A Robot Image Anomaly Detection Model with Multimodal Cues under Partial Image Defects

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ABSTRACT

In robotic systems, the challenge of defective image anomaly detection in multimodal environments has been a critical issue. Solving this problem holds significant implications for the environmental perception of mobile robots and product quality inspection for industrial robots. This study addresses this challenge by proposing a multimodal robot image anomaly detection model for images with defects, integrating multimodal fusion attention networks, generative adversarial networks, and fully connected networks. By comprehensively considering various perceptual modalities such as images, texts, and sounds, the model efficiently captures crucial information, enhancing the precision and robustness of anomaly detection. Through detailed experimental validation, our model significantly improves accuracy, recall, precision, AUC, and F1-score metrics. The results demonstrate that the proposed GA-MMA-FCN model provides an efficient and reliable solution for robot image anomaly detection in multimodal environments, offering crucial support for practical applications in robotic systems.

1. Introduction

Research on robot image anomaly detection [1] holds paramount significance in robotics and computer vision. Ensuring the reliability and safety of robotic systems is essential, particularly in industrial and critical applications. By developing advanced anomaly detection models [2], this research enables the identification of irregularities or defects in robot-captured images, facilitating early diagnosis of faults or damages. Such timely detection is pivotal in industrial automation, ensuring efficient manufacturing processes and reducing downtimes, thus leading to substantial cost savings [3]. Moreover, in applications like autonomous vehicles [4]or robotic surgeries [5], where human lives are at stake, accurate anomaly detection becomes a life-saving technology, ensuring real-time responses to unexpected situations. Consequently, research outcomes in robot image anomaly detection are pivotal for various industries, paving the way for safer, more efficient, and adaptive robotic technologies that can operate seamlessly in complex and unpredictable environments.

The application of multimodal deep learning [6] in image anomaly detection constitutes a significant advancement in computer vision. By integrating information from diverse modalities such as images, texts, and sensor data, multimodal deep-learning models offer a holistic understanding of complex scenes, allowing for more accurate and robust anomaly detection. This approach overcomes the limitations of unimodal methods, where singular data sources might lack comprehensive context.

In industrial contexts, where multiple sensor modalities [7] are often available, multimodal deep learning enables a thorough analysis of the environment, enhancing the detection of subtle anomalies that individual sensors might overlook. Furthermore, multimodal deep learning fosters a synergistic fusion of heterogeneous data, enabling enhanced feature extraction and representation learning [8]. The fusion of modalities enriches the feature space and provides a more nuanced understanding of the data, capturing intricate patterns and correlations essential for accurate anomaly detection. This comprehensive feature representation, derived from multiple modalities, significantly improves the model's ability to discern anomalies from normal patterns, leading to higher detection accuracy and lower false-positive rates. In addition to industrial applications, multimodal deep learning finds significant relevance in domains such as healthcare [9], autonomous systems [10], and security [11]. For instance, combining information from medical images, patient records, and sensor data can lead to more precise anomaly detection, aiding in early disease diagnosis and treatment planning [12]. In autonomous systems like self-driving cars, fusing data from cameras, LIDAR, and radar sensors enables robust anomaly detection on the road, enhancing the safety of autonomous vehicles [13]. The research in multimodal deep learning for image anomaly detection advances the capabilities of anomaly detection systems. It contributes to the broader field of artificial intelligence by addressing complex, real-world problems involving diverse data sources. Consequently, integrating multimodal deep learning techniques into image anomaly detection research holds immense scholarly and practical significance, paving the way for more sophisticated, adaptable, and accurate anomaly detection systems applicable across various domains. The deep learning models commonly used in the research on robot image anomaly detection are as follows:

Multimodal Variational Autoencoder (MVAE) [14]: MVAE can handle data from various sensors, such as vision and sound. Through the structure of the Variational Autoencoder, it can learn the latent distribution of each sensor modality, capturing features of anomalous events in the robot's environment more effectively. Its latent space structure enhances the accuracy and interpretability of anomaly detection.

Multimodal Generative Adversarial Network (MGAN) [15]: MGAN generates more realistic multimodal data by employing the Generative Adversarial Network structure. Simultaneously, it learns the features of anomalous events. In the context of robot image anomaly detection, MGAN can generate multimodal anomalous data, facilitating the model's better understanding of anomalous patterns.

Multimodal Recurrent Neural Network (MRNN) [16]: MRNN combines Recurrent Neural Networks with multimodal data and is suitable for handling sequential anomalous data. In robotics, temporal information often contains rich context and correlations. MRNN effectively utilizes this information, enhancing the accuracy of anomaly detection.

Cross-Modal Neural Networks (CMNN) [17]: CMNN introduces cross-modal loss functions, encouraging feature learning and exchange between sensor modalities. In the context of robot image anomaly detection, CMNN captures the relationships between images and other sensor data (such as depth sensors), improving the robustness of anomaly detection.

Tensor Fusion Networks (TFN) [18]: TFN uses tensor decomposition methods and handles high-order multimodal data. In robot image anomaly detection, TFN considers the high-order correlations among multiple sensor data, effectively extracting features and enhancing the precision and generalization of anomaly detection.

This paper proposes a method combining a range of deep learning models for solving the robot image anomaly detection problem with multimodal cues under partial image defects. First, defective images are completed using Generative Adversarial Networks (GAN) [19]. Subsequently,

Convolutional Neural Networks (CNN) [20] are employed to extract visual features, Recurrent Neural Networks (RNN) [21] capture textual information, and one-dimensional Convolutional Neural Networks [22] extract sound features. These modality-specific features are then integrated through a dedicated fusion layer, effectively leveraging the unique advantages of each data type. Finally, a Fully Convolutional Network (FCN) [23] is applied for precise image anomaly detection. The model maximizes the potential of GAN for image completion, harnesses CNN's expertise in visual pattern recognition, utilizes RNN for contextual understanding of textual data, and benefits from the efficiency of one-dimensional CNN in sound feature extraction. The introduced fusion layer ensures a comprehensive representation of multimodal data, enhancing the model's capability to recognize intricate patterns.

