change detection	[65]
	Integrated spatiotemporal decomposition & regression	Likelihood ratio test approach	[66],[67]
	Regions of interest of spatters, plumes, and melt pool	SVM, convolutional neural network (CNN)	[68]
	SIFT features based on melt pool image morphology	Bag of words (BoW); SVM	[69]
	Spectral intensity graph	SVM	[70][71]
	Multi-dimensional visual feature extraction from CT images	SVM	[72]
	Local intensity variation and surface texture features	Bayesian classifier	[73],[21]

Time Series Data	Summary statistics of acoustic emission signals	Logistic regression and artificial neural network (ANN); Physics-Guided Long Short-Term Memory (LSTM) Networks	[74], [75]
	PCA on acoustic emission AE signals	Hidden semi-Markov model (HSMM)	[76]
	Preprocessing of acoustic signals	DBN, SVM	[77]
	Wavelet-based signal decomposition	Spectral CNN and CNN	[50], [78]
	LSTM-autoencoder	Adaptive boosting and one-class SVM	[79]
	Graph Fourier transform	SVM, DT, KNN, LDA, K-Means, and NN	[80]
Point Cloud Data	Spectral graph theory-based methods	Sparse representation-based classification, NN, KNN, Naïve Bayes (NB), SVM, and DT	[81]
	Kernel correlation-based methods	Statistical control charting	[82]
	Low-rank tensor decomposition	One-class classification	[83]
	Recurrent network-based methods	One-class Graph NN	[84]

2.2. Feature Extraction Applications in AM

AM processes provide a data-rich environment, where a variety of sensors and metrological techniques can be applied for *in-situ* and *ex-situ* data acquisition [85], [86], [87]. For instance, in acoustic-based monitoring, signals can be generated from the plasma in selected laser melting (SLM) [66] and the stepper motors in fused deposition modeling (FDM) processes [67]. Similarly, in image-based monitoring, the inputs consist of both optical and thermal imagery [88]. Moreover, point cloud data can be obtained by 3D scanning to characterize the geometric accuracy and surface quality of the printed components [82]. Ultrasonic and X-ray CT data can also be collected for internal structure characterization [89] and thus leveraged for defect detection [62], [69]. These different data are of critical importance, as AM routinely encounters process induced issues such as cracks, delamination, rough surfaces, and lack of fusion, all of which stem from the layer-wise material deposition [90], [91]. Therefore, in-process data collection, processing, and modeling are needed to identify and mitigate the impacts of process variation and defect formation. However, the process data can be complex and contain high-dimensional time series, images, or even multidimensional tensors. The high dimensionality of the data makes the model training computationally expensive. Because of this, it can be beneficial to extract essential low-dimensional process features for monitoring, e.g., defect detection [52], [69], [92]. Following feature extraction, diverse ML and other modeling techniques can be employed to establish connections between these extracted process features and the occurrence of defects. Table 1 provides a summary of various methods for feature extraction and data-driven defect detection in AM. This collection of applications showcases the significance of dimensionality reduction-based feature extraction approaches in advancing the quality and defect monitoring capabilities within additive manufacturing. Overall, the availability of diverse feature extraction techniques provides an opportunity for more efficient, reliable, and high-quality production in the rapidly evolving AM industry.

2.3. Limitations and Challenges of Feature Extraction-based Methods

Feature extraction methods are significant tools in ML modeling for AM, but they demonstrate certain limitations that impact their applicability and effectiveness. Some key limitations include: (1) feature extraction methods may tend to oversimplify the AM data, which can potentially lead to information loss. When removing "irrelevant" process features, there is a risk of discarding subtle, yet significant patterns present in the original data, given the complex process dynamics in AM [93]. (2) The effectiveness of feature extraction methods heavily depends on the technique used for feature selection. Inaccurate or inappropriate selection methods can result in suboptimal feature sets and degrade the performance of machine learning models [94]. (3) Feature extraction for AM can be sensitive to noise and outliers due to high AM process uncertainty or sensing capacity, leading to the inclusion of irrelevant features [95]. (4) Purely data-driven feature extraction methods are tailored to specific AM datasets and may not generalize well across different AM systems [96]. These limitations and challenges highlight the need for careful incorporation of domain knowledge when applying feature extraction methods to AM.

3. Data Augmentation

3.1. Overview of Data Augmentation Techniques

Data augmentation is a widely used framework that involves techniques (such as transformation, sampling, and machine/deep learning) to create novel samples. The newly generated data should be similar to the actual data but with realistic diversity [97]. In practice, data augmentation can be utilized to (1) expand the sample size of the original dataset, (2) address the issues related to class imbalance, and (3) provide better model generalization. In AM applications, data augmentation techniques have been applied to solve the above-mentioned issues in small datasets with great success [98]. Furthermore, small datasets are also common in other areas such as medical imaging where data augmentation has also been utilized [99]. With effective data augmentation for small datasets, the effect of overfitting can also be potentially reduced, leading to better model performance [100]. Furthermore, data augmentation can also increase the diversity of the dataset and thereby improve the overall generalization of the model [101].

Depending on the dataset type (images, time series, etc.) and the various applications, data augmentation approaches can be grouped into three main categories: *traditional techniques*, *machine learning/oversampling techniques,* and *deep learning techniques*. As summarized in Figure 2:

- ***Traditional augmentation techniques*** consist of modifying the spatial features of a dataset. This approach includes geometric modifications (cropping, stretching, flipping, translation, rotation, zoom, image mix-up, etc.), intensity modification (contrast, brightness, color change), noise injection, and kernel filtering. These techniques are commonly used in computer vision [102].

