Enhanced Weakly Supervised Learning Method for Anomaly Detection in Aerospace Product Manufacturing Processes

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Abstract—**Detecting anomalies in the manufacturing process of aerospace products is of great significance for ensuring product quality and reliability. Traditional anomaly detection methods suffer from limited availability of anomaly samples and uncertain labels of monitoring data from multiple manufacturing procedures. Therefore, an enhanced weakly supervised learning method is proposed. First, an anomaly sample generating model is designed to enhance its volume. Then, a multi-network model is designed, where a series of instances learning networks are used to estimate anomaly scores of data from some procedures separately and a stacking network is used to determine whether the whole manufacturing process contains anomalies. The proposed approach is verified on an experimental dataset of star sensor manufacturing, and the results substantiate that it outperforms existing methods.**

Keywords—anomaly detection, imbalanced data, weakly supervised learning, aerospace product manufacturing

I. Introduction

In the manufacturing process of aerospace products, conservative process parameters and rigorous inspection measures are usually adopted to ensure product quality [1]. However, there are still cases where some products fail to pass the tests and are deemed non-compliant, even after completing all the process steps, leading to increased development costs, extended delivery cycles, and even failure in critical missions. The root cause of product quality issues lies in the inability to fully control the manufacturing process, where anomalies in certain process steps go undetected [2]. Therefore, accurately predicting and pinpointing anomalies in the manufacturing process is of great significance for ensuring product quality and reliability.

Traditional quality inspection methods are conducted after the completion of a certain process, which not only causes a delay but also makes it difficult to analyze and locate the specific causes of anomalies due to intermittent inspections. This approach fails to play a preventive or controlling role during the production process [3,4]. With the development of the Internet of Things and the implementation of systems like supervisory control and data acquisition (SCADA), the trend is shifting towards real-time monitoring of process parameters and equipment status during product manufacturing. Using methods such as machine learning and artificial intelligence to detect anomalies in real-time during the manufacturing process is becoming a future trend and a potential approach. This method, known as data-driven anomaly detection or prediction, has gradually become a research hotspot in anomaly detection during the manufacturing process [5-7].

Traditional anomaly detection methods are usually divided into three categories: supervised anomaly detection, semi-supervised anomaly detection, and unsupervised anomaly detection [8]. Supervised anomaly detection models need to learn the patterns of both normal and abnormal classes, which requires a sufficient number of anomaly samples. The main challenges are the imbalance in sample numbers and the accurate labeling of all samples. Semi-supervised anomaly detection assumes that only normal class data is labeled during training, with the model learning from these normal samples and detecting anomalies by assessing whether the observed samples conform to the normal class patterns. The main challenge here is that if the normal class is highly heterogeneous, the model may struggle to converge and have a high false alarm rate. Unsupervised anomaly detection assumes that normal instances are much more frequent than anomalies in the test data, searching for outliers based on the principle that normal class samples have a similar distribution. This method also faces high false alarm rates when the normal class is highly heterogeneous. In the context of anomaly detection in aerospace product manufacturing, traditional anomaly detection methods face two major challenges.

1) Anomalies in the manufacturing process are low-probability events, resulting in a significantly smaller number of anomalous monitoring data samples compared to normal samples. This significant imbalance in sample numbers limits the accuracy of machine learning models.

2) The monitoring data from the manufacturing process is unlabeled, and its classification can only be determined after the product has undergone testing. Moreover, product quality issues may have multiple causes. Therefore, while it is possible to

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determine whether the collection of monitoring data from multiple process steps for a single product contains anomalies, it is impossible to pinpoint the specific process or time when the anomaly occurred. In other words, the labels of the data samples are coarse-grained and uncertain, making it impossible to use conventional supervised learning models for detection.

To address the above issues, this paper proposes an enhanced weakly supervised learning method for anomaly detection in the aerospace product manufacturing process. First, an improved generative adversarial network is designed to learn anomaly samples and generate virtual anomaly samples, thereby increasing the number of anomaly samples and reducing the impact of sample imbalance on the machine learning model. Then, a multi-network ensemble model based on the multi-instance learning concept is designed, which adapts to the various monitoring signal characteristics of multiple process steps, enabling the model to learn and determine whether the data packet composed of monitoring data from multiple process steps in the aerospace product manufacturing process contains anomalies.

II. The Proposed Method

A. Overview of the Proposed Method

The proposed anomaly detection method comprises two stages: the model establishment stage and the online detection stage, as shown in Fig. 1.

