Imbalanced Data Classification via Generative Adversarial Network with Application to Anomaly Detection in Additive Manufacturing Process

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Abstract

Supervised classification methods have been widely utilized for the quality assurance of the advanced manufacturing process, such as additive manufacturing (AM) for anomaly (defects) detection. However, since abnormal states (with defects) occur much less frequently than normal ones (without defects) in the manufacturing process, the number of sensor data samples collected from a normal state outweighs that from an abnormal state. This issue causes imbalanced training data for classification models, thus deteriorating the performance of detecting abnormal states in the process. It is beneficial to generate effective artificial sample data for the abnormal states to make a more balanced training set. To achieve this goal, this paper proposes a novel data augmentation method based on a generative adversarial network (GAN) using additive manufacturing process image sensor data. The novelty of our approach is that a standard GAN and classifier are jointly optimized with techniques to stabilize the learning process of standard GAN. The diverse and high-quality generated samples provide balanced training data to the classifier. The iterative optimization between GAN and classifier provides the high-performance classifier. The effectiveness of the proposed method is validated by both open-source data and real-world case studies in polymer and metal AM processes.

Keywords: Additive Manufacturing (AM), Generative Adversarial Network (GAN), Imbalanced Data, Supervised Learning, Anomaly Detection.

1 Introduction

Advanced manufacturing processes, such as additive manufacturing (AM), are widely applied in various fields, including aerospace, healthcare, and the automotive industry (Liu et al., 2019). However, a major barrier preventing broader industrial adoption of the processes is the quality assurance of products. For example, surface defects exist, such as under-fill from the Fused Filament Fabrication (FFF) process shown in Figure 1. It is due to highly complex interactions in consecutive layers during printing. The defect causes a
deficiency in mechanical properties of the final product, such as density, tensile strength, and compressive strength (Hajalfadul and Baumers, 2021). Therefore, timely detection of the anomaly in the process is necessary so that corrective actions can be taken to mitigate the defects and improve the quality of products (Makes and Collaborative, 2017).

Recently, the development of sensor technologies and computational power offer online process data, providing excellent opportunities to achieve effective quality assurance through a data-driven approach (Liu et al., 2021). Specifically, those sensor data are usually in high volume in terms of both dimensionality and sampling frequency, having plenty of information about the manufacturing processes (Zhou et al., 2020). Therefore, it is very beneficial to investigate the underlying relationships between the sensor data and process quality state based on a data-driven perspective (Li et al., 2021). Utilizing the sensor data, supervised classification methods have been widely applied to online anomaly detection in the manufacturing process (Banadaki et al., 2020; Guo et al., 2019; Jin et al., 2019). This is because these methods can fully utilize the label information of the process state, resulting in more accurate and reliable detection results than unsupervised methods. Banadaki et al. (2020); Guo et al. (2019); Jin et al. (2019) utilized balanced training data collected from both normal and abnormal states in the manufacturing processes to achieve a high anomaly detection rate from classifiers (Choi et al., 2021).

Figure 1: Normal surface and Abnormal defect in AM process.

However, the manufacturing process is usually in a normal state (Li et al., 2021). Therefore, balanced training data assumed by the existing work (Banadaki et al., 2020; Jin et al., 2019) is expensive and not realistic. In reality, abnormal conditions, such as surface defects in AM process (Figure. 1), may happen but rarely. Consequently, the sensor data collected under abnormal states are smaller than those collected in a normal state, and may not be sufficient for training supervised classification methods. It causes imbalanced training data
among process states (Chawla et al., 2004), leading to compromised anomaly detection performance in actual manufacturing processes (Li et al., 2021). Specifically, when the number of training data from a normal state outweighs the number of abnormal states, the prediction in classification models tends to be biased towards the normal state (i.e., majority class) (Choi et al., 2021). This leads to a high probability of misclassifying samples from the abnormal states (i.e., minority classes).

To overcome this severe issue caused by imbalanced data problems in the manufacturing process, data augmentation can be applied to obtain balanced training data among process states. Simple data augmentation techniques such as rotation, flipping, and synthetic minority oversampling technique (SMOTE) (Chawla et al., 2002) are widely used for balancing training data in the supervised classification method for the manufacturing process because of their simplicity in application (Cui et al., 2020; Lee et al., 2020; Mycroft et al., 2020). However, such methods consider only local information; therefore, they cannot reflect the entire data distribution and overcome the problem of overfitting (Douzas and Bacao, 2018; Mikołajczyk and Grochowski, 2018). Recently, the generative adversarial network (GAN) (Goodfellow et al., 2014) has been actively used for data augmentation in manufacturing. This is because GAN generates more representative data than the simple augmentation method by learning the entire distribution of actual data through two neural networks: discriminator and generator (Antoniou et al., 2017; Kiyasseh et al., 2020). For example, Gobert et al. (2019) used conditional GAN to generate layer images from the metal AM process. In addition, Li et al. (2021) developed a novel GAN method considering temporal orders of the sensor signal from the polymer AM process to generate the balanced training signal data.

Utilizing GAN, the existing studies achieved high classification performance by training the classifier with the generated balanced training samples. The generated samples of each process state are realistic by learning the distribution of actual data. However, features enabling differentiation between process states (i.e., state-distinguishable features) that can further improve the classification performance have not been considered in the generation process from GAN in the previous studies.

This paper proposes a novel GAN-based data augmentation method in manufacturing to generate realistic and state-distinguishable generated data. Compared to a standard GAN
consisting of two players, i.e., discriminator and generator, the proposed method comprises three players, including a classifier. All players are jointly optimized in the proposed method to meet their respective goals. Specifically, the generator learns to generate data deceiving the discriminator. In contrast, a discriminator learns to distinguish whether data is from a generator or an actual process. This adversarial learning results in generating realistic samples from the generator. At the same time, the generator and classifier cooperate to generate distinctive samples among process states in the manufacturing process. Specifically, the classifier guides the generator to create samples that could benefit classification results. Then, the classifier is trained with balanced training data supplemented from generated samples of abnormal states. This iterative learning among three-player finally provides the classifier with high performance. Furthermore, the proposed method provides two terms in the objective function of the discriminator to improve the training stability of standard GAN. First, the proposed method provides a gradient penalty (Gulrajani et al., 2017) which improves training stability by regularizing the gradient of the discriminator (Fedus et al., 2017; Kodali et al., 2017). Second, the proposed method provides a task to the discriminator, preventing the discriminator from discerning the origin of data very well in the early stage of learning (Huang and Jafari, 2021). Both the penalty and the task contribute to generating diverse and better quality samples from the generator. The imbalanced surface images from the real AM processes are utilized to show the effectiveness of the proposed method. Specifically, the images from polymer and metal AM processes, namely, Fused Filament Fabrication (FFF) and Electron Beam Melting (EBM) processes, are applied to the proposed method in this paper.