- ***Machine learning/oversampling techniques*** consist of duplicating or synthesizing new samples by increasing the number of samples based on a minority class. These techniques include popular methods, such as random sampling and synthetic minority over-sampling techniques (SMOTE) [36]. Some variations of SMOTE include borderline-SMOTE (B-SMOTE) [103], or Adaptive Synthetic Sampling (ADASYN) [104]. In the context of time series analysis, the barycenter averaging (DBA) [105] time warping technique is one technique that can be used to generate new data based on existing time series data.

- ***Deep learning techniques*** involve using advanced neural networks to learn the data distribution and then generate synthetic samples. This method includes techniques such as neural style transfer (NST) to transfer and combine style features between two images [106]. The most popular deep learning-based data augmentation research is mainly on the development of generative models, such as the generative adversarial network (GAN) [107], the diffusion models (DM) [108], variational autoencoder (VAE) [109], normalizing flow (NF) [110], and energy-based models (EBM) [111].

Each of these techniques plays a crucial role in solving issues faced with small datasets and comes with its own distinct advantages and limitations.

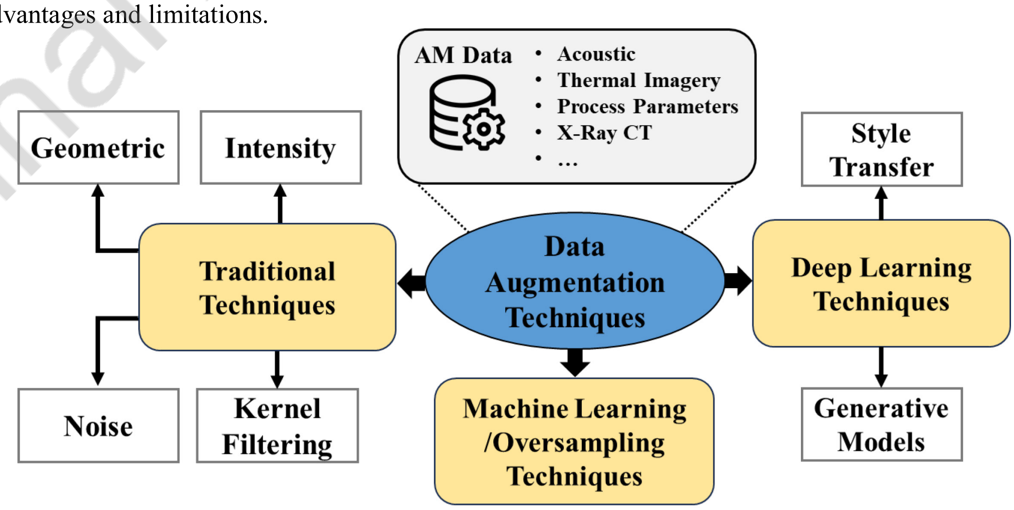

Figure 2: Overview of data augmentation frameworks.

3.2. Data Augmentation Applications in AM

In practice, certain AM process models are constrained in their training performance due to the inherently small sample size for certain products, and the rare occurrence of abnormal states (for defect detection cases). Moreover, deep learning models, which heavily rely on dataset quality, may perform poorly when trained on small or imbalanced datasets. Data augmentation techniques play a pivotal role in addressing these issues. Traditional augmentation, such as image rotation with affine transformation, has been combined with data annotation and self-supervised learning to predict scan direction and melt pool position in laser powder bed fusion (LPBF) AM [112].

Generative deep learning models (as illustrated in Figure 3), especially GANs, are among the most employed augmentation techniques in AM. For instance, Hertlein *et al.* [113] utilized the augmentation capability of a conditional GAN to generate images predicting the optimal structure used for topology optimization in AM design. The accuracy of the cGAN predictions has been shown to improve the iterations of topology optimization. Li *et al.* [114] proposed a data augmentation technique using an attention-stacked GAN (AS-GAN) framework applied to a sequential AM dataset. While GAN models have long dominated the generative models' domain, emerging diffusion models, such as denoising diffusion implicit models (DDIM), [115] are also demonstrating significant potential. Diffusion models can achieve state-of-the-art augmentation performance by perturbing the training data with noise and then generating/augmenting the dataset by denoising the perturbed data [116], [117]. In inkjet AM, monitoring the deposited droplets, specifically their volume, is crucial for improving the quality of the printed product. However, limitations in the micrometer scale and the number of texture features available make it challenging to fully explore the relationship between defects and their causes. To address this issue, Zhang *et al*. [118] utilized a multi-scale conditional diffusion model to restore distorted time series signals by generating signals without irregularities, thereby improving the volume consistency of the deposited material. Furthermore, Yangue *et al.* developed a novel DDIM model for data augmentation of FFF process layer-wise images [117]. This allows for an increase in the amount of available training data through high quality, synthetic image generation that can accurately capture the AM layer-wise variations.