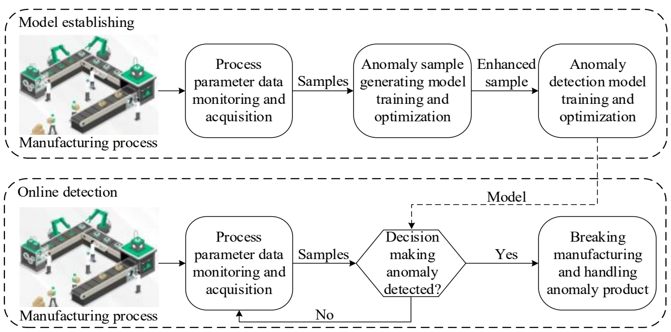


Fig. 1. Schema of the proposed method

In the model establishment stage, process parameters from the entire manufacturing process are collected through the SCADA system, which serves as the input for the anomaly detection model. Then, considering that the number of anomalous samples collected in the actual manufacturing process is much smaller than the number of normal samples, with an imbalance ratio often exceeding 10, which constitutes highly imbalanced data [9], this imbalance can cause the machine learning model to be biased toward recognizing samples as normal (thus achieving a high accuracy rate), limiting the model's accuracy in identifying anomalies. To address this, an improved generative adversarial network (GAN) model is designed to learn the patterns of a small number of anomalous samples and generate virtual anomalous samples, thereby increasing the number of anomalous samples. Finally, the real normal samples, anomalous samples, and generated virtual anomalous samples are combined as the training input for the anomaly detection model, which is then trained and optimized using the proposed multi-network ensemble model.

In the online detection stage, the SCADA system is also used to collect process parameter data during the manufacturing process, which is then input in real-time into the trained anomaly detection model. When an anomaly is detected, appropriate measures can be promptly taken to handle the product accordingly.

B. Anomaly Sample Generating Model

The anomaly sample generation model consists of two relatively independent network structures: the Generator (G) and the Discriminator (D). The role of the generator is to learn the distribution patterns of real anomaly samples and generate realistic virtual anomaly samples. It is defined as G: $Z\rightarrow X$, where Z is a space of random data that follows a normal distribution, and X is the sample space. The discriminator is defined as D: $X\rightarrow[0,1]$. Its role is to learn to distinguish whether a sample comes from the real dataset or from the virtual sample set generated by the generator. The output represents the probability that a sample comes from the real dataset. The ideal state of the discriminator is that its output is 1 when the input is a real sample and 0 when the input is a virtual sample.

G and D compete in a successive min-max problem with the following value function:

$$\min_G \max_D V(D,G) = E_{\mathbf{x}\sim p_{data}(\mathbf{x})}[\log D(\mathbf{x})] + E_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1-D(G(\mathbf{z})))] \quad (1)$$

Here, $\mathbf{x}\in X$ is sampled from the sample space, and $\mathbf{z}\in Z$ is sampled from the noise space. The architecture of these two networks is shown in Fig. 2. Here, L_1, L_2, and L_3 are the numbers of nodes in the layers of G, L_4, L_5, and L_6 are the numbers of nodes in the layers of D. α and r are respectively the parameters of the leaky ReLU and the dropout layer. $d_{\mathbf{z}}$ and m is the dimensions of $\mathbf{x}$ and $\mathbf{z}$.

The loss function of G and D is

$$L_{G,D}(l_i,\hat{l}_i,n) = -\frac{1}{n}\sum_{i=1}^{n}\left[l_i\log(\hat{l}_i)+(1-l_i)\log(1-\hat{l}_i)\right] \quad (2)$$

Here, l_i is the real label of the samples, and $\hat{l}_i$ is the label predicted by D.

By alternately optimizing the discriminator and the generator, the generator can be encouraged to learn how to generate virtual samples that are similar to real anomaly samples, which can then be used for subsequent model training.

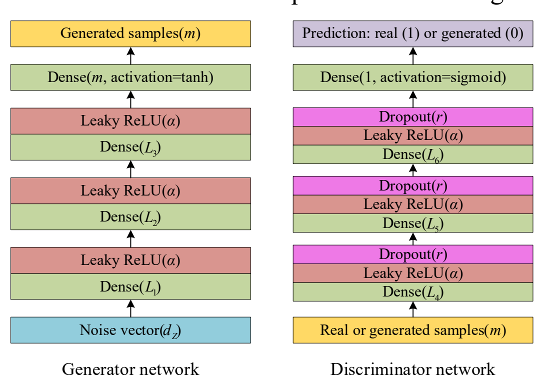


Fig. 2. The architecture of anomaly sample generating model

Considering the small number of real anomaly samples, there is a risk of mode collapse during training, where the generated virtual samples are not controlled by the input and are confined to a small subregion of the sample space with high redundancy, affecting the quality of the generated samples. To address this, a Dropout mask based on node connection strength is added to the discriminator to suppress nodes that are prone to collaboration, thereby preventing mode collapse, as shown in Fig. 3. Additionally, after the generator produces virtual samples, the discriminator is used to filter them to improve the quality of the generated virtual anomaly samples.