The rest of this paper is organized as follows. A brief review of related research work is provided in Section 2. The proposed methodology is presented in Section 3, followed by case studies with open-source and real AM data sets to validate its effectiveness in Section 4. Finally, conclusions are discussed in Section 5.

2 Review of Related Work

The relevant existing studies on anomaly detection approaches for the manufacturing processes are briefly reviewed first in Section 2.1, and subsequently, the existing data augmentation methods are summarized in Section 2.2. Afterward, the research gaps in the current
work are identified in Section 2.3.

2.1 Anomaly Detection Approaches for the Manufacturing Processes

The anomaly detection approaches for the manufacturing processes have been extensively studied. Recently, deep learning-based methods have been widely used. For example, Kyeong and Kim (2018) proposed using convolutional neural networks (CNNs) to classify mixed-type defect patterns in wafer bin maps in the semiconductor manufacturing process. Kwon et al. (2020) used deep neural networks to accurately classify melt pool images in the metal AM process concerning different laser powers, resulting in different porosity levels. Zhang et al. (2020) converted the vibration signal from the drive end bearing to the images. The images were used as training data of CNN for bearing fault diagnosis. In addition, Jia et al. (2019) applied CNN to extract the features from the infrared thermal images for the fault diagnosis of rotating machinery in the manufacturing process.

In addition to the deep learning-based methods, various machine learning-based methods are utilized in anomaly detection in the manufacturing processes. For example, Montazeri and Rao (2018) proposed a graph-theoretic approach to differentiate the distinctive thermal signatures of melt pool images, leading to poor abnormal surface finish from the metal AM process. Mahmoudi et al. (2019) also developed a novel anomaly detection framework in the metal AM process. The approach classified the process state by accounting for the spatial dependence among successive melt pools through the Gaussian process. For the polymer AM process, Liu et al. (2021) proposed a feature extraction method based on manifold learning to diagnose surface defects such as under-fill. Shen et al. (2020) also proposed a novel supervised feature extraction method to extract discriminant and informative features from the surface states in the FFF process. In addition to the several AM processes, Bhat et al. (2016) presented a classification method to diagnose the cutting tool condition in the manufacturing process by analyzing the machined surface. Specifically, a kernel-based support vector machine classifier was trained with the features extracted from the gray-level co-occurrence matrix of machined surface images. Wang and Chen (2019) proposed weight masks to extract rotation-invariant features for wafer map failure pattern detection in the semiconductor manufacturing process.
2.2 Data Augmentation Methods

The existing data augmentation methods from literature can be divided into two categories, sampling-based approaches, e.g., an oversampling technique, and deep learning-based approaches, e.g., GAN. In sampling-based approaches, Chawla et al. (2002) proposed the synthetic minority oversampling technique (SMOTE). It also has several extensions (Fernández et al., 2018). For example, many rules for regions of data to be oversampled are settled down, such as Borderline-SMOTE (B-SMOTE) (Han et al., 2005) and the adaptive synthetic sampling approach (ADASYN) (He et al., 2008). Furthermore, there exist hybrid methods, such as SMOTE editing the nearest neighbor (SMOTENN) (Batista et al., 2004) and SMOTE-Iterative partitioning filter (SMOTE-IPF) (Sáez et al., 2015). They remove unsuitable samples after SMOTE-based oversampling.

Recently, deep learning has become popular in data augmentation due to its access to big data and powerful computation (Shorten and Khoshgoftaar, 2019). GAN is one of the most widely applied approaches, which was first introduced by Goodfellow et al. (2014). GAN-based work for data augmentation exploits the GAN models, such as deep convolutional GAN (DCGAN) (Wang et al., 2017), cycle GAN (Zhang, 2018), and conditional GAN (cGAN) (Douzas and Bacao, 2018) to supplement the limited actual data by generated data. Balancing GAN (BAGAN) (Mariani et al., 2018) is a modified version of an auxiliary classifier GAN (Odena et al., 2017) that focuses on the generation of minority class samples. Moreover, Huang and Jafari (2021) proposed an enhanced version of BAGAN (BAGAN-GP) that overcomes the unstable training issue in BAGAN by providing an improved initialization method and gradient penalty technique (Gulrajani et al., 2017). Recently, Choi et al. (2021) proposed a three-player GAN that consists of a discriminator, generator, and classifier. In this method, the processes of generating samples and training classifiers are jointly optimized. It generates both realistic, and state-distinguishable generated samples that are beneficial to improving the classification results. However, this work follows a standard GAN structure (Goodfellow et al., 2014) that is prone to unstable learning resulting in limited diversity and poor quality of generated samples (Zhu et al., 2019).
2.3 Research Gap Analysis

The studies summarized in Section 2.1 contributed to anomaly detection in the manufacturing process. However, the work does not consider the imbalanced training data that usually occurs in reality. Instead, the literature requires a sufficient number of data from abnormal states, which is highly time-consuming and prohibitively costly. Research efforts in Section 2.2 provided data augmentation work to overcome the imbalanced training data issue in the manufacturing process. However, the sampling-based methods consider only local information; therefore, they cannot reflect the entire data distribution (Douzas and Bacao, 2018). Recently, GAN-based methods have been widely used because of their superior performance in data augmentation. However, the process of generating samples through GAN and the process of training a classifier with the generated samples are handled independently in most of the studies. It is critical to generate realistic samples that follow the distribution of actual samples through GAN. However, it is also important that the generated samples help improve the classifier performance as training data. To achieve this, the realistic samples must be well-distinguishable among the process states. Thus, this paper proposes a novel GAN-based data augmentation method for additive manufacturing applications where the processes of generating samples and training a classifier are jointly optimized. Furthermore, the proposed method provides several terms in the objective function of the discriminator to improve training stability and mitigate the gradient vanishing issue that may frequently occur during the GAN training (Gulrajani et al., 2017; Huang and Jafari, 2021). The effectiveness of the proposed method is validated with imbalanced surface images from actual AM processes described in Section 4.

