New Anomaly Detection in Semiconductor Manufacturing Process using Oversampling Method

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Abstract: Quality in the semiconductor manufacturing process, consisting of various production systems, leads to economic factors, which necessitates sophisticated abnormal detection. However, since the semiconductor manufacturing process has many sensors, there is a problem with the curse of dimensionality. It also has a high imbalance ratio, which creates a classification model that is skewed to multiple class, thus reducing the class classification performance of a minority class, which makes it difficult to detect anomalies. Therefore, this paper proposes AEWGAN (Autoencoder Wasserstein General Advertising Networks), a method for efficient anomaly detection in semiconductor manufacturing processes with high-dimensional imbalanced data. First, learn autoencoder with normal data. Abnormal data is oversampled using WGAN (Wasserstein General Additional Networks). Then, efficient anomaly detection within the potential is carried out through the previously learned autoencoder. Experiments on wafer data were applied to verify performance, and of the various methods, AEWGAN was found to have excellent performance in abnormal detection.

1 INTRODUCTION

Due to the influence of the recent fourth industrial revolution, the way of production in manufacturing is gradually being automated in digital way. In particular, the semiconductor manufacturing process is a very complex structure, and various production systems exist. Various sensor data are generated in real time from these automated production systems (Cen et al., 2017).

System failures in production systems affect the entire process and result in economic losses to the business. Therefore, sophisticated anomaly detection technology for sensor data is required. However, the semiconductor manufacturing process with various processes is composed of complex systems, which have many variables and have few abnormal data, so it is not easy to detect them.

Because of the variety of sensors that process, there are many variables in the data, which are likely to fall into the problem of curse of dimensionality (Indyk and Motwani, 1998). This is a problem in machine learning or deep learning where learning becomes more difficult and requires more data. In addition, the imbalance problem from less abnormal data than normal data occurs in a variety of real-world cases, such as fraud detection (Wei et al., 2013), medical diagnosis (Mazurowski et al., 2008), and semiconductor processes (Kerdprasop and Kerdprasop, 2011). This means when the number of instances in majority class is greater than the number of instances in minority class (Chawla et al., 2002). The ratio between the majority and minority class is called the imbalanced ratio. A high imbalance ratio causes the classifier to create a classification model that is biased against the majority class, thereby reducing the classification performance of the minority class (Chawla et al., 2004). For example, if the majority class has 99 instances and the minority class has one instance, classifying all instances into the majority class maximize misclassification error within the confusion matrix of the minority class.

In many practical cases, instances belonging to the minority class are often more important than majority class instances. Therefore, it is necessary to minimize misclassification errors within minority class instances while improving their classification performance.

In this paper, AEWGAN (Autoencoder Wasserstein Generative Adversarial Networks) is proposed as the way to solve high-dimensional imbalanced data in the semiconductor manufacturing

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process. First, train the autoencoder using normal data. Then, oversampling abnormal data through WGAN (Wasserstein Generative Adversarial Networks). Finally, oversampled data is inputted into the previously trained autoencoder to perform anomaly detection within the latent space, a reduced dimension.

The rest of this paper is organized as follows. Section 2, we look at the related work. Section 3, we address how proposed methods works with its architectural design. Section 4, describes experimental details and baseline methods while Section 5 discusses the conclusions.

2 RELATED WORK

2.1 Anomaly Detection

Anomaly means data with low true probability density (Harmeling et al., 2006), and data that does not follow expected normal patterns (Chandola et al., 2009). Anomaly detection is required because the analysis of data for any decision can affect the decision.

Anomaly detection is one of the classifications of data for analysis purposes and is part of data mining. Anomaly detection is used as important and meaningful information in various fields. Examples include fraud detection of credit cards, health monitoring of patients in the medical field, and fault detection at manufacturing (Hodge and Austin, 2004).

Various methods have been proposed for the detection of anomaly using data, not through domain knowledge. The general method is to find an approximation of the data. The method uses the basic assumption of manifold learning that normal and abnormal data can be embedded into a low-dimensional space with distinct differences. In other words, the method of finding an approximation is to use a combination of attributes that can capture the variability of the data (Chandola et al., 2009). This method includes the supervised learning method of knowing and analyzing the normal and abnormal status of each data at the algorithm learning stage, and the unsupervised learning method, which removes class labels and finds data showing different from most normal data. A typical method of unsupervised learning is an anomaly detection method using an autoencoder.