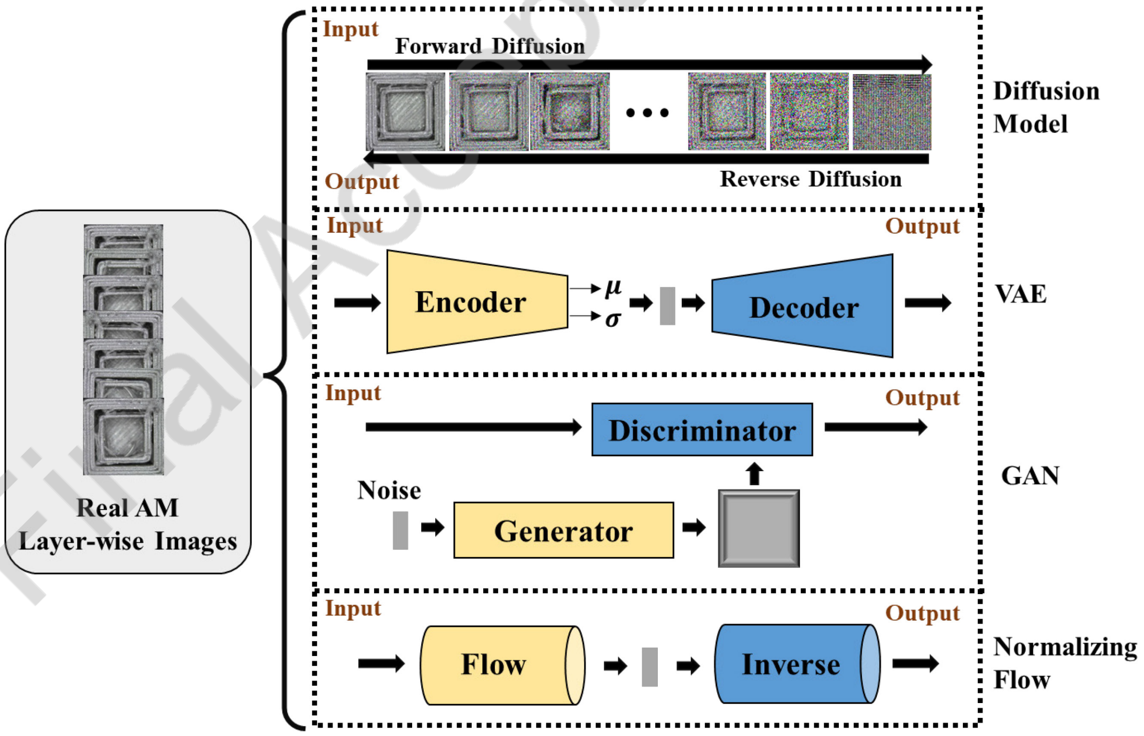

Figure 3: Examples of popular generative modeling techniques applied to AM.

One area where data augmentation has been greatly utilized is for addressing class imbalance problems. In AM defect detection studies, the minority class (defects) is typically smaller and imbalanced compared to the normal class. Several studies have attempted to tackle this imbalance issue using various techniques applied to various manufacturing systems including AM [119]. Some of these techniques include class-weighted techniques [50], semantic segmentation techniques [120], active learning [121], isolation forest [122], [123], and few-shot learning [124]. Furthermore, many studies still rely on data augmentation techniques, which can provide more diversity, versatility, and generalization to the dataset to address class imbalance problems for smaller class datasets [87]. Specifically, Chung *et al*. [125] proposed a GAN model incorporated with a classier for an effective cooperative training mechanism within an AM process, particularly for the supervised classification of imbalanced states. Moreover, a cluster-based adaptive data augmentation (CADA) has also been developed by Dasari *et al* [126] for oversampling of the minority class in the defects classification of AM. Table 2 summarizes examples of data augmentation techniques based on deep learning, oversampling, machine learning, and traditional techniques, all of which are applied to AM. This summary emphasizes the rise of deep learning techniques (such as GAN and diffusion models) over other techniques.

Table 2: Overview of data augmentation applications in AM

Methods	Algorithms	Applications	References
Deep learning-enabled generative models	GAN	Balance abnormal samples for anomaly detection	[97], [114], [125], [127], [128], [129]
	VAE	Defect detection	[130], [131]
	DDPM	Image super-resolution	[132]
	DDIM	Layer-wise monitoring of AM	[117]
	NF	Defect detection	[133]
Oversampling and machine learning	Cluster-based adaptive data augmentation (CADA)	Data augmentation	[126]
	Statistical shape analysis (SSA)	Augmentation for CNN geometric deviation prediction	[134]
	SMOTE	Augmentation for metal AM printability prediction	[128], [135]
	Bootstrapping	Augmentation for in situ porosity detection	[136]
	Stratified sampling with ensemble technique	Defect prediction	[137]
Traditional	Time stretching, pitch shifting, & amplifying	Acoustic data augmented to anomaly detection	[138]
	Flip	Augmentation for part quality detection	[139]
	Flip, crop, gaussian noise, and blur	Augmented data for part classification	[140]
	Translation, mirroring, brightness, & contrast	*In situ* video monitoring	[141]
	Gaussian Kernel and Gaussian noise	Quality analysis	[142]

3.3. Limitations and Challenges of Data Augmentation

Despite the advantages of employing data augmentation for small datasets, it also comes with some limitations. These limitations include (1) data/domain-specific complexity, (2) the risk of overfitting and limited effectiveness, and (3) the intracity of certain data augmentation techniques.

Firstly, certain types of AM data have different characteristics or feature complexities that could be challenging to address with certain data augmentation techniques. For instance, some traditional techniques are not suitable for direct application on time series data (e.g., signal data) [97]. Data complexity can also lead to augmentation techniques failing to understand the distributions of the datasets, resulting in issues such as mode collapse [143], generalization or optimization [144] and memorization issues [145].

Secondly, data augmentation can reduce the effectiveness of training by introducing more data duplication to the training and further overfitting the model. In other words, excessive data augmentation can introduce bias to the training, which can further deteriorate the level of overfitting of the model [100], [101]. Training effectiveness is also reduced by the introduction of more unrealistic patterns or little diversity or variations.