3 Proposed Research Framework

This section proposes a novel GAN-based data augmentation method. The structure of the proposed method is illustrated in Section 3.1. Specifically, the objective function of the proposed method is described in Section 3.2, followed by the training procedure in Section 3.3.
3.1 Three-Player Structure for Imbalanced Data Learning

Figure 2 shows the structure of the proposed method. The method consists of three players: a discriminator, generator, and classifier. The generator generates images of the manufacturing process from the random noise and corresponding state label. Among the generated images, the images of abnormal states are combined with the real imbalanced manufacturing process images, providing a balanced training sample to the classifier. To make the generated images beneficial to the classifier performance, the proposed method offers two methods: adversarial and cooperative learning. The roles of these two are provided as follows.

- Adversarial learning: The relationship between discriminator and generator follows the adversarial relationship from the GAN structure. The relationship enables both networks to compete with each other, resulting in realistic generated samples of the manufacturing process from the generator.

- Cooperative learning: The cooperative relationship between the generator and the classifier enables the generator to generate samples that are distinguishable among
process states in the manufacturing process (i.e., state-distinguishable samples) from the classifier.

Based on these two relationships, the generator generates samples of abnormal states in the manufacturing process with both properties (i.e., realistic and state-distinguishable). The generated samples are added to actual ones and provided as a balanced training batch that the number of training samples passing through the network at one time of a classifier. The iterative learning process among these three players finally provides a classifier with high performance. The detailed objective function and training procedures are explained in the following sections.

3.2 Objective Functions for Three-Player

In this subsection, the review of the generative adversarial network in the manufacturing process is described in Section 3.2.1 initially. Then, the objective functions of the discriminator, generator, and classifier are illustrated in Sections 3.2.2, 3.2.3, and 3.2.4, respectively.

3.2.1 Generative Adversarial Network in the Manufacturing Process

The idea of a Generative Adversarial Network (GAN) is to train two networks, namely, generator $G$ and discriminator $D$, with a minimax game for $V(D,G)$ demonstrated in Eq. (1) (Wang et al., 2017).

$$
\min_{G} \max_{D} V(D,G) = \mathbb{E}_{x_{r} \sim P(X_{r})}[\log(D(x_{r}))] + \mathbb{E}_{z \sim P(Z)}[\log(1 - D(G(z)))],
$$

where $z$ is the random noise and $x_{r}$ denotes real samples from the manufacturing process. Specifically, the generator is to generate samples of the manufacturing process $G(z)$ from $z$, and the discriminator is to distinguish whether the origin of input samples is from real ($x_{r}$) or generator ($G(z)$). In other words, the discriminator is to discern the input samples, while the generator synthesizes artificial samples to deceive the discriminator. This adversarial learning results in the distribution of newly generated samples, close to the underlying distribution of the actual samples in the manufacturing process, $P(X_{r})$.

As shown in Figure 2, the proposed method needs to provide balanced training samples among the manufacturing process states in every batch of a classifier. To achieve this, conditional GAN (Douzas and Bacao, 2018) is applied in the proposed method making
the process state label attached to the input of the generator and discriminator. It enables users to determine the number of generated samples from abnormal states of the manufacturing process to make a balanced batch. The objective function of conditional GAN is demonstrated in Eq. (2) as follows.

$$\min_G \max_D V(D, G) = \mathbb{E}_{(x_r, y_r) \sim P(X_r, Y_r)}[\log(D(x_r, y_r))] + \mathbb{E}_{(z, y_g) \sim P(Z, Y_g)}[\log(1 - D(G(z, y_g), y_g))]$$

(2)

where $y_r$ and $y_g$ denote the process state label of an actual and generated sample, respectively.

### 3.2.2 Objective Function of Discriminator

The objective of the discriminator in the proposed method is to maximize Eq. (2) through adversarial learning with the generator. Specifically, the discriminator learns to distinguish the input $(x_r, y_r)$ and $(G(z, y_g), y_g)$ are actual and generated, respectively. In addition, the proposed method provides two additional terms for stabilizing the learning process as training the GAN is unstable and hard to converge due to the difficulty of optimizing adversarial learning (Kodali et al., 2017).

First, the proposed method regularizes the gradient of the discriminator by providing the gradient penalty in the form of Eq. (3) as follows.

$$\mathbb{E}_{(\hat{x}, y_r) \sim P(\hat{X}, Y_r)}[(\|\nabla_{(\hat{x}, y_r)}D(\hat{x}, y_r)\|_2 - 1)^2],$$

(3)

where $\hat{x} = \alpha x_r + (1 - \alpha)G(z)$, and $\alpha$ is sampled uniformly between 0 and 1. It enforces 1-Lipschitz continuity to the discriminator (Davenport, 1951). The term is widely used in the previous work (Fedus et al., 2017; Gulrajani et al., 2017; Huang and Jafari, 2021) to overcome the limited diversity and poor quality of generated samples from GAN caused by adversarial learning.

Second, the proposed method provides an additional input consisting of the actual sample $(x_r)$ and a mislabeled process state $(y_m)$ to the discriminator. The discriminator learns to distinguish that the input $(x_r, y_m)$ is not an actual but generated sample because of the mislabeled process state by minimizing the following Eq. (4).

$$- \mathbb{E}_{(x_r, y_m) \sim P(X_r, Y_m)}[\log(1 - D(x_r, y_m))]$$

(4)
where $y_m$ is randomly sampled from the remaining labels in the manufacturing process except for the actual state label. Since the input provides an additional task for the discriminator to learn, it prevents the discriminator distinguishes very well between actual and generated samples before the generator approximates the actual sample distribution of the manufacturing process. Otherwise, the discriminator does not provide an informative gradient for the generator to learn (i.e., gradient vanishing problem (Tran et al., 2018)).

