Detecting Machine Anomalies: An Unsupervised Auto-GAN Framework

Bagiya lakshmi S(21011101029), Arun Kumar M(21011101024)

1. Introduction

Detecting anomalies in machine data is a critical task in various industrial applications, as it helps ensure the smooth functioning of equipment and prevents costly breakdowns. However, traditional anomaly detection methods often rely on labeled data, which can be scarce and impractical to obtain in real-world scenarios. To overcome this limitation, this paper presents an innovative unsupervised approach called "Detecting Machine Anomalies: An Unsupervised Auto-GAN Framework."

The key advantage of the unsupervised GAN framework lies in its ability to discover anomalies in an entirely data-driven manner. This not only reduces the burden of data labeling but also enables the detection of previously unseen anomalies that may not be present in the training data.

The proposed paper introduces AEGAN-AD, a novel GAN-based approach for unsupervised anomaly detection and localization in machine audio. The scope and applicability of this work are significant in several ways. Firstly, AEGAN-AD addresses the challenging problem of anomaly detection in machine audio, which has crucial applications in modern manufacturing and industrial sectors. By automatically identifying anomalous audio patterns. Secondly, the potential cross-domain adaptability of AEGAN-AD is noteworthy. By harnessing the power of GANs, this approach shows promise in generalizing across different machine types and working conditions. This versatility allows its deployment in various industrial settings, ranging from diverse manufacturing environments to maintenance applications in different domains.

2. Methodology

Our approach centers around the development of an AutoGAN (Autoencoder-Generative Adversarial Network) architecture, tailored to the nature of our data, which comprises spectrograms. The heart of the AutoGAN consists of a modified generator (G) and discriminator (D). G operates as an autoencoder, with its primary function being to reconstruct input data, in this case, mel-spectrograms. On the other hand, D is trained to differentiate between genuine data and reconstructed data. The architecture of D closely mirrors the encoder of G but incorporates a depth-wise convolution in its final layer to enhance the extraction of semantic embeddings.

During the training process, the generator is optimized using a feature matching loss, focusing on a sample-level constraint to eliminate ambiguity in anomaly detection. Embeddings are extracted from the discriminator, and their statistics are compared between real and reconstructed data. Layer normalization (LN) is applied to prevent interference between the statistics of the target domain and the source domain, preserving distinguishable features and supporting scalability across both domains.
Once the AutoGAN model is trained, it can be effectively employed for anomaly detection tasks.

2.1 Base architecture diagram and explanation:

One of the key refinements proposed in the paper is the introduction of a redesigned discriminator in the AEGAN-AD model. The discriminator plays a crucial role in aiding the generator (autoencoder) during both training and detection stages.

In the AEGAN-AD model, the discriminator is trained using the Wasserstein GAN with Gradient Penalty (WGAN-GP) objective. The last layer of the discriminator is replaced with a depth-wise convolutional layer to promote the extraction of rich semantic embeddings. This modified discriminator enables the model to learn meaningful features and provides a feature-level guidance for the generator during training, pushing it to focus on the essential representations rather than superficial noise.

Architectural Diagram:

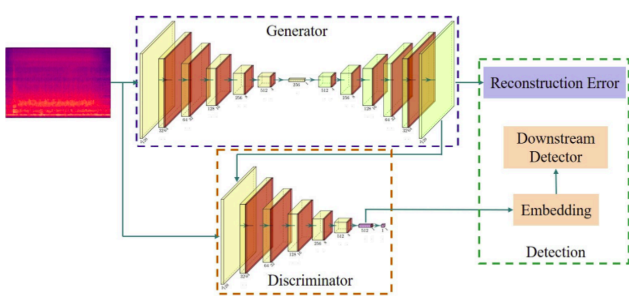

Fig 2.1

The generator tries to minimize the following loss function while the discriminator tries to maximize it. It is the same as a minimax game.

3. Studies

Table 2 presents the performance of Auto-GAN along with three baselines. Auto-GAN surpasses all three baselines on fan, Toycar, Toytrain, slider with an improvement of 1.81%, 7.11%, and 2.66% respectively, while the AEGAN-AD proposed performs slightly better on bearing and gearbox. Auto-GAN is with the best performance among all generative models with a general improvement of 3.84%, which demonstrates the superiority of our model.