Finally, data augmentation techniques, such as deep learning methods, tend to be computationally expensive in terms of time and resources. For instance, diffusion generative models such as DDPM can require very high computational costs for training before being able to generate high quality images [115]. Deep learning models also require the development of robust network architectures and the need for large datasets to train the model, both of which are not always easily achievable in AM practice. However, despite these limitations, strong data augmentation techniques could provide robust solutions for the many issues related to small-scale dataset usability in AM.

4. Transfer Learning

4.1. Overview of Transfer Learning

Transfer learning (TL) is another commonly used technique for improving model performance in situations where data may be very limited. TL allows us to leverage knowledge from one or more source datasets to improve the performance of a related, but slightly different target dataset [37]. This framework of knowledge sharing has seen great success in a variety of applications and industries, including medical image transfer [146], [147], industrial manufacturing and agriculture [148], [149], [150], speech and pattern recognition [151], and time series analysis [152], [153]. In addition to these general applications, TL has also shown promising results in enhancing the usability and effectiveness of small-scale datasets [41], [42], [154]. This is because TL frameworks require less data from each domain, facilitate reduced processing time, and are able to combine and leverage knowledge from multiple small, related groups of data [42].

In general, we can categorize three main approaches of TL, which include *instance-based transfer, feature-based transfer (domain adaptation),* and *model-based transfer* [25], [40]. These three different forms of TL cover most applications and provide a broader, more effective grouping mechanism to better discuss implementation techniques and are visualized in Figure 4.

- ***Instance-based transfer*** focuses on identifying and directly transferring the most similar-to-target samples from one or more source distributions, into a single target domain [155]. This approach aims to bolster and increase the number of training samples, which can result in a more accurate and robust model. A common approach to implementing instance-based methods is through a sample reweighting scheme between source and target samples [156], [157], [158].

- ***Feature-based transfer***, also known as *domain adaptation*, aims to capture and align feature distributions from the source to the target domains [40], [159]. This is a slightly different approach compared to instance-based transfer, as it works to identify and align key feature distributions within the data. This can lead to more accurate and efficient models, as it leverages additional source samples, while efficiently extracting and aligning the key features.

- ***Model-based transfer*** involves transferring knowledge from a pre-trained source model(s) to improve a related target model's performance [160], [161]. This approach does not involve any data or distribution alignment, as it relies primarily on transferring pre-trained source model parameters, and then fine-tuning the target model to better fit the target data. This allows the user to develop a more stable source model, where there is generally more data, and then fine-tune the performance to better fit the target data distribution.

Overall, there are a variety of different approaches and methods of implementing transfer learning, each with its own unique approach and distinct advantages.

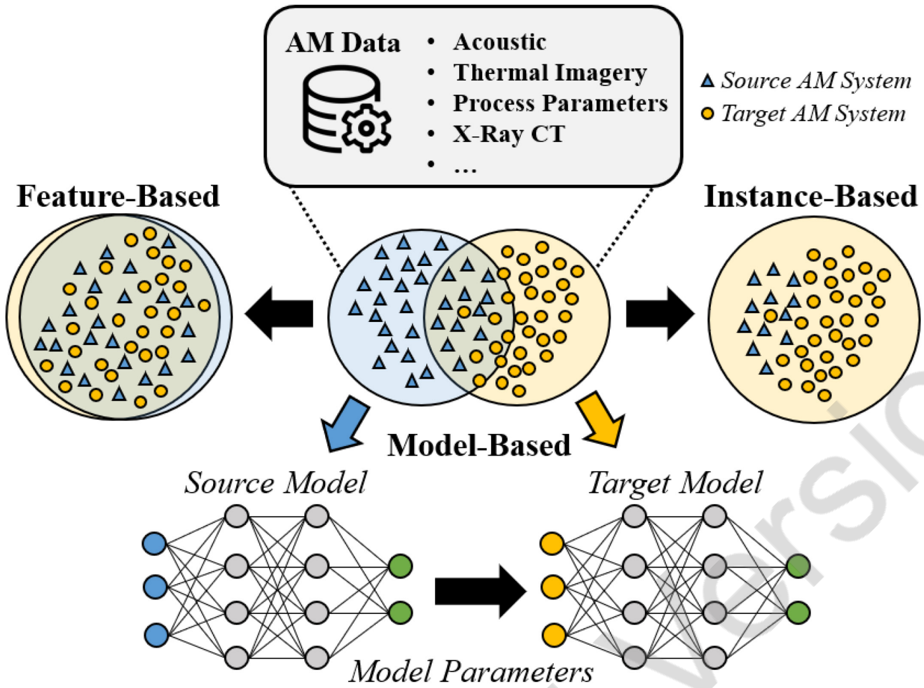

Figure 4: Overview of the three main forms of transfer learning, showcasing how to leverage and transfer source and target domain knowledge.