In summary, the objective function of the discriminator ($L^D$) in the proposed method is to minimize the following equation consisting of several losses.

$$L^D(Z, X_r, Y_r, Y_g, Y_m) =$$
$$-E_{(x_r, y_r) \sim P(X_r, Y_r)}[\log(D(x_r, y_r))]$$
\text{loss from real sample in discriminator}

$$-E_{(z, y_g) \sim P(Z, Y_g)}[\log(1 - D(G(z, y_g), y_g))]$$
\text{loss from generated sample in discriminator}

$$-E_{(x_r, y_m) \sim P(X_r, Y_m)}[\log(1 - D(x_r, y_m))]$$
\text{loss from mislabeled sample in discriminator}

$$+ \lambda E_{(\hat{x}, y_r) \sim P(\hat{X}, Y_r)}[(\|\nabla_{(\hat{x}, y_r)}D(\hat{x}, y_r)\|2 - 1)^2],$$
\text{loss from gradient penalty}

where $\lambda$ is the coefficient of the gradient penalty term. The first three losses in Eq. (5) are related to losses when the discriminator misclassified the origin of the real, generated, and mislabeled sample. The last loss represents the loss related to the gradient of the discriminator.

### 3.2.3 Objective Function of Generator

The objective of the generator is to generate samples via learning the distribution of actual samples of the manufacturing process ($P(X_r)$) by minimizing Eq. (2). Alternatively, the proposed method trains the generator to maximize Eq. (6) to avoid the saturation problem occurring when minimizing Eq. (2) in practice (Goodfellow et al., 2014).

$$E_{(z, y_g) \sim P(Z, Y_g)}[\log(D(G(z, y_g), y_g)).$$

In addition to Eq. (6), the generator in the proposed method has an additional term in the objective function related to the classifier. In contrast to an adversarial relationship with
a discriminator, the cooperative relationship is designed between the generator and classifier to generate well-distinguishable samples among process states in the manufacturing process. To achieve this, the classification loss from labels of generated samples is provided to the objective function of the generator (2nd term in Eq. (7)). Finally, the generator in the proposed method is trained by minimizing its objective function \( L^G \), Eq. (7).

\[
L^G(Z, Y_g) = -\mathbb{E}_{(z,y_g) \sim P(Z,Y_g)}[\log(D(G(z,y_g), y_g))]
\]

\[
= -\mathbb{E}_{(z,y_g) \sim P(Z,Y_g)}[y_g \log(C(G(z,y_g)))] + \mathbb{E}_{(z,y_g) \sim P(Z,Y_g)}[\log(D(G(z,y_g), y_g))],
\]

where \( -\mathbb{E}_{(z,y_g) \sim P(Z,Y_g)}[y_g \log(C(G(z,y_g)))] \) (2nd term in Eq. (7)) denotes the cross-entropy loss of generated samples from the classifier.

3.2.4 Objective Function of Classifier

The objective function of the classifier \( L^C \) consists of the classification loss from both real and generated samples of the manufacturing process as Eq. (8). As described in Figure. 2, the samples from the generator are supplemented with real samples from the manufacturing process to make balanced training data in every batch of the classifier. The classifier is optimized to minimize the classification loss from both actual and generated sample by minimizing Eq. (8).

\[
L^C(Z, X_r, Y_r, Y_g) = -\mathbb{E}_{(x_r,y_r) \sim P(X_r,Y_r)}[y_r \log(C(x_r))]
\]

\[
= -\mathbb{E}_{(z,y_g) \sim P(Z,Y_g)}[y_g \log(C(G(z,y_g)))] + \mathbb{E}_{(x_r,y_r) \sim P(X_r,Y_r)}[y_r \log(C(x_r))].
\]

In particular, \( -\mathbb{E}_{(z,y_g) \sim P(Z,Y_g)}[y_g \log(C(G(z,y_g)))] \), a common term in both Eqs. (7) and (8) enables cooperative learning between the generator and classifier.

3.3 Training Procedure

To train the three players in the proposed method, the method adopts an alternating gradient descent method among the training of generator, discriminator, and classifier. Before starting alternating optimization, the auto-encoder is pre-trained with the existing imbalanced samples from the manufacturing process. Auto-encoder is trained to minimize
the reconstruction error of inputs. Auto-encoder is widely used for initialization of generator in GAN because it leads to stable learning and helps the generator learn common data set knowledge (Mariani et al., 2018). The pre-trained decoder from an auto-encoder is initialized as the generator in the proposed method. After the pre-training step, the three players are optimized alternatively. First, the discriminator is trained with a batch from actual and generated samples to minimize Eq. (5). Sequentially, a batch from generated samples is utilized to update the generator by minimizing Eq (7). Finally, the classifier is trained by minimizing Eq. (8) with balanced training data from all the process states in the manufacturing process. Specifically, a batch \( m \) from actual data is sampled first. Then, the remaining samples from abnormal states \( m_g \) are generated from the generator to make a balanced training set. The alternating training procedure is iterated until it reaches the pre-defined epochs. The overall training procedure of the proposed method is illustrated in Algorithm 1. The parameters of a discriminator, generator, and classifier are denoted as \( \theta_d \), \( \theta_g \), and \( \theta_c \), respectively.

**Algorithm 1:** Training Procedures of the proposed method.

**Require:** Initialize the parameters of three players (i.e., \( \theta_d \), \( \theta_g \), and \( \theta_c \));
- P-Epoch: Number of epochs in the pre-training;
- A-Epoch: Number of epochs in the alternating loop;
- Batch size: Size of samples \( m \) in each batch.