The three contribution points of this paper are as follows.

1) This study introduces a novel approach for seamlessly integrating multi-modal sensor data collected by robots, including visual, textual, and auditory information. By leveraging the unique strengths of each sensor, visual data providing rich image details, textual data offering contextual descriptions, and auditory data capturing environmental sounds, the proposed model enables a comprehensive understanding of the robot's surroundings. This enhanced perception significantly improves the accuracy and robustness of anomaly detection across diverse robotic environments.

2) The research employs Generative Adversarial Networks (GANs) to restore defective images intelligently. In robotic applications, image data may be compromised due to sensor malfunctions or occlusions. By effectively restoring these images, the study addresses the challenge of missing or corrupted data, ensuring the input information's completeness. This capability strengthens the robot's environmental perception and supports more precise decision-making.

3) The study integrates deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to incorporate contextual information from multiple data modalities—images, text, and sound. Such contextual information is invaluable in robotic applications, as it can provide essential correlations and context. For instance, textual descriptions may help clarify image content, while auditory signals could offer insights into the surrounding environment. By effectively combining these diverse sources, the model gains a deeper, more holistic understanding of the scene, thereby improving its ability to detect complex anomaly patterns.

In the rest of this paper, we will introduce the recently related work in section 2. Section 3 presents the proposed methods: overview, GAN layer for image defect completion, multimodal data feature extraction layer, FCN layer for image anomaly detection and a multimodal attention mechanism. Section 4 introduces the experimental part, including practical details, comparative experiments, and an ablation study. Section 5 includes a conclusion.

2. Related work

2.1 Multimodal Image Anomaly Detection Model

In the realm of robotics, the application of multimodal image anomaly detection [24] models offers a plethora of advantages, leveraging the integration of diverse sensory data to enhance robotic perception, decision-making, and adaptability in complex environments. First and foremost, these

models facilitate comprehensive perception by integrating information from various sensors such as visual cameras, microphones, and textual inputs. This amalgamation provides a holistic, multidimensional understanding of the surroundings, enabling robots to perceive intricate details and nuances in the environment. These models significantly contribute to enhanced robustness by capturing data from different modalities. Utilizing multimodal data ensures the system's stability in scenarios where one sensor modality may fail due to interference or noise. Redundancy across modalities guarantees that even if one source is compromised, other modalities can compensate, preserving the integrity of the perception system. The improved accuracy of anomaly detection is another notable advantage. These models access a richer information by fusing multimodal features, enabling more precise anomaly identification. The synthesis of diverse features enhances the discrimination power of the model, leading to lower false positive rates and increased overall detection accuracy.

Additionally, multimodal models offer adaptive versatility by allowing robots to dynamically select and integrate sensor data based on task requirements and environmental conditions. This adaptability is crucial in real-world applications where the robot needs to handle diverse tasks in changing surroundings.

Furthermore, these models enable robots to achieve a deeper contextual understanding. By combining textual information with visual and auditory data, the model gains insights into the semantic context of the scene. This semantic understanding is invaluable in human-robot interaction scenarios, where interpreting contextual cues is vital. Moreover, in dynamic environments, the ability to fuse temporal and spatial information across different modalities equips robots with the capability to track anomalies over time, enabling the prediction and proactive management of potential issues.

However, several challenges and limitations remain. One significant drawback is the complexity involved in feature fusion. Integrating heterogeneous data from multiple modalities often requires sophisticated algorithms and strategies, making the fusion process computationally intensive. Achieving an optimal fusion scheme that maximizes the strengths of each modality while minimizing information loss presents a non-trivial challenge. Additionally, data misalignment and calibration discrepancies between different sensors can impede the accurate fusion of multimodal data. Variations in sensor technologies, resolutions, and calibration methods can lead to misalignments, affecting the quality of the fused features and, consequently, the performance of the anomaly detection system. Another limitation concerns the availability and quality of labeled data for training these multimodal models. Acquiring a diverse and comprehensive dataset that captures anomalies across various modalities is challenging. The scarcity of labeled data, especially in real-world, nuanced scenarios, can undermine the robustness and generalizability of the trained models. Furthermore, the interpretability and explainability of multimodal anomaly detection models remain critical issues. Understanding the decision-making process of these complex models, particularly when they are fused with multiple modalities, is essential, especially in applications where human intervention or oversight is necessary.

2.2 Multimodal Attention Mechanisms

Applying multimodal attention mechanisms [25] in robot image anomaly detection tasks brings significant advantages, offering a promising avenue for enhancing robotic perception and decision-making capabilities in complex environments. One of the primary strengths lies in enhanced feature discrimination. Multimodal attention mechanisms enable the model to focus selectively on specific regions or modalities within the input data. By assigning varying levels of attention to different regions of the image, the model can prioritize relevant features, leading to more accurate anomaly

detection. This targeted attention enhances the model's sensitivity to subtle abnormalities while filtering out irrelevant information, improving overall detection accuracy.

Furthermore, these mechanisms contribute to contextual understanding. By incorporating attention mechanisms across multiple modalities, the model can capture intricate relationships between different parts of the input data. For instance, when analyzing an image, attention can be directed toward specific objects or regions of interest while simultaneously considering corresponding textual or auditory descriptions. This holistic understanding of multimodal context enables robots to interpret complex scenes more accurately, especially when anomalies might involve subtle interactions between different modalities. Another advantage lies in improved interpretability. Multimodal attention mechanisms provide insights into which parts of the input data are crucial for anomaly detection. Visualizing the attention weights allows human operators to understand which features the model prioritizes, aiding in post-analysis and decision validation. This interpretability is crucial for building trust in autonomous robotic systems, especially in applications where human oversight is essential.