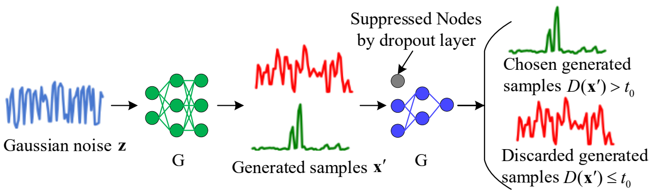


Fig. 3. The screening process of the generated samples

C. Anomaly Detection Model

In general supervised classification problems, the labels of all normal and anomaly samples are precise. However, in the anomaly detection problem in the aerospace product manufacturing process addressed in this paper, it is only possible to determine whether a collection of monitoring data from multiple process steps contains anomalies. The monitoring data for individual process steps or procedures do not have precise labels. This paper proposes a multi-network ensemble anomaly detection model based on the concept of multi-instance learning, with its framework shown in Fig. 4.

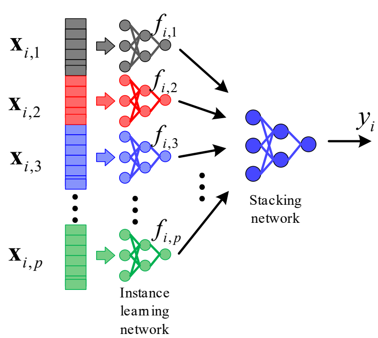


Fig. 4. The framework of the proposed anomaly detection model

For a sample set consisting of N samples $X = \{\mathbf{x}_1, \mathbf{x}_2, \cdots \mathbf{x}_N\}$, the ith sample is composed of p sub-sample segments (instances), denoted as $\mathbf{x}_i = \{\mathbf{x}_{i,1}, \mathbf{x}_{i,2}, \cdots \mathbf{x}_{i,p}\}$. Each instance can be represented as a q-dimensional feature vector. First, p individual learners are designed, with each individual learner taking one instance as input to learn the features of the corresponding process segment monitoring data and predict the instance anomaly score $f_{i,1}, f_{i,2}, \cdots, f_{i,p}$. The outputs of the individual learners collectively determine the sample's class. Therefore, an ensemble network is designed and added on top of the individual learners, taking all individual learner outputs $f_{i,1}, f_{i,2}, \cdots, f_{i,p}$ as input to predict the sample's class y_i.

The architecture of the proposed anomaly detection model is shown in Fig. 5. Considering that the sample input in this paper is primarily vectors and arrays, the structure of the individual learners adopts a commonly used 3-layer network structure. The ensemble network's input is the vector composed of the outputs of the individual learners, with relatively low dimensionality, so a 2-layer network structure is used. The anomaly detection model can also use the cross-entropy loss function:

$$L_1(y_i, \hat{y}_i, N) = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (3)$$

Here, y_i is the real category (anomaly sample labeled "1" or normal "0"), $\hat{y}_i$ is the anomaly score predicted by the model.

Considering that the output of each instance also has discriminative significance, for normal samples, all individual learners' predicted values for the instances should be close to 0. For anomaly samples, at least one individual learner's predicted value for an instance should be close to 1. Therefore, an additional training loss term is added:

$$L_2 = \sum_{i=1}^{N} \frac{1}{2} \left(\max_{1 \le j \le p} f_{i,j} - y_i \right)^2 \quad (4)$$

Additionally, in anomaly samples, normal instances usually dominate, with only a few instances being anomalous. Therefore, the prediction results of the instances should be sparse. Consequently, an additional training loss term is added:

$$L_3 = \sum_{i=1}^{N} \left(y_i \sum_{j=1}^{p} f_{i,j} \right) \quad (5)$$

The final total loss function of the anomaly detection model is obtained as:

$$L_{AD} = L_1 + \lambda L_2 + \eta L_3 \quad (6)$$

Here, $\lambda, \eta \ge 0$ are separately the weight of L_2 and L_3.