3.1 Dataset description and link:

Anomalous sound detection (ASD) is the task to identify whether the sound emitted from a target machine is normal or anomalous. Automatically detecting mechanical failure is an essential technology in the fourth industrial revolution, including artificial intelligence (AI)-based factory automation

The main challenge of this task is to detect unknown anomalous sounds under the condition that only normal sound samples have been provided as training data. In real-world factories, actual anomalous sounds rarely occur and are highly diverse. Therefore, exhaustive patterns of anomalous sounds are impossible to make and/or collect deliberately. This means we have to detect *unknown* anomalous sounds that were not observed in the given training data.

https://dcase.community/challenge2020/task-unsupervised-detection-of-anomalous-sounds

3.2 Base architecture Result:

Machine Type	bearing	bearing	gearbox	toycar	toytrain
AUC	76.03	65.83	75.27	74.06	78.46

Table 1

Space for improvement:

Fine-tuning the model's hyperparameters, refining the discriminator's architecture, or using ensemble methods might be explored.

4. Refinements

In this work, we propose a refined architecture, referred to as AutoGAN+, as an enhancement to the existing network for anomaly detection. Building upon the foundations of the original AutoGAN, we introduce several key modifications to optimize the model's performance.

AutoGAN+ incorporates an extended search space, enabling it to explore a wider range of network configurations and activation functions. Moreover, we introduce regularization techniques to mitigate overfitting, thereby enhancing the model's generalization capability. The AutoGAN finds the best network model for our system, thereby increasing the AUC.

Architectural Diagram:

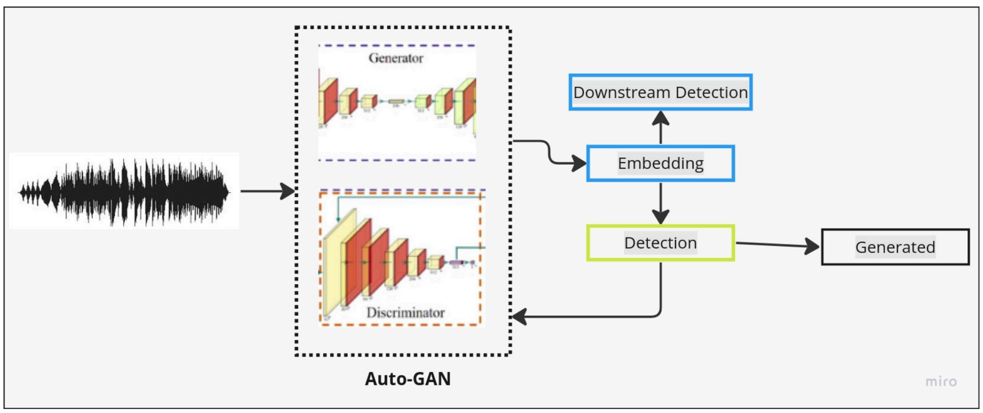

Fig 4.1

4.1 Comparison of results with references:

Machine Type	GANomaly	Yamashita	AEGAN-AD	**Auto-GAN**
bearing	55.4	60.24	**76.03**	75.12
fan	53.6	62.37	65.83	**67.64**
gearbox	53.44	70.62	**75.27**	72.22
toycar	63.1	72.15	74.06	**81.17**
toytrain	52.48	69.25	78.46	**81.12**