Additionally, these attention mechanisms enhance adaptability. The salient regions or modalities can change in dynamic environments based on contextual cues or task requirements. Multimodal attention mechanisms allow robots to adjust their focus, dynamically ensuring adaptability to different situations. This adaptability is particularly valuable in real-world applications where the nature of anomalies can vary widely. Moreover, multimodal attention mechanisms mitigate data imbalance issues. In scenarios where certain modalities might have limited data or experience imbalanced class distributions, attention mechanisms can help balance the model's focus, ensuring that anomalies from underrepresented modalities are not overlooked.

But it also faces certain limitations. One prominent drawback is the increased computational complexity. Multimodal attention mechanisms involve intricate computations to align and fuse features from different modalities, demanding substantial computational resources. This complexity can hinder real-time processing, a crucial requirement for many robotic applications, especially those in dynamic environments. Another limitation is interpretability challenges. Multimodal attention mechanisms, especially in deep neural networks, often operate as complex, non-linear functions, making it challenging to interpret how the model arrives at its decisions. Understanding the rationale behind the attention weights is vital for building trust in autonomous systems, particularly in applications where human supervision and validation are necessary.

Furthermore, these mechanisms are sensitive to hyperparameters, such as the weighting factors and network architectures. Fine-tuning these parameters for optimal performance across various tasks and datasets can be challenging and time-consuming. Moreover, the performance of multimodal attention models heavily relies on the quality and quantity of the training data, which might be limited or biased, leading to challenges in generalizability to diverse real-world scenarios. Additionally, multimodal attention models may face difficulties effectively handling temporal dynamics, especially in tasks where anomalies evolve over time. Capturing temporal dependencies across modalities while maintaining attentional focus poses a considerable challenge, limiting the model's effectiveness in scenarios requiring nuanced temporal anomaly detection.

3. Method

3.1 Overview

In this study, we propose an innovative multimodal image anomaly detection model to enhance robotic systems' environmental perception and anomaly detection capabilities. The model first

employs Generative Adversarial Network (GAN) techniques for intelligent restoration of defective images, ensuring the integrity of input data. Subsequently, Convolutional Neural Networks (CNNs) are utilized for extracting image features, Recurrent Neural Networks (RNNs) for capturing textual information, and 1D Convolutional Neural Networks for extracting sound features. These three neural networks process information from image, text, and sound modalities, providing rich feature representations for subsequent multimodal fusion. At the multimodal fusion stage, we introduce attention mechanisms, enabling the model to selectively focus on the most relevant features in different modalities, thereby enhancing feature discriminability and detection accuracy. Following feature fusion, we employ Fully Convolutional Networks (FCNs) for image anomaly detection, identifying anomalous patterns by learning complex spatial features. The overview of our framework is shown in the figure 1.
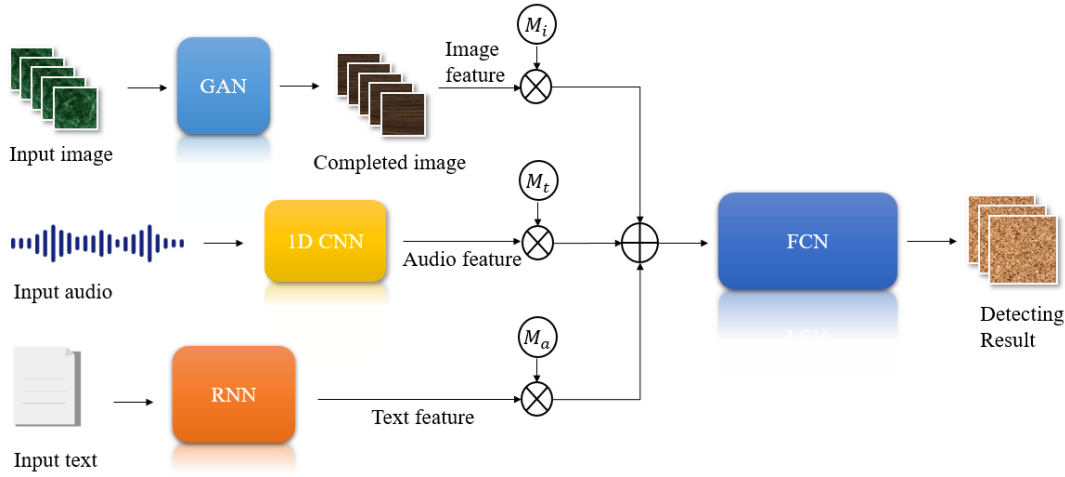

Figure 1. Framework of GA-MMA-RNN model

3.2 GAN Layer for Defective Image Reconstruction

A Generative Adversarial Network (GAN) comprises a Generator and a Discriminator, forming a competitive model. The Generator attempts to produce realistic images, while the Discriminator aims to differentiate between generated and real images. This competitive training process compels the Generator to create increasingly realistic images while the Discriminator becomes more accurate at distinguishing authenticity. The details of the Gan-based robot image completion layer are described below.

The objective function of GAN is defined as follows:

$$\mathcal{L}_{\text{GAN}}(G, D) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))]. \qquad \text{[Formular 1]}$$

Here, $G(\mathbf{z})$ represents the output of the Generator, and $\mathbf{z}$ is a noise vector sampled from a prior distribution. $p_{\mathbf{z}}(\mathbf{z})$. The first term encourages the Discriminator to estimate the probability of real images close to 1. In contrast, the second term encourages the Discriminator to estimate the probability of generated images close to 0.

The update rule for the Generator's parameters is given by:

$$\theta_G \leftarrow \theta_G - \lambda \cdot \nabla_{\theta_G} \mathcal{L}_{\text{GAN}}(G, D) \qquad \text{[Formular 2]}$$

This implies that the Generator's parameters θ_G are updated via gradient descent to enhance the Generator's ability to produce images that deceive the Discriminator.