4.2. Applications of Transfer Learning in AM

On top of the broad impact and implementation of these models, some approaches to transfer learning have already been implemented in AM, including examples of instance-, feature-, and model-based TL. These different applications cover everything from process parameter estimation to process monitoring and defect modeling, including transferring knowledge between processes and materials. Tang *et al*. provide a detailed survey covering various applications of TL in AM [25]. One unique instance of TL in AM implements instance-based transfer learning to use prior experimental data for process optimization of a target printing process in laser-based AM [162]. In their framework, the previous experimental process optimization data are directly leveraged as initial experimental data to guide the sequential target optimization studies. This ultimately reduced the amount of costly and time-consuming optimization experimentation needed for the target study [162]. In addition, another study leverages feature-based TL to develop a statistical transfer learning framework to predict the shape-dependent variations of novel printed geometries [25], [163]. This was accomplished by using the shape-dependent part of source geometries and creating a shared latent space around these local features. This shared latent space from the source examples can then result in a trained model that can be applied to predict the shape-dependent parts of novel geometries. In addition to this example, a handful of other research applications have focused on applying model-based TL for shape deviation prediction in AM [164], [165], [166], [167]. Furthermore, Senanayaka *et al*. leveraged a hybrid model- and instance-based TL framework to better understand the effects of AM process conditions on the thermal-defect relationship [168]. This work focuses on initially grouping similar source and target samples, training source models, and then transferring parameters from multiple models to develop a more accurate target classifier. Finally, TL has also been leveraged for predicting distortion, as well as transferring machine calibration and compensation knowledge [169], [170]. Despite these specific applications, TL is a generally less researched and less implemented solution for handling small datasets, as compared to feature extraction approaches in AM. However, there have been several promising implementations of TL in metal-based AM, detailed in Table 3, which showcases the potential to further improve model accuracy in small-scale dataset applications.

4.3. Limitations and Challenges for Transfer Learning

Despite the potential advantages associated with TL, there are some key limitations related to implementing TL in AM, which are primarily focused on (1) high process variability and AM setup diversity; and (2) data privacy concerns.

Firstly, there are a variety of factors that can affect the resulting distribution of AM process data, including material properties, process parameters, part geometry, and environmental factors. Because of the significant diversity between AM applications, there can be difficulty directly implementing off-the-shelf TL methods for AM. This is because most traditional approaches to TL rely on the source and target datasets being similarly structured and distributed [171]. Without sufficient understanding of the relationships between those AM systems, there is a significant risk of negative transfer in TL, which can jeopardize the modeling performance and lead to misleading decisions [25].

Secondly, there are significant data privacy and intellectual property theft concerns that arise when externally sharing thermal process data and related process knowledge [29], [172], [173], [174]. This stems from the idea that the AM process data can potentially contain sensitive design information that can be extracted and leveraged to perform re-identification attacks [60]. These malicious attacks are designed to extract geometric information and utilize it to identify critical design aspects or entire part geometries from available data. This can then be leveraged to recreate the part and steal the intellectual property of the AM user. This is a serious concern for a variety of AM applications, especially for instances of *rapid prototyping*, where design information is considered highly confidential [29]. Without the development of secure data sharing frameworks [29], [60] or implementation of decentralized learning frameworks, such as federated learning [175], [176], there is a significant threat of intellectual property theft when participating in collaborative modeling or data sharing.

Table 3: Overview of transfer learning algorithms in AM

Methods	Applications	References
Instance-based	Support rapid process modeling in aerosol jet printing.	[177]
	Leverage data from previous studies for laser-based AM.	[162]
Feature-based	Support rapid process modeling in aerosol jet printing via affine transformation.	[177]
	Transfer shape features to predict shape-dependent parts.	[163]
Model-based	Quantify uncertainty in LPBF via transfer learned process maps.	[178]
	Model shape deviation via transfer learning across processes.	[167]
	Predict distortion via Bayesian model transfer among materials	[169]
	Grouped similarity transfer learning for understanding the effects of process conditions.	[168]
	Model transfer for fine-tuning neural network for the prediction of deposition height in directed energy deposition (DED).	[179]
	Improved model of kinematics induced geometric variations in AM parts via CNN fine-tuning.	[171]
	Transfer common information from a surface to a new one with only low-resolution data.	[163]
	Transfer source model to retrain a target model for monitoring of a different material in LPBF.	[180]
	Material-adaptive monitoring for wire-arc AM via a property-concatenated transfer learning.	[181]
	Transfer model parameters across polymer composites for predicting stress-strain curves.	[182]

5. Future Research Opportunities and Directions

Although there has been a generous amount of research addressing the small-scale data challenge in AM, there are still a few key challenges and opportunities for future research. The opportunities focus primarily on *Knowledge Fusion* and *Improved Learning Strategies*, which encompass both the inclusion of additional domain knowledge to the modeling, as well as leveraging more advanced learning techniques for model training to improve the usability of existing data. The general overview of these approaches is outlined in Figure 5. On the other hand, some of the key challenges to be addressed relate primarily to how practitioners can participate in data sharing and collaborative modeling, while simultaneously ensuring their data and intellectual property are kept confidential if needed. As the interconnectedness of machines, computers, and personnel continues to increase, data privacy is becoming a more prominent concern and has become an increasingly important area of research. Overall, this overview is not all-inclusive, but rather focuses on a few prominent research areas.

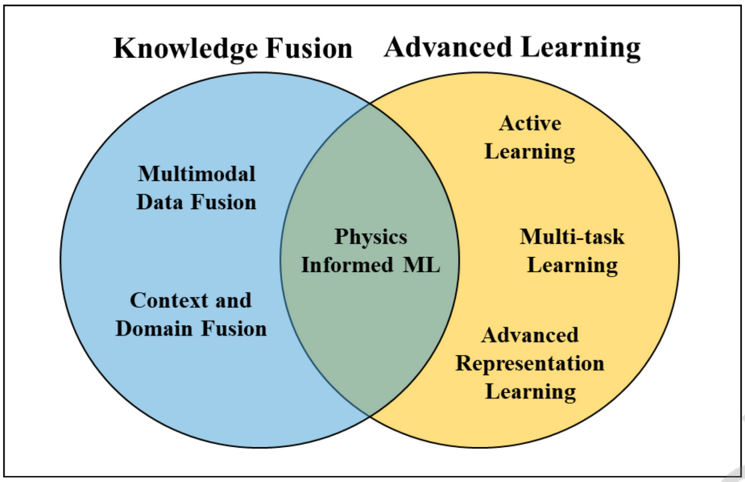

Figure 5: Overview of opportunities to improve small-scale data usability and address remaining challenges.