The Autoencoder is an unsupervised neural network model which learns that output values can be reconstructed similarly to input value. It consists of encoder and decoder, as shown in Figure 1. Encoder compresses input data from the input layer to the hidden layer. Decoder reconstruct compressed data through the encoder.

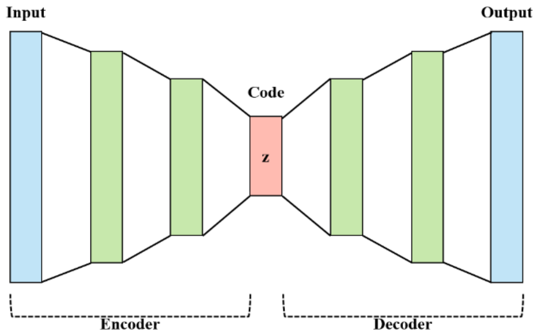


Figure 1: Architecture of an autoencoder.

In equation (1) f_θ is the result of the execution of the encoder and θ means the parameter of W and b. In equation (2) g_ϕ is the result of the execution of the decoder and ϕ means the parameter W', b'. In each equation, $W(W')$ stands for weight, $b(b')$ stands for bias, s for activation function (Vincent et al., 2010).

$$f_\theta = s(Wx + b) \tag{1}$$

$$g_\phi = s(W'h + b') \tag{2}$$

The procedure for anomaly detection through the autoencoder is as follows:

(1) Using normal data only, learn encoder and decoder to create a model.
(2) Pass abnormal data into the model learned above.
(3) Check abnormal data that has been reconstructed to the original data through the decoder.
(4) Calculate the anomaly score as shown in equation as the difference between the original and the restored data.

$$\text{Anomaly Score} = \left\| \boldsymbol{x} - g_\phi(f_\theta(\boldsymbol{x})) \right\|^2 \tag{3}$$

(5) If the anomaly score is greater than the critical point, determine as the anomaly.

2.2 Imbalanced Data Processing Technique

Classification performance is more affected by the majority class than by the minority class (Akbani et al., 2004). Classification performance demands data that is uniformly distributed for each class, but actual semiconductor manufacturing process data are often extremely biased for some class. Using this imbalanced data will lead to learning outcomes and performance degradation, resulting in economic damage within the business (Freeman, 1995).

Oversampling is a popular method of anomaly detection using imbalanced data. It focuses on the bias between class in data where the ratio of abnormal data to normal data is overwhelmingly small.

This paper solves the imbalance by using oversampling techniques such as Figure 2.

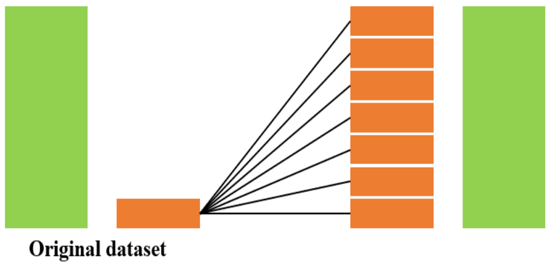


Figure 2: Using oversampling techniques.

Typical oversampling techniques include RO (Random Oversampling) (Liu, 2014), and SMOTE (Synthetic Minority Oversampling Technique) (Chawla et al., 2002), Borderline SMOTE (Han et al, 2005) (More, 2016).

RO is a method of random copying instances in the minority class to compensate for insufficient data. There is no loss of information, but there is a possibility of overfitting because it simply copies minority class. SMOTE, a method that has been developed to supplement this, is a method of generating new synthetic samples using k-NN (k-Nearest Neighbors), focusing on minority class instances. In other words, artificial data is generated by selecting a point on the line that connects one of the closest neighbors in the data space to an object of a minority class. However, since sampling is performed without loss of information but does not take into account the location of adjacent majority class instances when generating data, class can overlap or creates noise, and high-dimensional data is not efficient. Borderline SMOTE is a method of generating synthetic data intensively near the classification boundary. It is characterized by better classification performance than SMOTE by generating more data on the classification boundary. Recently, it has been proposed to use GAN (Generative Adversarial Networks) to learn the distribution of minority class to generate artificial data (Douzas and Bacao, 2018). The use of WGAN as a method to solve the GAN shortcomings of vanishing gradient or mode collapse was also proposed (Wang et al., 2019).