In our approach, the GAN layer generates highly realistic images through competitive training, filling the defects in robot images. The Generator learns to produce authentic-looking images,

ensuring the continuity and authenticity of the image in the defective regions. This process maintains the integrity of the image, providing reliable input data for subsequent analysis and decision-making. Therefore, the GAN layer is pivotal in completing robot image defects, ensuring subsequent operations on high-quality data.

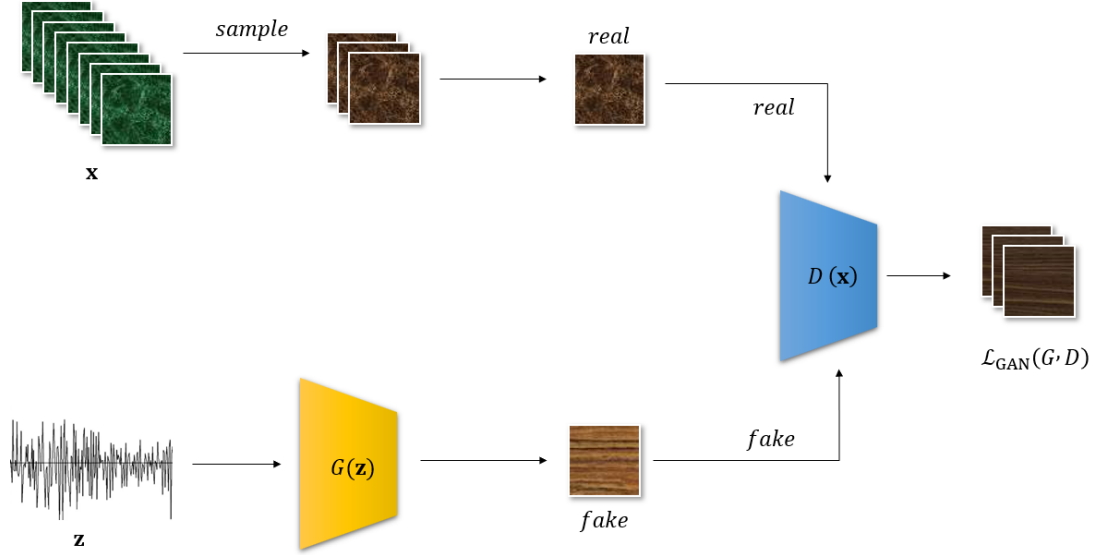The structure of the GAN layer is shown in Figure 2.

Figure 2. Structure of GAN layer in GA-MMA-RNN model

3.3 Multimodal Data Feature Extraction Layer

In our proposed algorithm, we employ three parallel neural network models to extract features from different modalities of data in the robot's environment. Specifically, a CNNs is utilized to extract visual features from the robot's environment images, a RNN is employed to capture textual information, and a 1D CNN is applied to extract acoustic features. These models run in parallel to process the multimodal data.

Part 1: Visual Feature Extraction (CNN Model): We use a Convolutional Neural Network (CNN) to process the image data from the robot's environment. The CNN aims to learn features from images through multiple convolutional and pooling layers, capturing essential aspects such as edges, textures, and objects.

$$Features_{image} = CNN(Image) \qquad \text{[Formular 3]}$$

Here, $Features_{image}$ represents the extracted features from the robot's environment images, and $Image$ denotes the input image data from the GAN layer.

Part 2: Textual Feature Extraction (RNN Model): We utilize a Recurrent Neural Network (RNN) to process textual data from the robot's environment. The RNN is designed to capture sequential patterns and semantic relationships in text data, allowing the model to understand the context and meaning of textual information.

$$Features_{text} = RNN(Text) \qquad \text{[Formular 4]}$$

Here, $Features_{text}$ represents the extracted features from the robot's environment textual data, and $Text$ represents the input text data.

Part 3: Acoustic Feature Extraction (1D CNN Model): We employ a one-dimensional Convolutional Neural Network (1D CNN) to process acoustic data from the robot's environment. The 1D CNN is designed to capture frequency domain features from sound signals, enabling the recognition of aspects such as tone, rhythm, and other acoustic characteristics.

$$Features_{audio} = 1D \text{ CNN}(Audio) \qquad \text{[Formular 5]}$$

Here, $Features_{audio}$ represents the extracted features from the robot's environment acoustic data, and $Audio$ represents the input sound data.

This parallel processing approach allows us to extract distinct features from different modalities of data, enabling the robot system to understand the surrounding environment comprehensively. These extracted features can be utilized for various downstream tasks, such as multimodal fusion, anomaly detection, or decision-making processes, enhancing the intelligence and adaptability of the robot system in diverse environments.