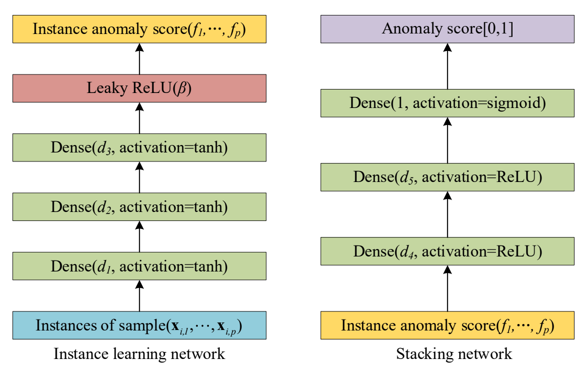


Fig. 5. The architecture of the anomaly detection model

III. ENGINEERING APPLICATIONS

A. Dataset Description

The proposed method was tested using a set of process parameter monitoring data and corresponding performance test results from the production process of a star sensor. The monitoring and performance testing data of the star sensor's production process cover 12 procedures and include 86 types of attributes, such as the grayscale and mean of star point images, the mean square error of grayscale sums, maximum grayscale value, minimum grayscale value, focal length, principal point location, radial distortion, tangential distortion, background energy grayscale mean, and other testing indicators, as detailed in Table I, where "No." is the procedure number.

TABLE I. THE TECHNOLOGICAL PARAMETERS FROM THE PRODUCTION PROCESS OF A STAR SENSOR

Phase	No.	Technological parameters
Assembly process	10	Mounting corner thickness, mass.
	20	Temperature, humidity, adhesive curing time.
	30, 40	Thickness at joints, focal length, calibration accuracy, principal point coordinates, tangential distortion, etc.
	50	Current, response time, impedance, etc.
Performance testing	80	Voltage, power consumption, impedance, grayscale, etc.
	110, 140	Image grayscale value/and/relative deviation, energy concentration, energy difference, tilt angle.
Environmental testing	90	Voltage, power consumption, impedance, grayscale, etc.
	100	Power consumption, impedance, roll/pitch/yaw angles.
	120	Focal length, calibration accuracy, principal point coordinates, tangential distortion, etc.
	130	Assembly accuracy, adhesive components, temperature, humidity, curing time.

A total of 434 sets of testing and calibration data for star sensors were collected. The quality classification of the products was based on their final calibration accuracy, as shown in Table II. Calibration accuracy includes three metrics: overall accuracy, noise equivalent angle, and low-frequency error. Products with deviations in all three metrics are classified as the lowest quality level. These corresponding samples are categorized as anomalous, while the samples from the remaining products are classified as normal. In total, 402 normal samples and 32 anomalous samples were obtained.

TABLE II. ANOMALY CLASSIFICATION CRITERIA FOR PRODUCT TESTING METRICS

Overall accuracy	Noise equivalent angle	Low-frequency error
X-axis<2.05	X-axis<1.76	X-axis<0.90
Y-axis<2.06	Y-axis<1.73	Y-axis<0.99
Z-axis<16.55	Z-axis<14.87	Z-axis<6.67

B. Experimental Setup

The dataset was divided into two subsets. Seventy percent of the normal and abnormal samples were randomly selected as training samples. The rest thirty percent of the samples were used to assess the performance of the proposed approach.

TABLE III. SETTINGS OF THE AFOREMENTIONED PARAMETERS

Model	Parameter setting
Anomaly sample generating model	$d_z = 8,\ L_1 = 8,\ L_2 = 16,\ L_3 = 32$
	$r = 0.3,\ L_4 = 32,\ L_5 = 16,\ L_6 = 8$
	$m = 86,\ \alpha = 0.2$
Anomaly detection model	$\beta = 0.2,\ d_1 = 16,\ d_2 = 4,\ d_3 = 1$
	$d_4 = 8,\ d_5 = 4$
	$\lambda = 0.5,\ \eta = 0.1$

The proposed approach was implemented using TensorFlow [10] and scikit-learn [11]. The parameters of the anomaly samples generating model and the anomaly detection model aforementioned were specified in Table III. The networks of the proposed models were trained using the Adam optimizer [12] with a learning rate of 0.0001.

To evaluate the performance of the proposed models, true positive rate (TPR), false positive rate (FPR), and receiver operating characteristic (ROC) curves are adopted as evaluation metrics. TPR and FPR are decomposed as:

$$TPR = \frac{TP}{TP + FN} \tag{7}$$

$$FPR = \frac{FP}{FP + TN} \tag{8}$$

Here, *TP*, *FP*, *TN*, and *FN* are defined by the confusion matrix, as shown in Table IV.