These methods focus primarily on generating data for the minority class. Therefore, in performing anomaly detection in this paper, abnormal data with relatively small proportion in the semiconductor manufacturing process are oversampled using WGAN.

3 PROPOSED METHOD

We propose a framework that integrates the concept of autoencoder in Section 2.1 and the oversampling method using WGAN in Section 2.2. The overall architecture is showed in Figure 3. The model consists of three main steps. The first step is to go through the process of normalizing the raw data and then create a model of learning the encoder and decoder of the autoencoder using normal data only. The second step is to perform an oversampling over the WGAN until the number of objects in the abnormal data is equal to the number of objects in the normal data. As a final step, pass abnormal data that has been oversampled in the second step to the autoencoder model created in the first step. Anomaly detection is then performed by utilizing a classifier in the latent space of the autoencoder.

3.1 Step 1: Autoencoder

Effective anomaly detection requires a model that can classify abnormal and unobserved data only with normal data. By learning autoencoder with normal data only, it is possible to classify normal and abnormal data that has not yet been observed at later time (An and Cho, 2015; Sun et al., 2018).

The autoencoder model learns a combination of attributes that can express normal data well within the potential under the basic assumption of manifold learning. This represents a reduction in dimension and can solve the curse of dimensionality.

3.2 Step 2: Oversampling with WGAN

Manufacturing data are mostly in the normal category. However, abnormal data is often more important than normal data. This imbalance is problematic because it results in large misclassification errors within abnormal data, thereby reducing the classification performance. Therefore, we usethe oversampling method which is to randomly generate abnormal data as way to address the imbalance of abnormal data.

The problem is that traditional oversampling methods do not use the distribution of data. WGAN is an algorithm that complements the shortcomings of the GAN, a method using probability distribution

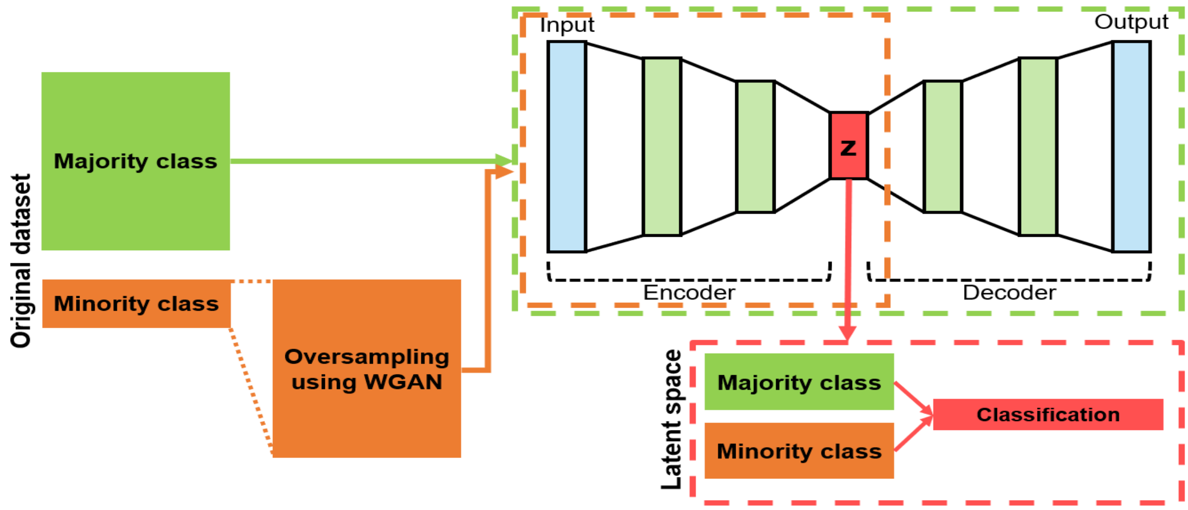


Figure 3: Architecture of AEWGAN.

in a minority class (Arjovsky et al., 2017).

$$D(x) = 1^{\forall} x \in p_r, D(x) = 0^{\forall} x \in p_g \quad (4)$$

$$min_G max_D \mathrm{V(D, G)} = E_{x \sim p_r(x)} log D(x) + E_{z \sim p_z(z)} \log\left(1 - D\big(G(z)\big)\right) \quad (5)$$

Typical problems with the GAN include vanishing gradient and mode collapse. Vanishing gradient refers to the problem of equation (4) being satisfied when discriminator is perfect, and the loss function of equation (5) being close to zero, thus failing to obtain the gradient in the course of learning. In equation (4) and equation (5), p_r represents actual data, p_g represents generated data, and p_z represents a latent vector that follows the gaussian distribution. Mode collapse is a problem in which the generator always produces the same results in the course of learning.