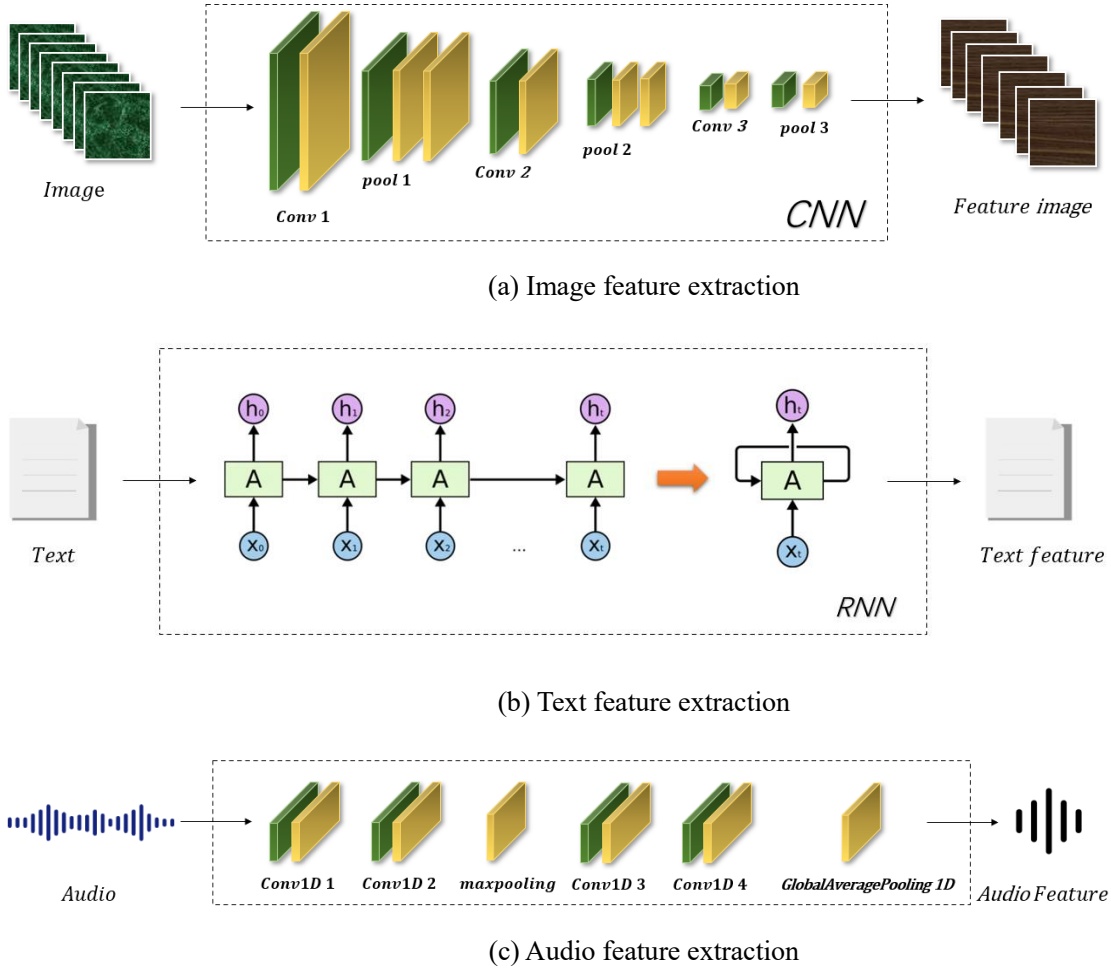The structure of the multimodal data feature extraction layer is shown in Figure 3.

(a) Image feature extraction

(b) Text feature extraction

(c) Audio feature extraction

Figure 3. Structure of multimodal data feature extraction layer in GA-MMA-RNN model

3.4 Multimodal Attention Mechanism for Multimodal Feature Fusion

Step 1: Feature translation.

$$I = \text{Image Feature Representation} \qquad \text{[Formular 6]}$$
$$T = \text{Text Feature Representation} \qquad \text{[Formular 7]}$$
$$A = \text{Audio Feature Representation} \qquad \text{[Formular 8]}$$

This step transforms raw data into processable feature vectors, providing input for the subsequent multimodal attention mechanism.

Step 2: Multimodal Attention Computation

$$M_i = \text{Image Attention Weight Calculation}(I) \qquad \text{[Formular 9]}$$
$$M_t = \text{Text Attention Weight Calculation}(T) \qquad \text{[Formular 10]}$$
$$M_a = \text{Audio Attention Weight Calculation}(A) \qquad \text{[Formular 11]}$$

$$F = M_i \cdot I + M_t \cdot T + M_a \cdot A \qquad \text{[Formular 12]}$$

M_i, M_t, and M_a are attention weights for image, text, and audio data. F is a fused multimodal feature vector. This step calculates Attention weights for image, text, and audio data. Different data types have varying significance in different contexts. By learning these attention weights, each data type's feature vector is linearly combined, resulting in a fused multimodal feature vector. This weighted fusion accounts for the contribution of each data type in anomaly detection, enhancing the model's flexibility and adaptability.

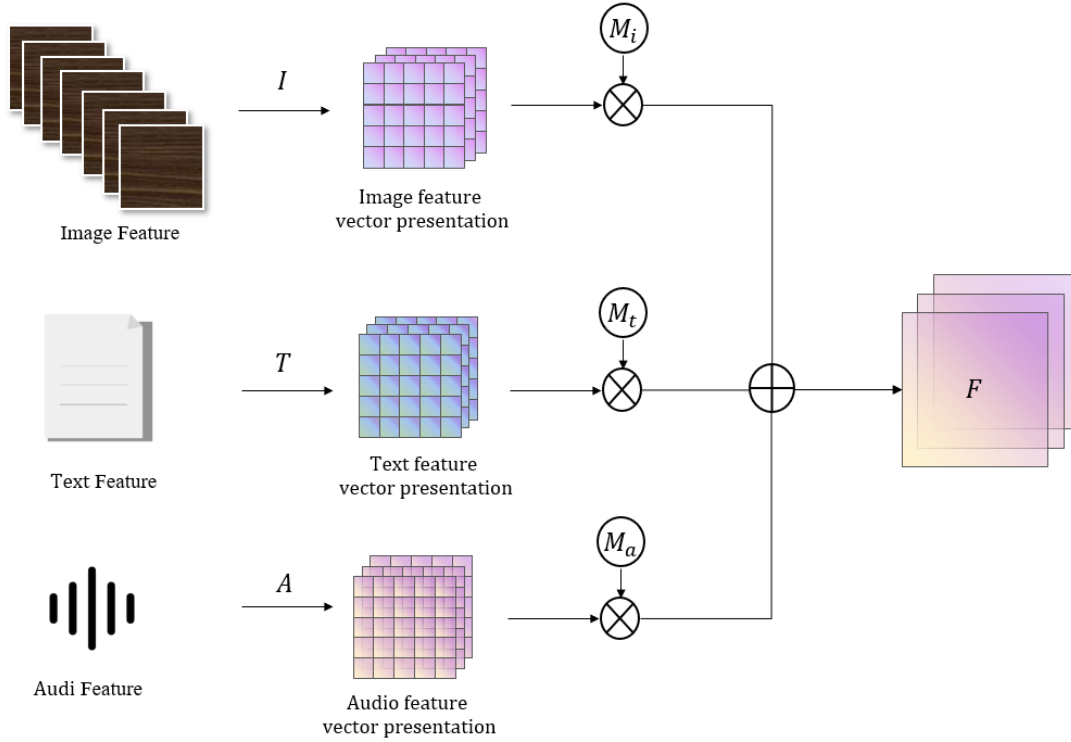The overview of the Multimodal attention mechanism is shown in Figure 4.