5.1. Advanced Learning

5.1.1. Active Learning

More advanced and strategic approaches to how ML models are trained can have a major impact on how the final model is able to perform, especially in cases with a limited amount of labeled training data. One popular learning strategy is known as *Active Learning* (AL), which is specifically designed to improve training efficiency by querying and identifying informative points in the instance space and then leveraging an external source to provide labels for the selected samples [183], [184]. In many cases, this involves leveraging an experienced human user to provide the model with feedback for the labeled samples, which is commonly referred to as human-in-the-loop ML [183], [185], [186], [187]. This iterative training process results in improved efficiency, reduced data annotation costs, and the ability for the model to achieve improved performance and generalizability, as compared to traditional supervised learning methods [183], [185]. In general, active learning has been successfully deployed in a variety of applications, including for natural language processing models [183], [184], [188], remote sensing and image analysis [184], [189], [190] and industrial applications of fault detection and uncertainty quantification [191], [192], [193]. For AM, active learning has been leveraged to improve *in-situ* process monitoring capabilities [194], [195], [196], enhanced ink-jet droplet pinch off behavior prediction [197], and prediction capabilities for tensile properties of additively manufactured components [198].

In addition to the traditional form of AL, there is also a variation known as *Incremental Learning* (IL), which is sometimes also referred to as *Lifelong Learning* or *Continual Learning.* IL is similar to the traditional form of active learning, where the model is continuously learning from new data over time [199], [200], [201]. This approach is useful when there can be changes in the data distributions over time or instances of concept drifting, where it may be impractical to completely retrain the model whenever new data are available. Furthermore, this is a more resource-efficient approach to training as the objective is for the model to learn from incremental amounts of new data, without forgetting the previous information [202], [203]. Applications of IL include medical-based applications [201], [202], object detection and segmentation [200] and wire-arc AM defect detection [204]. Overall, AL can be especially useful for small-scale AM datasets, where AM labeling costs can be prohibitive due to time, cost, and labor limitations [20], [194].

5.1.2. Multi-task Learning (MTL)

A second approach for advanced learning strategies is referred to as *multi-task learning,* where the focus is developing frameworks and ML models that can exploit existing relationships between related tasks to improve the generalization and model(s) performance on these tasks [205], [206], [207]. The foundation of this framework focuses on the idea that learning multiple tasks jointly allows for knowledge from one task(s) to be leveraged for other task(s) to improve the generalizability performance of all tasks [206]. This specifically works to help handle data availability and sparsity challenges, where the amount of labeled data from one task may be inadequate to train an accurate learner [205]. Furthermore, MTL is closely related to TL, where the goal of TL to leverage data from a source task to improve performance on a target task [206], [208], [209]. However, there are two key distinctions between MTL and TL [206], [208]: (1) *all tasks and related data are treated with equal weight,* whereas TL focuses most attention on the performance of the target task, (2) *the flow of knowledge for MTL is shared between all tasks*, whereas TL generally shares knowledge from the source task to the target task. In general, there are a wide range of applications for multi-task learning, including natural language processing [210], computer vision [211], and time series predictions [212], among others [208]. In addition to traditional applications, due to their similarity and relation to TL, there has been research focused on blending together TL, MTL, and Federated Learning approaches to further improve data usability and model performance in cases of shared data [209], [213]. Overall, MTL learning provides a unique and promising direction for enhancing the learning strategy when leveraging limited, small-scale data in AM.

5.1.3. Advanced Representation Learning

There is also an approach to overcoming the limited data challenge by altering how the data is represented and learned through machine learning models. Two examples of this approach include *Granular Computing* and *Siamese Networks*, which can both be powerful approaches, but are not fully utilized in AM. Furthermore, these techniques can have limitations in terms of generalization, data dependency, model complexity, or simplicity.

Granular computing is the concept of processing highly complex information across multiple levels of granularity [214], [215]. This focuses on changing the representation of complex information through deconstruction into smaller, more manageable granules. These granules can capture different levels of detail and variance in the data. Example usage of granular computing includes outlier and fault detection [216], [217], text classification [218], and improving federated learning frameworks [215]. Overall, this unique approach makes it a potentially promising option for handling some of the inherent variability and uncertainty in complex AM process data and AI-based modeling.

Siamese networks take another approach to representation learning, in which the main objective is to extract meaningful information through similarity comparison of input vectors [219], [220], [221]. This framework leverages two identical neural network architectures, where each is able to learn a hidden representation of a defined input [220], [222]. The two architectures work in parallel and output a semantic similarity measure of the projected representation for each input. Traditionally, these architectures are used for image-based applications [222], including signature and facial verification [222], few-shot learning [223], and visual tracking tasks [224], [225]. There are some applications of Siamese networks for AM [226], [227]; however, there are still opportunities for more in-depth investigation and broader application of these frameworks in AM.