WGAN uses WD (Wasserstein Distance) such as equation (5) instead of JS (Jensen-Shannon) divergence as an indicator of the distance between the two probabilities distributions. Even when the two distributions do not overlap in low-dimensional manifolds, WD still has meaningful values and is expressed continuously, thus solving the problem of vanishing gradient and mode collapse (Arjovsky et al., 2017).

$$W(p_r, p_g) = \inf_{\gamma \sim \prod(p_r, p_g)} \mathbb{E}_{(x,y) \sim \gamma}[\|x - y\|] \quad (6)$$

In equation (6), $\prod(p_r, p_g)$ represents a set of possible combined probability distributions between the actual data p_r and the generated data p_g.

$$W(p_r, p_g) = \frac{1}{k} \sup_{\|f\|_L \le K} \mathbb{E}_{x \sim p_r}[\mathrm{f}(x)] - \mathbb{E}_{x \sim p_g}[f(x)] \quad (7)$$

$$L(p_r, p_g) = W(p_r, p_g) = \max_{w \in W} \mathbb{E}_{x \sim p_r}[f_w(x)] - \mathbb{E}_{z \sim p_r(z)}[f_w(g_\theta(x))] \quad (8)$$

However, because it is not possible to estimate the number of possible cases, the newly modified form of equation (7) is used using Kantorovich-Rubinstein duality. When this is applied to equation (5) which is the GAN's loss function, the WGAN's loss function is expressed as an equation (8).

The $\|f\|_L \le K$ of equation (7) means K-Lipschitz continuous and there is a real value $K \ge 0$ that satisfies $|f(x_1) - f(x_2)| \le K|x_1 - x_2|$. In WGAN, identifiers will not be direct criteria for identifying actual and generated data, instead learning K-Lipschitz continuous to find a good f. The smaller the loss function in the learning process, the smaller the WD becomes, the closer the constructor's resultant value is to the actual data.

Therefore, oversampling is performed using the WGAN until the number of instances in the abnormal data is equal to the number of instances in the normal data.

3.3 Step 3: Anomaly Detection in Latent Space

Latent space is the space expressed using a combination of attributes that can capture the variability of data along the basic assumption of manifold learning that normal and abnormal data can

Table 1: Performance Comparisons.

Model	Raw			RO			SMOTE			GAN			AEWGAN		
	LR	SVM	RF	LR	SVM	RF	LR	SVM	RF	LR	SVM	RF	LR	SVM	**RF**
Precision	0.786	0.660	0.300	0.843	0.872	0.861	0.855	0.891	0.847	**1.000**	**1.000**	0.991	**1.000**	**1.000**	**1.000**
Recall	0.282	0.437	0.034	0.919	0.950	0.982	0.919	0.942	0.963	0.993	0.992	0.991	0.994	0.992	**0.997**
F-measure	0.384	0.515	0.060	0.879	0.909	0.918	0.886	0.916	0.901	0.996	0.996	0.996	**0.997**	0.996	0.996
AUC	0.641	0.718	0.517	0.874	0.906	0.912	0.882	0.912	0.894	0.996	0.996	0.995	**0.997**	0.996	0.995

be embedded into a low-dimensional space with distinct differences.

The autoencoder previously learned from normal data, will learn how to use a combination of attributes that can capture the variability of normal data within the latent space. Then, when abnormal data that has been oversampled through the WGAN is entered into the input value, it appears to be a different combination of attributes than it was before, so it is judged to be anomaly. Therefore, anomaly detection is carried out by utilizing the classifier within the latent space.

4 EXPERIMENTAL SETTING

The data used in the experiment for performance verification in this paper are semiconductor wafer data provided by the UEA & UCR Time Series Classification Repository (Olszewski, 2001). It consists of a set of 152 different sensor values measured in the semiconductor manufacturing wafer process and is the imbalanced ratio of 10.7% with 762 abnormal data out of 7,164 data. In order to match 762 abnormal data similarly to the 3-sigma of the actual process, this paper conducted the experiment using only 30 data.