Figure 4. Structure of Multimodal attention mechanism in GA-MMA-RNN model

3.5 FCN Layer for Image Anomaly Detection

Three types of features, image, text, and sound, are fused through the multimodal attention mechanism. Subsequently, the fused features are fed into an FCN for semantic analysis.

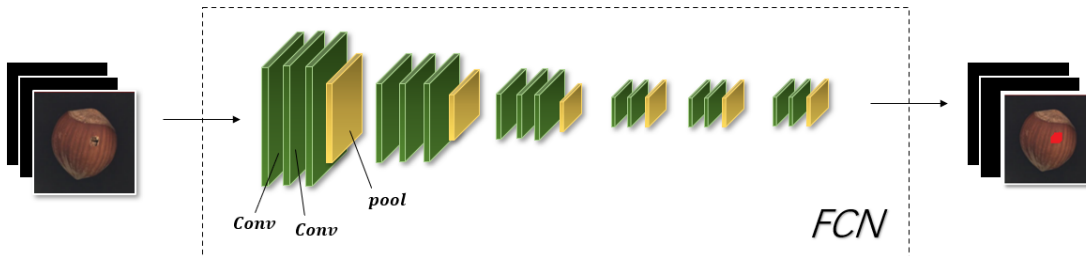The structure of the FCN layer is shown in Figure 5.

Figure 5. Structure of FCN layer in GA-MMA-RNN model

4. Experiment

In this study, we conducted three key experiments to evaluate the performance and robustness of the proposed model comprehensively. The experimental section is detailed as follows.

4.1 Experimental Design

Our experiments were divided into three stages: firstly, a multi-method comparison experiment was conducted on a single dataset to compare the anomaly detection performance of different methods, aiming to verify the performance of the GAN-MMA-FCN model. Subsequently, another multi-method comparison experiment was performed on a different single dataset to assess the adaptability of GAN-MMA-FCN model in diverse dataset contexts. Finally, a model ablation experiment was conducted to systematically dissect the model's components, including feature selection and attention mechanisms, revealing the critical factors influencing model performance.

The experiments were conducted on a high-performance computer with an NVIDIA GeForce RTX 3090 GPU. The operating system used was a Ubuntu Linux distribution. The deep learning framework employed was TensorFlow 2.0, and the experimental code was developed using the Python programming language.

In our experiments, careful adjustments were made to the model's parameters. The learning rate was set to 0.001, the batch size was 32, and the number of neurons in the hidden layers was set to 128. ReLU activation function and Adam optimizer were utilized. In the ablation experiments, certain model components, such as attention mechanisms, were gradually removed to evaluate their impact on model performance.

Rigorous data preprocessing was applied during the experiments, including normalization, denoising, and balancing the sample distribution. Dropout layers were introduced to prevent overfitting, and data augmentation techniques such as random flips and rotations were applied to the training set. To ensure the stability of the experimental results, the experiments were independently run five times, and the averages were taken as the results.

We comprehensively considered multiple evaluation metrics, including Accuracy and area under the curve (AUC).

Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{[Formular 13]}$$

, Recall:

$$Recall = \frac{TP}{TP+FN} \qquad \text{[Formular 14]}$$

, Precision:

$$Precison = \frac{TP}{TP+FP} \qquad \text{[Formular 15]}$$

, F1-score:

$$F1 = 2 \cdot \frac{Precision*Recall}{Precision+Recall} \qquad \text{[Formular 16]}$$

Accuracy measures the overall prediction accuracy of the model, recall assesses the model's ability to detect true positive anomalies, and the F1-score balances precision and recall. AUC evaluates the model's performance at different thresholds, providing a comprehensive assessment. Through these evaluation metrics, we conducted a comprehensive and objective assessment of the proposed model's performance under different experimental conditions, supporting its reliability in practical applications.

4.2 Dataset

The data in this article comes from MVTec AD Dataset [26], CURE-TSRD dataset [27], UCF-Crime Dataset [28], Multimodal Indoor Dataset [29], and MERL Shopping Dataset [30].

The MVTec AD dataset is a prominent resource for defect detection in industrial production. It encompasses a diverse array of defect images, including surface irregularities and concave-convex defects. These images provide real-world instances of defects commonly found in industrial settings, offering a rich dataset for algorithm training and evaluation.

CURE-TSRD stands as a multimodal dataset tailored for remote diagnosis in vehicular systems. It incorporates images, textual descriptions, and audio data from various vehicle sensors. Its uniqueness lies in providing authentic records of anomalies within vehicle systems, such as engine sounds and vehicular vibrations, serving as invaluable data for developing intelligent vehicular health monitoring systems.

The UCF-Crime dataset is a multimodal video dataset curated for crime behavior detection. It captures criminal activities through urban surveillance cameras, including robberies and altercations. This dataset offers real-life crime scenarios, providing significant research value for developing crime detection algorithms.