5.2. Knowledge Fusion

5.2.1. Multimodal Data Fusion

As previously mentioned, AM is a data-rich environment, meaning that practitioners are able to collect a diverse range of different data types from the AM process [228], [229]. These various data streams relate to different aspects of the AM process itself and allow the ability to measure the process variability from multiple perspectives [228], [230]. This idea is commonly referred to multimodal data fusion and has become an increasingly popular research topic in AM [231], [232], [233], [234]. By leveraging multimodal data, practitioners can leverage two or more different types of AM data to improve the efficiency and effectiveness of their ML models [233]. Here, fusible data might include ex-situ data (e.g., post-processed CT data [89], [232]) and *in-situ* sensing (e.g., layer wise imagery [231], [234], acoustic [231], vibration [235], and a variety of other data types [26]). However, the diversity of this data does not directly translate to increased sample sizes, which is a key challenge for AM practitioners. In summary, the multimodal data fusion approach focuses on improving the robustness and accuracy of ML models by including and supplementing data from various, complimentary data sources.

Another approach to fusing additional data and knowledge into the ML modeling framework focuses on leveraging *simulation-based* data to further improve model performance and generalization in cases of limited data [236], [237], [238], [239]. Simulation-based data allows for the generation of data samples that are representative of the physical process or parameters being modeled. This can result in the ability for simulated data to be directly leveraged with the existing, real-world data to increase the diversity and size of limited training data [239], [240], [241], [242]. In addition, simulation data can also be leveraged to directly train a general ML model for the application. This pretrained model can then be further fine-tuned using the real-world samples and experimental data [237], [243], [244], [245]. There has been some interest in leveraging simulation-based data for

AM, specifically for metal-based AM [246], [247], [248]; however, there are still significant research opportunities in this field [237].

5.2.2. Context and Domain Fusion

Furthermore, there has been increasing research interest in context-aware machine learning to further improve ML performance. Contextual learning focuses on implementing real-world context and domain-specific knowledge into the model and training data space [249], [250], [251]. A specific and increasingly popular method of contextual learning is known as the Physics Informed ML (PIML) approach. The goal with PIML is to include prior knowledge about the physics related to the specific domain or application being modeled [242], [252] into the ML model. The PIML framework bridges the two approaches of *Knowledge Fusion* and *Advanced Learning*, as depicted in Figure 5. This is because PIML frameworks can be applied to both the preprocessing stages and training stages of the ML model [87], [251], [253]. This is accomplished by either constraining or preprocessing the training data based on the related system physics [242], [251], or incorporating partial differential equations into the training process itself [242], [251], [252]. The use of either approach to PIML can result in a more robust model with enhanced generalizability and interoperability [87], [242], [252]. For AM applications, the use of PIML is rapidly growing and shows the potential for continued growth for defect detection and reduction [254], [255] and developing a stronger understanding of process-structure-property relationship [87], [256], [257], [258]. In summary, researchers and practitioners need to be aware of data-driven modeling constraints and alternative approaches, such as PIML, to maximize the effectiveness of model implementation in AM.

5.3. Privacy Challenges for ML in AM

Despite the potential opportunities for future work as described previously, there are still some concerns when it comes to sharing data and collaborating across multiple, independent AM users. collaborative modeling and data sharing is a potentially strong way to improve prediction performance, but does create data privacy concerns once the data is shared outside of the organization, especially within AM [60]. The two most common approaches of collaborative modeling are *Centralized* and *Decentralized Collaborative Modeling*, where the data is aggregated and fed to a central model or the central model is decentralized to each local user, respectively. These two approaches are outlined in Figure 6.

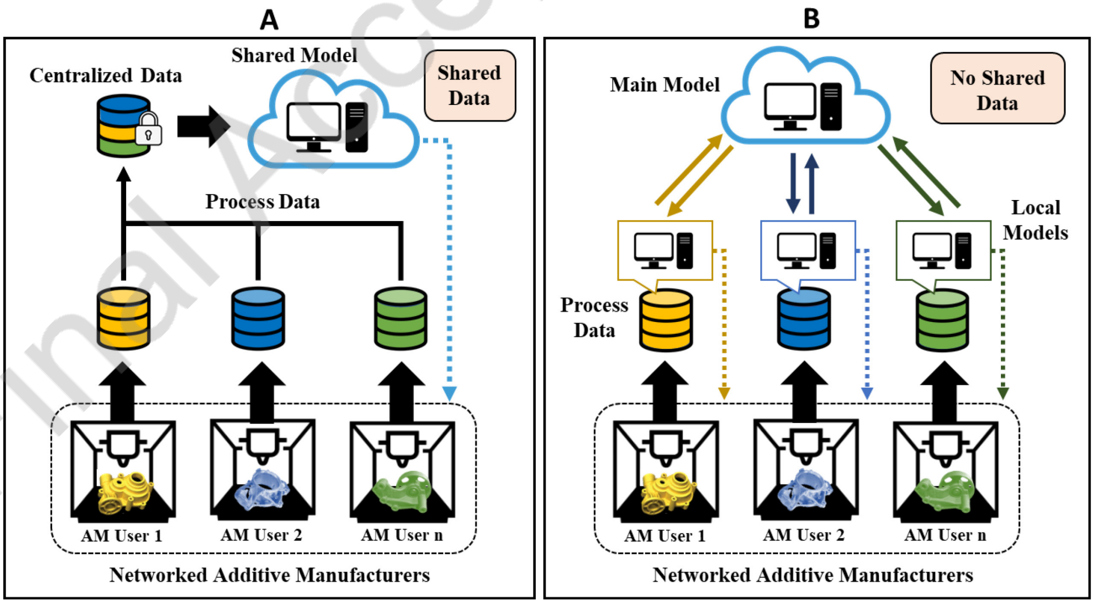

Figure 6: An overview of the two key approaches for enhancing collaborative modeling security and privacy: (A) depicts centralized collaborative modeling, where local user data is secured and aggregated; (B) depicts a decentralized collaborative modeling framework, where models are trained locally.