To verify AEWGAN's performance, compare the original data, RO, SMOTE, and methods using the GAN. Use LR (Logistic regression, SVM (Support Vector Machine), and RF (Random Forest) as the classifier for performance evaluation. Use the equation (9) precision, equation (10) recall, equation (11) F-measure, and equation (12) AUC (Area Under Curve), depending on the results of the table for the confusion matrix in Table 1.

To check for anomaly detection, the t-SNE (t-Stochastic Neighbor Embedding) method was used to transform the distances between data stochastically. Because t-SNE shows stable embedded learning results over other algorithms for visualization, it is suitable for expressing potential space in two dimensions.

Table 2: Confusion Matrix.

	Actual: Yes	Actual: No
Predicted: Yes	TP (True Positive)	FP (False Positive)
Predicted: No	FN (False Negative)	TN (True Negative)

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

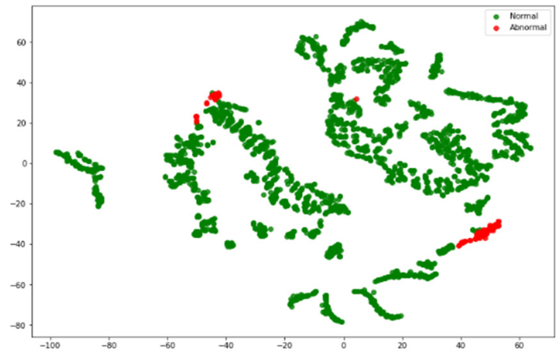
$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$F - measure = \frac{2TP}{2TP + FP + FN} \tag{11}$$

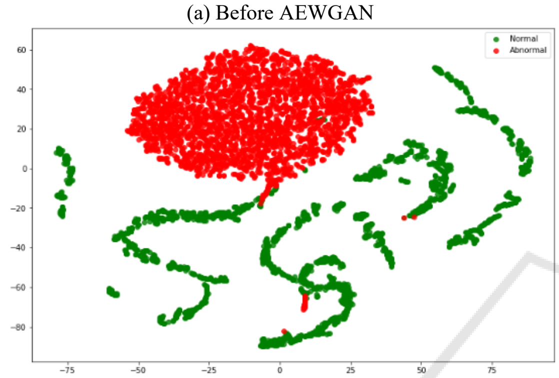
$$AUC = \frac{True\ Positive\ Rate}{1 - False\ Positive\ Rate} \tag{12}$$

Table 2 shows performance comparisons of abnormal class between 15 or more detection models of wafer data. All the results of the experiment were better compared to the raw data. As a result, the performance of GAN and AEWGAN is better than RO and SMOTE. It also confirmed that AEWGAN, the proposed method rather than using the GAN, improved the results by improving the shortcomings of the GAN.

In addition, the raw data and the data with AEWGAN were compared as t-SNE as way to determine if anomaly detection was carried out. Figure 4(a) is a result of t-SNE for the raw data, resulting in a severe imbalance and difficulty in separating normal from abnormalities. The result of applying AEWGAN is Figure 4(b). Unclassified data has been easily discriminated against, and imbalanced data problem has also been solved.



(a) Before AEWGAN



(b) After AEWGAN

Figure 4: Embedding using t-SNE.

In summary, the proposed method using AEWGAN in this paper has shown excellent results in terms of sampling and anomaly detection for wafer data, which is high-dimension imbalanced data.

5 CONCLUSIONS

We observed proposed AEWGAN show an efficient abnormal detection method of semiconductor manufacturing process data with high dimensional imbalance characteristics. AEWGAN first proceeded with the autoencoder learning using normal data only. Then, the abnormal data was oversampled using the WGAN and put into the previously learned model as an input value. Finally, we carried out anomaly detection within the latent space.

In the experiment, semiconductor wafer data with an extreme imbalance of 152 dimensions were used. The results of the experiment showed that the AEWGAN of this paper, performed better classification performance in abnormal data compared to other models and that efficient anomaly detection was also performed in visual comparisons through t-SNE.

The method is expected to be applicable to semiconductor manufacturing processes with various production systems, i.e. data with many variables and few abnormal data, so it is likely to be practical and applicable to a wide variety of areas. Future work to be undertaken not only will detect the manufacturing process sensor data but also time series data affected by past values. It is thought that quantitative comparisons will be needed in the future.

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