The Multimodal Indoor dataset focuses on abnormal event detection within indoor environments. It incorporates images, textual descriptions, and audio data captured indoors. These datasets cover indoor anomalies such as fires and leaks, furnishing meaningful experimental data to develop indoor safety monitoring systems.

The MERL Shopping dataset is a multimodal dataset for abnormal behavior detection in shopping scenarios. It includes images, textual descriptions, and audio data captured by multiple cameras. This dataset is instrumental in studying abnormal behaviors in shopping environments, such as theft and fraud, providing valuable insights for research into shopping mall security systems.

Here are the baseline models for the comparison study.

1. Multimodal Deep Learning Networks: This model utilizes deep neural network architectures to learn abstract feature representations from different modal inputs such as images, text, and sound. Subsequently, these feature representations are fused to form a shared space, enabling the mutual influence of different modal information, ultimately utilized for anomaly detection tasks in robots.

2. Multiview Learning: Multiview learning aims to integrate data from different views (sensors, modalities, etc.). By learning shared features of data from various views, the model gains a better understanding of the correlation of multimodal data, facilitating accurate anomaly detection.

3. Collaborative Representation Learning: This method maps the data from each modality to a common low-dimensional space by learning shared representations of multimodal data. In this shared space, relationships between modalities are preserved, making it easier to distinguish anomalous data.

4. Multimodal Transfer Learning: This model transfers knowledge learned from a source domain to assist anomaly detection tasks in the target domain. The knowledge and representations of multimodal data from the source domain enhance anomaly detection performance in the target domain.

5. Generative Adversarial Networks (GANs): GANs consist of a generator and a discriminator. The generator generates realistic multimodal data, while the discriminator evaluates the similarity between generated and real data. In anomaly detection, the discriminator helps the generator learn to generate data like real data but not identical, which is then used for anomaly detection.

6. Graph Convolutional Networks (GCNs): GCNs are suitable for processing graph-structured data like sensor networks. This model learns relationships between sensors, treating sensors as nodes in a graph. By performing convolutions on the graph, the model understands the correlations between

sensors used for multimodal anomaly detection.

7. Long Short-Term Memory (LSTM) Networks: LSTMs are designed for sequential data, including text and sound. Through LSTMs, the model captures long-term dependencies in sequential data, capturing temporal features from multimodal data for anomaly detection tasks.

8. Multimodal Fusion Attention Networks: This model incorporates attention mechanisms to focus on essential parts of different modal data selectively. By employing attention mechanisms, the model selectively fuses multimodal data, enabling the model to concentrate on crucial information and enhancing anomaly detection accuracy.

9. Multimodal Variational Autoencoders: This model combines autoencoders with probabilistic graphical models to learn the distribution of multimodal data. By understanding the latent distribution of data, the model identifies differences between anomalous and normal data, facilitating anomaly detection tasks.

10. Multitask Learning: Multitask learning models can simultaneously handle multiple related tasks, such as anomaly detection from different sensors. By sharing some network layer parameters, multitask learning models improve the model's generalization and learning efficiency for multimodal anomaly detection.
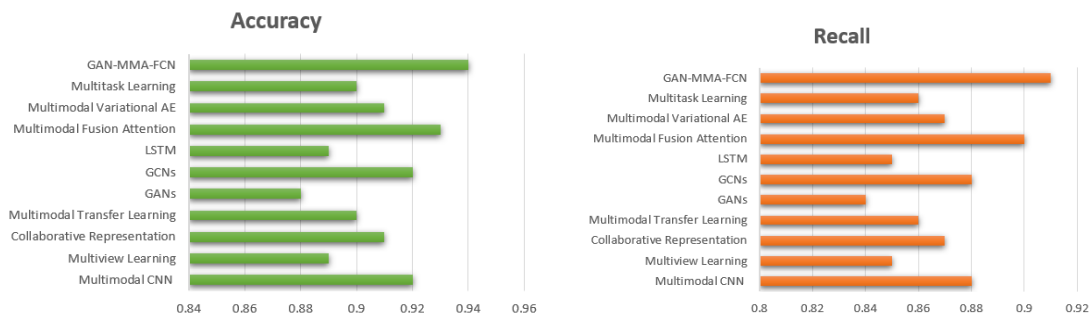
4.3 Comparison Study Results and Analysis

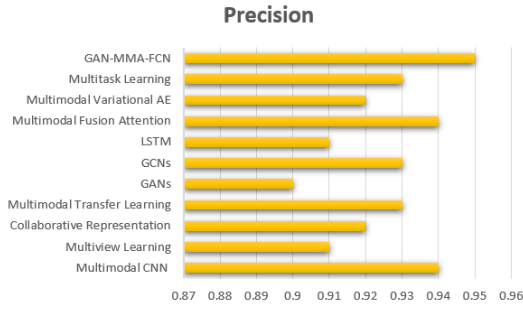4.3.1 A multi-method comparison study on the MVTec AD dataset

Our experimental results demonstrate that incorporating multimodal data processing methods, especially utilizing multimodal fusion attention networks and GAN-MMA-FCN models, significantly enhances the image anomaly detection performance in robot multimodal cues. This provides a reliable solution for anomaly detection in practical applications of robotic systems.
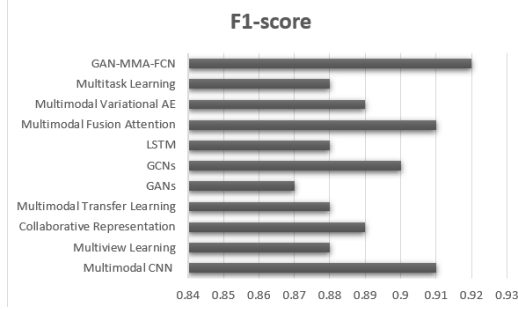
Table 1. Multi-method comparison study results