TABLE IV. CONFUSION MATRIX FOR RESULTS OF ANOMALY DETECTION

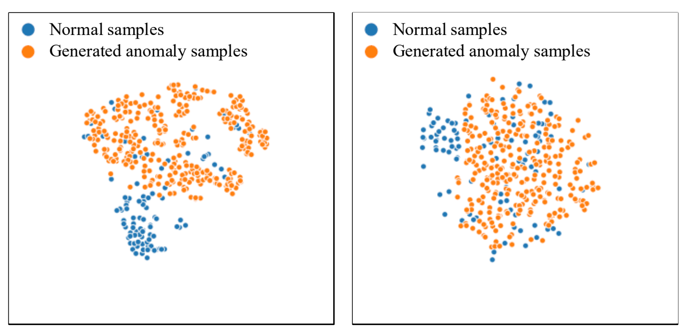
	True abnormal class	True normal class
Predicted abnormal class	*TP*	*FP*
Predicted normal class	*FN*	*TN*

C. Results and Performance Analysis

The experimental results are presented in two parts: the performance evaluation of the anomaly sample generating model and the performance evaluation of the anomaly detection model.

1) Performance of the Anomaly Sample Generating Model

To evaluate the performance of the proposed anomaly sample generating model, the t-distributed stochastic neighbor embedding (t-SNE) [13] method is adopted to reduce the samples from high dimensions to two dimensions. Then the two-dimensional distribution map of the normal sample and generated anomaly samples can be drawn to visualize relationships and densities between these two categories of samples.



(a) Generated samples with screening of D (b) Generated samples without screening

Fig. 6. The two-dimensional distribution map of the normal sample and generated anomaly samples

The two-dimensional distribution map graphs are presented in Fig. 6. Compared with Fig. 6 (b), two categories of samples in Fig. 6 (a) can be fairly partitioned, and the intra-class consistencies of both categories are better. Namely, the overlaps between the generated anomaly samples with screening of D and normal samples are less than those of generated samples without screening. And the generated anomaly samples with screening of D are less similar to normal samples, compared with the generated samples without screening. Therefore, the distribution map graphs substantiate that screening with D improves the quality of generated samples.

2) *Performance of the Anomaly Detection Model*

The proposed anomaly detection approach is an enhanced weakly supervised learning (EWSL) method. To evaluate its performance, three different types of multi-instance learning methods, namely support vector machines for multiple-instance learning (MI-SVM) [14], RBF neural networks for multi-instance learning (RBF-MIP) [15], multiple instance neural networks (MI-Net) [16], are adopted for comparison. TPR, FPR, ROC curves, and the area under the ROC curve (AUC) are adopted as criteria.

Fig. 7 presents the ROC curves of the proposed and the three comparison methods. the proposed EWSL method can reach a higher TPR than all other methods with the same FPR, can reach a lower FPR than other methods with the same TPR, and achieves the highest AUC. Table V details the specific results of the proposed and the three comparison methods. All the results are drawn from the default thresholds of the methods rather than thresholds obtained from the AUC.

The ROC curves and the specific results substantiate that the proposed EWSL method notably outperforms other comparison methods.

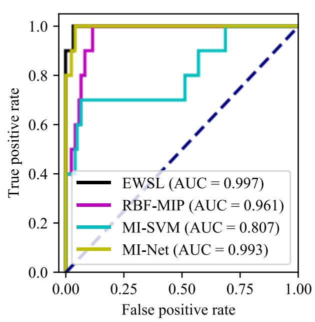


Fig. 7. The ROC curves of the proposed and the comparison methods

TABLE V. THE RESULTS OF THE PROPOSED AND COMPARISON METHODS

Method	TPR	FPR
EWSL	1	0.0331
RBF-MIP	0.9	0.0826
MI-SVM	0.7	0.0661
MI-Net	1	0.0413

IV. CONCLUSION

In this paper, an enhanced weakly supervised learning method is proposed to detect anomalies in aerospace product manufacturing processes. The approach is based on the multi-instance learning concept. To address the problem that anomaly samples are significantly rare, an anomaly sample generating model is designed to enhance its volume. To address the problem that the monitoring data from multiple manufacturing procedures have no certain labels, a multi-network ensemble model is designed, where a series of instances learning networks are used to estimate anomaly scores of data from some procedures separately and a stacking network is used to determine whether the whole manufacturing process contains anomalies. The proposed approach is verified on an experimental dataset of star sensor manufacturing, and the results substantiate that it outperforms existing methods.

For future work, locating the specific manufacturing procedures and moments the anomaly occurred is interested and significant.

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