**Procedure:**

[Pre-Training Generator]
Initialize: epoch=1
while epoch \( \leq \) P-Epoch do
  Sample a batch of \( m \) samples from \( X_r \)
  Train auto-encoder \( (\theta_g) \)
  epoch + +
end while

[Alternating Optimization]
Initialize: epoch=1
while epoch \( \leq \) A-Epoch do
  Sample \( m \) samples from \( X_r, Z, Y_g, Y_m \)
  Train a discriminator \( (\theta_d) \) by minimizing Eq. (5)
  Sample \( m \) samples from \( Z, Y_g \)
  Train a generator \( (\theta_g) \) by minimizing Eq. (7)
  Sample \( m \) samples from \( X_r \)
  Sample \( m_g \) from \( Z, Y_g \) of abnormal states to balance the batch
  Train a classifier \( (\theta_c) \) by minimizing Eq. (8)
  epoch + +
end while
4 Real-World Case Studies

This section provides several case studies to show the effectiveness of the proposed method. Section 4.1 demonstrates the advantages of the proposed method based on the ablation study. The method is deeply self-analyzed in various aspects in this section. Sections 4.2, 4.3, and 4.4 provide comparative case studies with benchmark methods across multiple data sets. Specifically, open-source data is used in Section 4.2. In addition, the surface image data from two real AM processes, namely, Fused Filament Fabrication (FFF) and Electron Beam Melting (EBM) processes are utilized in Section 4.3 and 4.4, respectively, to show the effectiveness of the proposed method in real AM process. The performance is evaluated by the classification results from the imbalanced training data set. The framework of all case studies is Keras with TensorFlow backend. The studies are performed by an NVIDIA Tesla P4 GPU with 8GB memory.

1) Benchmark Methods: For the benchmark methods, both the sampling-based and GAN-based approaches described in Section 2.2 are used. In the sampling-based methods, SMOTE (Chawla et al., 2002), B-SMOTE (Han et al., 2005), and ADASYN (He et al., 2008), which are implemented in the imbalanced-learn library in python, are adopted. For the GAN-based approaches, two state-of-the-art methods, CDRAGAN (Huang and Jafari, 2021), and BAGAN-GP (Huang and Jafari, 2021) are selected. In addition, Cooperative GAN (Choi et al., 2021), which jointly optimizes GAN and the classifier, is determined as one of the benchmark methods. Finally, classification performance without any data augmentation method is provided as the baseline.

2) Hyperparameters and Experimental Settings: The optimizer for the proposed method is the Adam algorithm (Kingma and Ba, 2014) with a learning rate of 0.0002 and momentum of 0.5 and 0.9 (Huang and Jafari, 2021). To make the networks in the proposed method irrespective of the image size, all the image inputs are resized as 64×64×channels. The dimension of the random noise (z) is 128. Since the proposed method deals with image data, the auto-encoder with convolution layers is used for pre-training (Huang and Jafari, 2021). In addition, the discriminator and generator are designed with a convolution layer, leakyReLu layer, and transpose convolution layer. For the classifier, Convolutional Neural Network (CNN) is utilized in the case studies since CNN extracts the features from the
raw data directly, resulting in superior performance in image classification (Dhillon and Verma, 2020). For a fair comparison, the CNN with the same hyperparameters is used for all the methods. Besides, the unique hyperparameters of each method, such as the scheduling parameter in the Cooperative GAN (Choi et al., 2021), are searched within a specific range following the guidelines provided in the literature and determined with the values that showed the best performance. The detailed hyperparameters of the generator, discriminator, and classifier are provided in Appendix A.

3) Performance Evaluation Measure: The classification performance is evaluated by the value of the F-score, precision, and recall (Powers, 2020). Precision and recall are related to the level of type I and type II errors, respectively. F-score can be formulated by Eq. (9), which is the combination of precision and recall.

\[
F\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{9}
\]

Since this paper aims to improve the classification accuracy with the imbalanced training data, case studies with various balanced ratios are provided. A balanced ratio is defined as the ratio between the training data size of minority and majority classes. All the case studies in this section repeat ten times, and the average of ten repetitions is provided as the performance measure.

4.1 Ablation Studies

The ablation study is conducted with MNIST fashion data (Xiao et al., 2017). From the 1000 images of each of three labels, namely, T-shirt, Pullover, and Dress, imbalanced training data is constructed as described in Table 1. The balanced ratio between the majority and minority classes is 0.10. The remaining images are used as testing data.

| Data Set   | Majority Class | Minority Class       | Balanced Ratio | Majority Class Training Samples | Minority Class Training Samples |
|------------|----------------|----------------------|----------------|---------------------------------|---------------------------------|
| MNIST fashion | T-shirt        | Pullover, Dress     | 0.10           | 800                             | 80                              |

The study is carried out by sequentially adding each ablation component since each component cannot be implemented without the previous components. The role of each component is validated through the ablation of a baseline and three variants, as illustrated in Table 2. Baseline trains classifier with imbalanced training data without any data augmentation. Instead, Variant 1 uses a conditional version of standard GAN (i.e., CGAN

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(Mirza and Osindero, 2014)) to provide balanced training data of the classifier by generating additional minority class samples ($G(z, y_g)$ in Section 3). Furthermore, Variant 2 jointly trains the classifier and CGAN by providing cross-entropy losses ($y_r \log(C(G(z, y_g)))$, and $y_r \log(C(x_r))$ in Section 3) so that generator in the CGAN produces distinctive samples among the process states. Finally, Variant 3, which is the proposed method, adds the terms ($\|\nabla D(\hat{x}, y_r)\|_2$, and $D(x_r, y_m)$ in Section 3) that are related to stabilizing the learning process in the objective function of discriminator in Variant 2.

Table 2 shows the results of the ablation study. In addition to F-score, Precision, and Recall, Frechet Inception Distance (Dowson and Landau, 1982) (FID) is used as an additional performance measure in the ablation study. FID is a metric used to evaluate the quality of images generated by GAN. Specifically, it is a metric between two multidimensional Gaussian distributions that are the distribution of neural network features from the real and generated images, respectively. FID is computed from the mean and the covariance of the activation function of the network as follows:

$$FID = \|\mu_r - \mu_g\|^2 + \text{Tr}(\Sigma_r + \Sigma_g - 2(\Sigma_r \Sigma_g)^{1/2}),$$

where $\mu_r$ and $\Sigma_r$ are the mean and standard deviation from real images, respectively. Likewise, $\mu_g$ and $\Sigma_g$ are those from generated images, respectively. The smaller FID represents that the generated images follow the distribution of real images resulting in better quality and diversity (Chen et al., 2021). In Table 2, the FID scores of each label are presented. 1500 images of each label from real and generated images, respectively, are used to calculate the FID.