Table 2

4.2 Proof:

```
bearing > train.log
INFO - Train starts at: 2023-10-14 19:44:50
INFO - Seed: 100
INFO - Machine Type: bearing
INFO - ============== TRAIN CONFIG SUMMARY ==============
INFO - feat: [fft_num: 2048] [mel_bin: 128] [frame_hop: 512] [graph_hop_f: 1]
INFO - set: [dataset: dev]
INFO - net: [act: ['leakyrelu', 'relu']] [normalize: {'d': 'ln', 'g': 'ln'}] [nz: 256] [ndf: 32] [ngf: 32]
INFO - train: [lrD: 0.0002] [lrG: 0.0002] [batch_size: 128] [epoch: 60]
INFO - wgan: [feat_match_eff: 0.1] [match_item: {'mu': 1}] [ncritic: 1] [lambda_gp: 10]
INFO - ========= Train Machine Type: bearing =========
INFO - ============== MODEL TRAINING ==============
INFO - ---------------------------------------------------------------------------------------------------------
INFO - epoch 0: [recon: 4.7722e-03] [d2g: 9.4281e-04] [gloss: 4.8665e-03] [time: 4628s]
INFO - =======> [AUC_s: 0.7512] [AUC_t: 0.7316] [pAUC: 0.5977] [hmean: 0.6863] [metric: G_x_1_min] [best: 0.6863]
```

```
INFO - ========= Train Machine Type: fan =========
INFO - ============== MODEL TRAINING ==============
INFO - ---------------------------------------------------------------------------------------------------------
INFO - epoch 0: [recon: 5.0332e-03] [d2g: 9.2574e-04] [gloss: 5.1258e-03] [time: 4689s]
INFO - =======> [AUC_s: 0.6764] [AUC_t: 0.4329] [pAUC: 0.5399] [hmean: 0.5319] [metric: G_z_cos_min] [best: 0.5319]
```

```
INFO - ========= Train Machine Type: gearbox =========
INFO - ============== MODEL TRAINING ==============
INFO - ---------------------------------------------------------------------------------------------------------
INFO - epoch 0: [recon: 4.4625e-03] [d2g: 1.2382e-03] [gloss: 4.5863e-03] [time: 5046s]
INFO - =======> [AUC_s: 0.7229] [AUC_t: 0.6448] [pAUC: 0.5621] [hmean: 0.6365] [metric: D_maha] [best: 0.6365]
```

```
INFO - ============== MODEL TRAINING ==============
INFO - ---------------------------------------------------------------------------------------------------------
INFO - epoch 0: [recon: 4.6219e-03] [d2g: 1.6316e-03] [gloss: 4.7851e-03] [time: 4789s]
INFO - =======> [AUC_s: 0.8113] [AUC_t: 0.4126] [pAUC: 0.5022] [hmean: 0.5312] [metric: G_z_cos_sum] [best: 0.5312]
```

```
INFO - ============== MODEL TRAINING ==============
INFO - ---------------------------------------------------------------------------------------------------------
INFO - epoch 0: [recon: 3.6846e-03] [d2g: 1.0061e-03] [gloss: 3.7852e-03] [time: 4614s]     miro
INFO - =======> [AUC_s: 0.8117] [AUC_t: 0.6307] [pAUC: 0.5702] [hmean: 0.6563] [metric: G_z_2_min] [best: 0.6563]
```

5. Conclusion:

In conclusion, the project "Anomaly Detection using AutoGAN" has yielded promising results and insights into the application of this novel approach to the specific domain of anomaly detection, leveraging mel-spectrograms. The developed AutoGAN architecture, with its modified generator and discriminator, has demonstrated its potential in capturing complex patterns within the data, enabling the detection of anomalies effectively.

Throughout the project, we observed the advantages of utilizing a feature matching loss for training the generator, along with a sample-level constraint, which proved

essential in reducing ambiguity in anomaly detection. Extracting embeddings from the discriminator and comparing statistics between real and reconstructed data has enhanced the robustness and reliability of the model.
Layer normalization played a crucial role in maintaining the integrity of data statistics across domains, thereby preserving distinguishable features and enabling scalability.

References:

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[2] MIMII DG: SOUND DATASET FOR MALFUNCTIONING INDUSTRIAL MACHINE INVESTIGATION AND INSPECTION FOR DOMAIN GENERALIZATION TASK https://arxiv.org/pdf/2205.13879.pdf

[3] TOYADMOS2: ANOTHER DATASET OF MINIATURE-MACHINE OPERATING SOUNDS FOR ANOMALOUS SOUND DETECTION UNDER DOMAIN SHIFT CONDITIONS https://arxiv.org/pdf/2106.02369.pdf

[4] DESCRIPTION AND DISCUSSION ON DCASE 2022 CHALLENGE TASK 2: UNSUPERVISED ANOMALOUS SOUND DETECTION FOR MACHINE CONDITION MONITORING APPLYING DOMAIN GENERALIZATION TECHNIQUES https://arxiv.org/pdf/2206.05876.pdf

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