Anomaly Detection Mechanism for Manufacturing Defects

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Abstract. The global metalworking and manufacturing industry serves as a cornerstone of the economy, responsible for producing a wide range of essential consumer products. Yield rate stands as a critical indicator within manufacturing, exerting direct influence over production costs and customer contracts. High-end products frequently comply with stringent zero-defect standards, where even a single defective item incurs significant costs and damages company reputation. Advances in manufacturing quality inspection notwithstanding, mature metalworking processes typically achieve high yield rates, resulting in a minimal quantity of defective products and presenting challenges in defect detection and classification, commonly referred to as the limited data problem. Anomaly detection emerges as an effective method for overcoming obstacles posed by limited data, concentrating on the identification and differentiation of data points that diverge from established patterns, representing potential anomalies or defects. The infrequency of defects necessitates precise detection within a large dataset dominated by normal samples. The paper introduces an Anomaly Detection Mechanism for Manufacturing Defects, leveraging the capability of the GANomaly model to discern subtle distinctions within similar data. By employing extensive training on majority class datasets, this model demonstrates effectiveness in detecting manufacturing defects, with the objective of minimizing return costs and preventing losses in reputation attributable to undetected defective items.

Keywords: Anomaly Detection · Limited Sample · Manufacturing Defects

1 Introduction

The global metalworking and manufacturing industry is a cornerstone of the economy, with numerous consumer products derived from various manufacturing processes. In manufacturing, yield rate is one of the most critical indicators, as it directly impacts production costs and customer delivery contracts. High-end products often adhere to strict "zero defects" standards, where even a single defective item among the shipped products can lead to significant return costs, contractual penalties, and severe damage to

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a company's reputation. Consequently, research into manufacturing quality inspection has gained considerable attention in recent years. However, given the high yield rates in mature metalworking processes, typically exceeding 90%, the occurrence of defective products is rare. This rarity, coupled with the objective of detecting defects, significantly increases the difficulty of classification tasks, a scenario referred to as limited data.

Anomaly detection is an effective method for addressing the challenges posed by limited data. The fundamental principle of anomaly detection is to identify and distinguish data points that deviate from established patterns, often flagging them as potential anomalies or outliers. These anomalies may indicate faults, fraud, diseases, or other critical conditions requiring attention. The challenge in anomaly detection lies in the fact that anomalies usually constitute only a small fraction of the overall data, making it difficult to accurately identify them within a vast pool of normal data.

Traditionally, anomaly detection methods have been exemplified by One-Class SVM (Support Vector Machine) [1]. One-Class SVM is a technique designed to handle single-class datasets, with the primary objective of separating normal data from anomalies [2]. It constructs a boundary in high-dimensional space to maximize the distance from normal data, thereby effectively detecting anomalies [3]. Besides One-Class SVM, other common anomaly detection methods include Isolation Forest [4], Autoencoders [5], and Gaussian Mixture Models (GMM) [6]. Isolation Forest, an unsupervised learning method based on tree models, isolates anomalies by randomly selecting features and split values, offering high efficiency and accuracy in high-dimensional data [7]. Autoencoders, based on neural networks, compress and reconstruct data to learn low-dimensional representations, effectively identifying anomalous samples [8]. Gaussian Mixture Models, a probabilistic model, estimate the data distribution by modeling a mixture of Gaussian distributions, detecting anomalies that deviate from the main distribution [9].

Recent advancements in data science and machine learning have led to the increasing application of deep learning techniques in anomaly detection, especially for complex and high-dimensional datasets. Methods such as Deep Autoencoders [10], Variational Autoencoders (VAE) [11], and Generative Adversarial Networks (GANs) [12] build complex models that learn latent representations of data, thereby enhancing the performance of anomaly detection [13]. Among these, GANomaly, a GAN-based anomaly detection approach, learns the distribution of normal data by training both a generator and a discriminator, enabling effective identification of anomalies during testing [14]. This method has demonstrated superior performance in unsupervised anomaly detection tasks across various experiments.

The structure of this paper is as follows: Sect. 2 defines effective quality anomaly detection methods, Sect. 3 discusses the design of future experiments, and the final section provides directions for future research.

2 Proposed Method

This study proposes an Anomaly Detection Mechanism for Manufacturing Defects with Limited Samples. The primary objective is to detect defective products in manufacturing processes through an anomaly detection mechanism, thereby reducing return costs and mitigating reputational damage caused by undetected defects. The challenge stems from the limited availability of defective samples, making it difficult to distinguish between defective and normal products, which complicates classification tasks. To overcome this, the study utilizes the GANomaly model, known for its ability to effectively identify subtle differences within similar data. The model is trained on a large dataset of majority class samples and subsequently employed to detect anomalous defective products in the manufacturing process (Fig. 1).

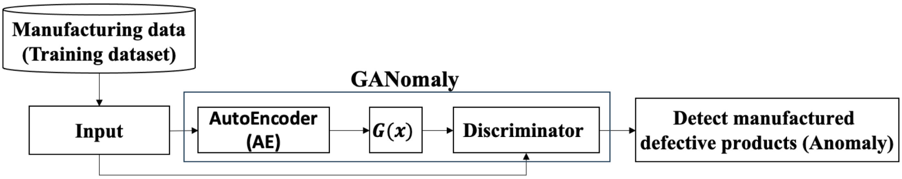

Fig. 1. Architecture of the proposed method

This method is primarily used to detect the rare occurrence of defective products by training on normal product data using a GAN-based approach. The underlying principle is based on Autoencoders, which typically reduce data to a lower-dimensional space and then reconstruct the original data from these lower-dimensional representations, ensuring that key information is preserved.

In this study, GANomaly is trained using normal product manufacturing data along with a very limited amount of defective product manufacturing data. When test data is passed through the trained Autoencoder, it is projected into a lower-dimensional representation, denoted as G(x). Both G(x) and the original input data are then evaluated by a Discriminator, which assigns an anomaly score. If the score falls below a specified threshold, the data is classified as anomalous defective product data [14].

3 Model Evaluation

In defect product classification, accurate detection of defective products is crucial. Consequently, anomaly detection tasks emphasize detecting defective anomalies over overall metrics. A certain level of misclassification where normal products are erroneously identified as defects may be acceptable. Additionally, overall accuracy remains important to avoid excessive misclassification that could undermine trust in the model, a common issue in anomaly detection tasks [15] (Table 1).

$$Precision = \frac{TP}{TP + FN} \tag{1}$$

$$Recallrate = \frac{TP}{TP + FP} \tag{2}$$

Table 1. Confusion matrix for manufacturing dataset.

	Actual Condition		
Prediction Condition		Defect	Normal
	Defect	TP (True Positive)	FP (False Positive)
	Normal	FN (False Negative)	TN (True Negative)

4 Conclusions

In this paper, we propose an Anomaly Detection Mechanism for Manufacturing Defects. The primary objective is to address the issue of insufficient defective data in production by training an anomaly detection model using only normal product data and a very limited amount of defective data. An evaluation model is also designed accordingly. Future work will involve validating the approach in real manufacturing environments and effectively addressing the challenging yield issues present in current manufacturing settings.

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