Table 2: Performance evaluation in ablation studies.

|                         | $G(z, y_b)$ | $y_r \log(C(x_r))$, $y_g \log(C(G(z, y_b)))$ | $\|\nabla D(\hat{x}, y_r)\|_2$, $D(x_r, y_m)$ | F-score | Precision | Recall | FID T-shirt | FID Pullover | FID Dress |
|-------------------------|-------------|-----------------------------------------------|-----------------------------------------------|---------|-----------|--------|-------------|-------------|----------|
| Baseline                | $\times$    | $\times$                                      | $\times$                                      | 0.783   | 0.785     | 0.873  | NA          | NA          | NA       |
| Variant 1               | $\checkmark$ | $\times$                                      | $\times$                                      | 0.791   | 0.789     | 0.879  | 235.8       | 224.1       |          |
| Variant 2               | $\checkmark$ | $\checkmark$                                 | $\times$                                      | 0.806   | 0.797     | 0.886  | 192.3       | 234.9       | 227.9    |
| Variant 3 (Proposed)    | $\checkmark$ | $\checkmark$                                 | $\checkmark$                                 | 0.830   | 0.814     | 0.900  | 109.3       | 142.9       | 184.3    |

The performance of all the measures of Variant 1 improves compared to the baseline. It shows the effectiveness of GAN for supplementing imbalanced training data. In Variant 2, an improvement in the performance of all measures is achieved compared to the first
ablation. This implies that joint training of GAN and classifier guides the generator to generate samples beneficial to the classifier, that is, both realistic and state-distinguishable samples. It consequently improves the performance of the classifier. Finally, when both terms stabilizing the learning process of GAN are added, which is the proposed method (Variant 3), the performances are significantly improved since stable training enables the generator to generate more realistic and state-distinctive samples. Figure. 3 shows the quality of generated images in each step in the ablation study. Figure. 3 (a) represents the actual images from each label. Figures. 3 (b), (c), and (d) illustrate the generated images of each label from Variant 1, 2, and the proposed method, respectively. Like the results of the FID score in Table 2, the quality of generated samples is improved as each ablation is added.

Beyond the image quality and FID score, Figure. 4 shows the effectiveness of the generated samples from the proposed method based on the comparison between the feature of generated and actual samples. Specifically, Figure. 4 represents the t-distributed Stochastic Neighbourhood Embedding (t-SNE) of the feature from the intermediate layer of the classifier in the proposed method. t-SNE is a tool for visualizing high-dimensional data (Dimitriadis et al., 2018). It is a nonlinear dimensionality reduction technique suitable for incorporating high-dimensional data into lower dimensional data (2-D or 3-D) for visualization. ‘•’ and ‘x’ in Figure. 4 denote the feature in the intermediate layer of classifiers from real and the generated samples in the balanced training batch, respectively. For a
balanced training batch, the minority class has many ‘×’ in each batch. Figure 4 (a) shows the distribution alignments of actual and generated samples are different at epoch 0. Since the proposed method learns to generate realistic and distinctive samples for the classifier, Figure 4 (b) shows that the features of generated samples (‘×’) correctly follow those of actual samples (‘•’) according to their respective labels at epoch 300. In addition, features from each label are clearly separated. The balanced training data with these properties let the proposed method achieve high classification performance.

![t-SNE of the feature from the intermediate layer of the classifier from the proposed method in epochs (a) 0 and (b) 300.](image)

**4.2 Open-Source Data Case Studies**

This section provides comparative studies using the open-source image data set. MNIST fashion (Xiao et al., 2017) and CIFAR-10 (Recht et al., 2018), which are widely used for the evaluation of image-based classifiers, are selected. In MNIST fashion data, five labels related to upper clothes are selected for the analysis. This step provides high similarity among the classes to make a challenging problem (Choi et al., 2021). For CIFAR-10 data, Airplane, Automobile, and Ship images are selected for the same reason as the MNIST fashion data. In each label of MNIST fashion and CIFAR-10 data, 1000 and 1500 images are collected, respectively. Then, imbalanced training data is provided in Table 3. The remaining data sets are used as testing data.

Table 4 shows the performance evaluation of the proposed and benchmark methods in two open-source data sets. The proposed method achieves the best performance in most of the measures in both data sets. Compared to a baseline using imbalanced training data to
train the classifier, the sampling-based method such as SMOTE, B-SMOTE, and ADASYN generally achieves similar or worse performance. Since both case studies have a small number of minority data, the sampling-based method has limitations in generating various data that can cover the testing data. In contrast, the GAN-based methods usually achieve better performance than sampling-based methods since their generators learn the true distribution and produce various training data for the classifier. Especially, the generator from the proposed method provides more diverse and better quality images by jointly optimizing the classifier, resulting in improvements in classification results.

Table 4: Performance evaluation in open-source data case studies.

|                | MNIST fashion |        |        | CIFAR-10 |        |        |
|----------------|---------------|--------|--------|----------|--------|--------|
|                | F-score | Precision | Recall | F-score | Precision | Recall |
| Baseline       | 0.621     | 0.650     | 0.696   | 0.617     | 0.661     | 0.670   |
| SMOTE          | 0.612     | 0.645     | 0.687   | 0.618     | 0.660     | 0.669   |
| B-SMOTE        | 0.610     | 0.643     | 0.683   | 0.642     | 0.642     | 0.631   |
| ADASYN         | 0.604     | 0.639     | 0.679   | 0.559     | 0.638     | 0.627   |
| CDRAGAN        | 0.632     | 0.657     | 0.703   | 0.597     | 0.648     | 0.655   |
| BAGAN-GP       | 0.634     | 0.661     | 0.708   | 0.634     | 0.664     | 0.680   |
| Cooperative GAN| 0.619     | 0.646     | 0.693   | 0.619     | 0.628     | 0.656   |
| Proposed       | 0.642     | 0.664     | 0.713   | 0.652     | 0.655     | 0.684   |