5.3.1. Centralized Collaborative Modeling

Sharing data between users allows for a collection of independent manufacturers to develop a larger, more effective set of training samples. This can result in the development of more accurate and robust models, which are trained on these larger and more diverse, collaborative sets of training data [29]. However, directly sharing data outside of an organization can put AM users at risk for data privacy breaches and intellectual property theft due to design attributes that can be embedded in the process data [29], [259]. To combat this significant threat, two key different approaches to data privacy and security can be leveraged to improve the safety of this shared data.

Firstly, the use of *encryption* and *access control methods* can provide a strong barrier to the protection of data privacy and security [260], [261], [262], [263], [264]. Encryption-based methods, such as homomorphic encryption, allow users to leverage an encryption key to randomize the data and put it into an unrecognizable state. In turn, the receiving party leverages a decryption key to reverse the encryption and leverage the data [261], [265], [266]. Homomorphic encryption, in particular, provides the added benefit of being able to perform computation and analysis on the encrypted data, making it easier to use the data than traditional methods [267]. However, an important limitation of using encryption is the reliance on encryption/decryption keys, which create a potential vulnerability that can be exploited by malicious actors [268], [269], [270].

Secondly, the development of *de-identification mechanisms for the shared data* provides an additional measure focused on data privacy [271], [272]. The goal behind these frameworks is to selectively identify, obscure, and protect the confidential design aspects of the data being shared. This allows for the data to be leveraged in a collaborative data sharing framework, while simultaneously ensuring that there are added data privacy protections for the data. This framework is depicted in Figure 6A. There exists a wide range of applications for these algorithms, including in healthcare [273], [274], computer vision [259], [275], [276], and AM [29]. These frameworks work towards providing an added layer of protection that can be blended with existing security measures, such as encryption, to enhance data privacy and intellectual property protection.

5.3.2. Decentralized Collaborative Modeling

The second approach to overcome the challenge of privacy concerns when sharing data is *Federated Learning* (FL). This approach leverages a decentralized framework for training ML models, without the exchange of client data [277], [278]. A baseline model is stored at a central server, where copies of this model are then shared with each client. These clients can then train and update the shared model with their local data, without exchanging private data to the central server. From here, the model updates from the local stage are then shared with the main model via an aggregation technique. This iteration continues, further improving the model performance and allowing clients to leverage small-scale data and still achieve an effective ML [277], [278], [279]. This framework is highlighted in Figure 6B. In general, this approach improves the data privacy and security concerns associated with traditional collaborative modeling by removing the need to share local data outside of the client of origin [176], [280]. In addition, FL has been implemented in a variety of advanced manufacturing applications [175], [281], including metal-based AM [282], [283], [284]. There are also a variety of resources exploring the use of Federated Transfer Learning (FTL), which focuses on using data from different feature spaces, in a FL framework, to enhance usability and privacy [285], [286], [287], [288]. FTL has been implemented in a variety of applications, including healthcare wearable technology, autonomous driving, and image steganalysis [285].

However, it is important to note that there are still vulnerabilities and limitations associated with the FL approach. *Firstly*, there is the risk of possible model-poisoning and other back-door attacks, which can compromise data privacy [289], [290]. *Secondly*, FL can also suffer from communication latency, which is caused by the need for frequent communication between nodes during the learning process [291]. Overall, there are some key challenges that come with leveraging FL; however, there is also great potential for developing secure frameworks for sharing knowledge among different AM users to improve model performance on small-scale metal-based AM process data.

5.4. Key Research Opportunities

There still exists a need to further explore different ways of implementing and leveraging these tactics. From some of the previously discussed limitations, there are a handful of clear research directions to further improve the applicability of these methods. Firstly, for feature extraction, there is a need for the development of more robust feature extraction techniques, specifically tailored to AM. This is because AM processes exist in a data-rich environment, yet they still possess a high level of variability and diversity across processes and applications. Because of this, a lot of off-the-shelf feature extraction may not be applicable to each type of data collected from the AM process. This can lead to difficulty in aligning the different features into a shared space for process and defect modeling. Secondly, for data augmentation, there are some similar challenges as some of the state-of-the-art methods are not designed to capture the detailed features in the AM process data. Many generative techniques, such as GAN models and diffusion models (DDIM/DDPM) are developed based on computer-vision applications, which have large, developed training sets. In order to better tailor these techniques for AM, research into more robust variations and modifications is needed. Thirdly, in the case of transfer learning, there is not a widespread application of feature- and instance-based methods. These methods have not been explored as widely as the model-based methods have, which provides an opportunity for future investigation. In addition, many current TL models do not consider how transferring AM process knowledge can lead to compromises in user intellectual property and other data privacy concerns. Recent work by Fullington *et al*. has addressed some of these initial concerns, but there is still a need for developing and compounding additional privacy measures [29].

6. Conclusion

This research aims to provide a detailed overview of the available techniques for enhancing small-scale data set usability, as well as explore their current and potential application for AM. These various methods include implementing (1) feature extraction techniques, which aim to enhance the usability by identifying and extracting low-dimensional key attributes from the raw data, (2) data augmentation techniques, which aim to increase the diversity and size of the training data through augmenting the data, and (3) transfer learning approaches, which allow users to leverage one or more source datasets to improve a target model performance by sharing and aligning knowledge between them. Furthermore, there have already been a handful of successful applications of these enhancement techniques for AM applications, specifically geared towards porosity prediction, process monitoring, and parameter optimization.

Acknowledgements

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

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