4.3 Polymer Additive Manufacturing Process Data Case Studies

In this section, surface images from the FFF process are used to explore the effectiveness of the proposed method. A Hyrel System 30M 3-D printer equipped with a 0.5 mm extruder nozzle is used for this case study. Figure 5 (a) shows a front view of the printer. Acrylonitrile butadiene styrene (ABS), with a diameter of 1.75 mm, is used as a filament for printing. In this study, a digital microscope camera is utilized for high-quality image acquisition at a sampling frequency of 1 Hz. The camera is mounted near the extruder to collect images.
of the surface that are being printed (Figure. 5 (b)). Based on the design of experiments in Liu et al. (2019), the surface images for normal, under-fill caused by feed rate, and under-fill caused by the cooling fan, as shown in Figure. 6, can be obtained by setting up the specific machine parameters in the software controller (Figure. 5 (c)). Two process states which are the under-fill caused by feed rate and under-fill caused by the cooling fan, are the abnormal states that cause quality deterioration in the FFF process (Liu et al., 2019; Shen et al., 2020). To increase the size of image samples, the region of interest is one-third of each

![Figure 5](image1.png)  
**Figure 5:** (a) Front view of Hyrel system 30M; (b) Digital Microscope Camera; (c) Software Controller.

image in Figure. 6 with the size of $460 \times 213 \times 3$. Therefore, each image collected from a microscope provides three image samples. In total, there exist 915 samples from the normal process state, and 591 and 459 samples from under-fill caused by feed rate and cooling fan, respectively. In this section, case studies with various balanced ratios between normal and

![Figure 6](image2.png)  
**Figure 6:** (a) Normal; (b) Under-fill caused by feed rate; (c) Under-fill caused by a cooling fan. The red rectangle represents the regions of interest in each image.

abnormal states of the FFF process are provided. The balanced ratios of training data are provided in Table 5, where the minority classes are denoted as the cause of abnormal states in the process. The remaining images in each process state are used as testing data.
Table 5: Imbalanced training data samples in Polymer AM case studies.

| Majority Class | Minority Class | Balanced Ratio | Majority Class Training Samples | Minority Class Training Samples |
|---------------|---------------|----------------|---------------------------------|---------------------------------|
| Normal        | Under-feed, Under-fan | 0.10           | 800                             | 80                              |
| Normal        | Under-feed, Under-fan | 0.15           | 800                             | 120                             |
| Normal        | Under-feed, Under-fan | 0.20           | 800                             | 160                             |

Figure 7 shows the performance evaluation of the proposed and benchmark methods in various balanced ratios. The performances of all the methods are improved when the number of training samples in minority classes increases (i.e., the balanced ratio increases). This is because a large number of samples provides more information for the generator to learn the real distribution. In every balanced ratio, the proposed method achieves the best performance in all the measures, which shows the effectiveness of the realistic and state-distinguishable generated samples in the AM process. In addition, the proposed method performs better than cooperative GAN, which also jointly optimizes GAN and classifier but follows the basic objective function of the discriminator in GAN. This demonstrates the effectiveness of diverse and better quality samples generated through regularizing the gradient of the discriminator and an additional task provided to the discriminator in the proposed method. Sampling-based methods show worse performance than GAN-based methods in general since the methods only consider the local information resulting in limited diverse generated images (Douzas and Bacao, 2018).

Figure 7: F-scores, precisions, and recalls in FFF process case studies under different balanced ratios.
Figure 8 shows the t-SNE of the feature from the intermediate layer of classifiers from the proposed method in epochs 0 and 300 when the balanced ratio is 0.20. Like Section 4.1, ‘•’ and ‘×’ represent features of actual and generated samples, respectively. The colors differentiate each process state in the FFF process. To make a balanced training data, two abnormal states in the FFF process have adequate generated samples (‘×’) than actual samples (‘•’) in each batch. Compared to epoch 0 (Figure 8 (a)), features in epoch 300 (Figure 8 (b)) show that the features from generated samples (‘×’) of abnormal states of the FFF process follow those of actual samples (‘•’) correctly to each process state. Based on these balanced training data in the FFF process, the classifier achieves the best prediction results compared to benchmark methods. Figure 9 shows the samples of actual and generated images denoted as ‘•’ and ‘×’ in Figure 8 (b), respectively. The generated images (Figure 9 (b)) are realistic and distinguishable among process states based on both adversarial and cooperative learning in the proposed method. In addition, the majority samples, which are the samples from the normal state in the FFF process, provide shareable feature information such as common texture and color to the generation of minority samples (i.e., abnormal states). It mitigates the over-fitting problem that occurs when a small number of abnormal state samples exist in the FFF process for training the generator (Choi et al., 2021).
Figure 9: Samples of each process state in the FFF process from (a) real; (b) generator when the balanced ratio is 0.2.

4.4 Metal Additive Manufacturing Process Data Case Studies

This section uses metal AM data from the electron beam melting (EBM) process to evaluate classification performance. The machine ARCAMQ10 plus is utilized to print samples from the EBM process using Ti-6Al-4V powder. The dimensions of the printed sample are 15 mm × 15 mm × 25 mm. In the EBM process, there exist three different scan strategies, i.e., Dehoff, Raster, and Random (Kirka et al., 2017). The different scan strategies provide different surface patterns for the printed samples. After printing three different samples with each scan strategy, a 3-D scanner captures detailed 3-D information about the top surface (15 mm × 15 mm) quality (Wang et al., 2021). The images shown in Figure 10 are the surface patterns of the Raster, Dehoff, and Random, respectively. The objective of classification in this case study is to identify the scan strategy from the surface images. For each image in Figure. 10, the size is 824 × 1118 × 3. To obtain multiple training samples, 322 images of sizes of 120 by 120 are collected from the upper part of each image (300 × 1118 × 3) since the bottom parts of the surface image with letters and numbers
have many defects such as porosity. Specifically, the collected images are highly overlapped in the horizontal directions (114 pixels) to have plenty of samples. Since the Raster scan strategy is commonly used and similar to the common AM bi-directional path; the strategy is considered a majority class (Nandwana and Lee, 2020; Saville et al., 2021). Therefore, the scan strategies with Dehoff and Random are determined as minority classes in these case studies. From the 322 images from each scan strategy, the various balanced ratios of training data are designed as in Table 6. The remaining images in each scan strategy are used as testing data.

Table 6: Imbalanced training data samples in Metal AM case studies.

| Majority Class | Minority Class | Balanced Ratio | Majority Class Training Samples | Minority Class Training Samples |
|----------------|----------------|----------------|---------------------------------|--------------------------------|
| Raster         | Dehoff, Random | 0.3            | 150                             | 45                             |
| Raster         | Dehoff, Random | 0.4            | 150                             | 50                             |
| Raster         | Dehoff, Random | 0.5            | 150                             | 75                             |

Figure 11 shows the performance evaluation of the proposed and benchmark methods in the EBM process. In this case study, most of the sampling-based methods show better performance than baseline, but the GAN-based methods usually represent worse results than baseline. This might be caused by the highly overlapped actual samples. Compared

Figure 11: F-scores, precisions, and recalls in EBM process case studies under different balanced ratios.
to the polymer AM case study, the number of actual images is small and highly overlapped since we only have a single image of the top surface. Therefore, it does not provide enough information for the GAN-based methods to learn the true distribution. Relatively, the sampling-based methods show better performance because the actual images are highly overlapped with each other. Still, the proposed method achieves the best results compared to benchmark methods by generating balanced training samples that are both realistic and scan strategy-distinguishable. t-SNE results in Figure 12 show similar results to that of the FFF process. In epoch 300, the features from generated samples follow those of corresponding scan strategies from actual samples.

Figure 12: t-SNE of the feature from the intermediate layer of classifiers from the proposed method in epochs (a) 0 and (b) 300 in the EBM process when the balanced ratio is 0.3.

Figure 13 shows the actual and generated samples of all the scan strategies from the proposed method denoted as ‘.’ and ‘×’ in Figure 12 (b), respectively. Compared to the actual images in Figure 13 (a), the generated images in the EBM process (Figure 13 (b)) are realistic and distinguishable according to each scan strategy, which is possible through
cooperative learning in the proposed method. Similar to the normal state in the FFF process, the samples from the Raster scan strategy provide the common feature information for the generation process of the remaining strategies.

5 Conclusions

This paper proposes a novel GAN-based data augmentation method to deal with the imbalanced training data issue in the manufacturing process. The method consists of three-player, namely, generator, discriminator, and classifier, that are jointly optimized. Through the adversarial learning between the generator and the discriminator, the generator generates realistic samples of abnormal states in the manufacturing process. At the same time, the cooperative learning between the generator and classifier enables the generator to generate the state-distinguishable samples of the manufacturing process. The generated samples are added to actual samples and provided as a balanced training batch for a classifier. In addition, the method includes several terms in the objective function in the discriminator that make stable learning possible resulting in better quality and diverse generated samples. The iterative learning process among these three players finally provides a classifier with high performance in classification results. The effectiveness of the proposed method is validated in both open-source and actual AM processes data. Specifically, the method achieves the best performance compared to benchmark methods in the various balanced ratio of training data between normal and abnormal states in both the FFF and EBM processes.

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A Structure and Hyperparameters in the Methods

In this section, the detailed structure and hyperparameters of the proposed and benchmark methods are provided. Table 7 provides the hyperparameters of each method. The gradient penalty coefficient is determined as 10 as suggested by Huang and Jafari (2021); Kodali et al. (2017). The scheduling parameter in the Cooperative GAN, is searched within a specific range ([0.1, 0.9]) following the guidelines provided in the literature (Choi et al.,

| Methods               | Parameters                              | Value       |
|-----------------------|-----------------------------------------|-------------|
| SMOTE, ADASYN         | Nearest K samples                       | 5           |
| B-SMOTE               | Type                                    | 1           |
|                       | Nearest K samples                       | 5           |
|                       | Number of iterations                    | 300         |
|                       | Training ratio                          | 10          |
|                       | between generator and discriminator      |             |
|                       | Optimizer                               | Adam        |
|                       | Learning rate                           | 0.0002      |
|                       | Momentum                                | $\beta_1 = 0.5, \beta_2 = 0.9$ |
| CDRAGAN               | Hidden layers (Discriminator)           | 4 blocks of |
|                       |                                        | [Conv2D, LeakyRelu] |
| BAGAN-GP              | Hidden layers (Generator)               | 4 blocks of |
|                       |                                        | [Conv2D-Transpose, LeakyRelu, BatchNormalization] |
| Proposed              | Number of Kernels in each block         | (64,128,128,256) |
|                       | Number of Kernels in each block         | (128,128,64,Number of channel) |
|                       | Kernel sizes                            | (4,4)       |
|                       | Strides                                 | (2,2)       |
|                       | Padding                                 | Same        |
|                       | Activation functions                    | LeakyRelu, Tanh |
|                       | Kernel initializer                      | Random Normal(sd=0.02) |
|                       | Slope of Leaky Relu                     | 0.2         |
| CDRAGAN, BAGAN-GP     | Gradient Penalty Coefficient            | 10          |
| Proposed              |                                        |             |
| Cooperative GAN       | Range of scheduling parameter           | [0.1,0.9]   |
| Proposed              |                                        |             |
| BAGAN-GP, Proposed    | Epochs in pre-training                  | 300         |
2021) and selected with the values that showed the best validation performance. Table 8 shows the hyperparameters of the classifier in case studies. Convolutional Neural Network is used for the classifier. For a fair comparison, all the methods use the same classifier as described in Table 8.

| Parameters          | Value                      |
|---------------------|----------------------------|
| Number of epochs    | 300                        |
| Optimizer           | Adam                       |
| Learning rate       | 0.0002                     |
| Momentum            | $\beta_1 = 0.5, \beta_2 = 0.9$ |
| Hidden Layers       | 4 blocks of [Conv2D, LeakyRelu] |
| Number kernels in each block | (32,32,128,256) |
| Kernel sizes        | (4,4)                      |
| Strides             | (2,2)                      |
| Padding             | Same                       |
| Activation functions| Leaky Relu, Softmax        |
| Kernel initializer  | Random Normal (sd=0.02)    |
| Slope of Leaky Relu | 0.2                        |