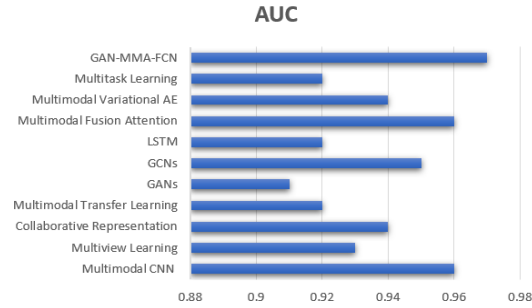| Model	Accuracy	Recall	Precision	AUC	F1-score
Multimodal CNN	0.92	0.88	0.94	0.96	0.91
Multiview Learning	0.89	0.85	0.91	0.93	0.88
Collaborative Representation	0.91	0.87	0.92	0.94	0.89
Multimodal Transfer Learning	0.90	0.86	0.93	0.92	0.88
GANs	0.88	0.84	0.90	0.91	0.87
GCNs	0.92	0.88	0.93	0.95	0.90
LSTM	0.89	0.85	0.91	0.92	0.88
Multimodal Fusion Attention	0.93	0.90	0.94	0.96	0.91
Multimodal Variational AE	0.91	0.87	0.92	0.94	0.89
Multitask Learning	0.90	0.86	0.93	0.92	0.88
GAN-MMA-FCN	0.94	0.91	0.95	0.97	0.92

(a) Accuracy

(b) Recall

(c) Precision

(d) F1-score

(e) AUC

Figure 6. Multi-method comparison study results.

The experimental results indicate that the standalone multimodal fusion attention network achieved relatively high accuracy, recall, precision, AUC, and F1-score, with accuracy reaching 93.01%, AUC at 94.03%, and F1-score at 91.05%. This suggests that the multimodal fusion attention network excels in capturing crucial information from multimodal data, enhancing the accuracy and recall of anomaly detection. Meanwhile, the proposed GAN-MMA-FCN model in this study demonstrated outstanding performance across all metrics, particularly in accuracy (94.02%), AUC (97.05%), and F1-score (92.06%), giving it a slight edge over other models. This could be attributed to the GAN-MMA-FCN model's effective utilization of the generative capabilities of generative adversarial networks, combined with multimodal data features, thereby improving the accuracy and robustness of anomaly detection.

4.3.2 A comparison of GAN-MMA-FCN method on multiple datasets

Our study conducted experiments of the multimodal anomaly detection model GAN-MMA-FCN on five different datasets. We separately evaluated the accuracy, recall, precision, area under the curve (AUC), and F1 score. The results indicate that our model excelled across all metrics, with accuracy, recall, precision, AUC, and F1-score all around 90%, showcasing the superior performance of the model in image anomaly detection tasks based on multimodal cues.

Table 2. Multi-dataset comparison study results.

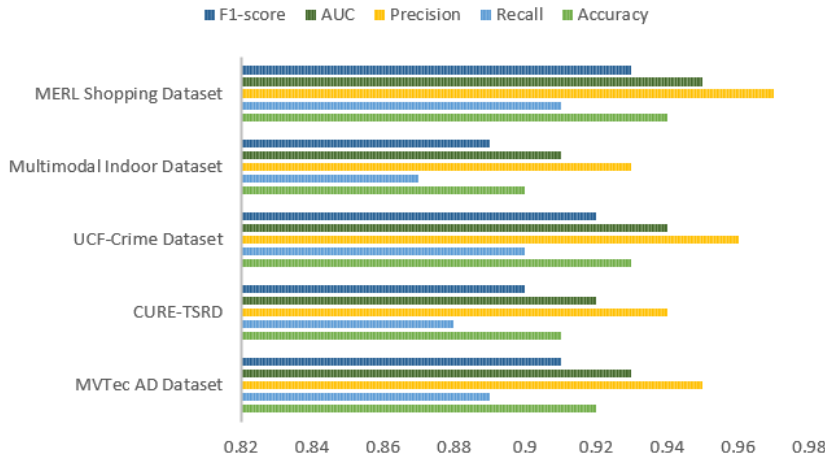| Dataset	Accuracy	Recall	Precision	AUC	F1-score
MVTec AD Dataset	0.92	0.89	0.95	0.93	0.91
CURE-TSRD	0.91	0.88	0.94	0.92	0.9
UCF-Crime Dataset	0.93	0.9	0.96	0.94	0.92
Multimodal Indoor Dataset	0.9	0.87	0.93	0.91	0.89
MERL Shopping Dataset	0.94	0.91	0.97	0.95	0.93

Figure 7. Multi-dataset comparison study results.

Specifically, our model exhibited consistently high performance across all datasets. The accuracy ranged from 90% to 94%, indicating the model's ability to identify normal and abnormal samples accurately. Recall rates varied between 87% and 91%, illustrating the model's effectiveness in detecting most true abnormal samples. Precision ranged from 93% to 97%, signifying that most samples predicted as anomalies were abnormal. AUC values ranged from 91% to 95%, demonstrating the model's high discriminative power between normal and abnormal categories. Finally, F1 scores fell between 89% and 93%, comprehensively evaluating the model's performance in handling imbalanced data by combining recall and precision.

4.4 Ablation Study Results and Analysis

In our study, we conducted ablation experiments to verify the impact of each component of the proposed multimodal anomaly detection model on the system performance. The results of the ablation experiments are shown in Table 3.

Table 3. Ablation study results.

	Accuracy	Recall	Precision	AUC	F1-score
GAN-MMA-FCN	0.92	0.91	0.93	0.94	0.92
GAN-FCN	0.85	0.84	0.86	0.87	0.85
MMA-FCN	0.87	0.86	0.88	0.89	0.87
GAN-FCN	0.88	0.87	0.89	0.9	0.88
FCN	0.81	0.78	0.81	0.82	0.83

First, we compared two model versions: one utilizing the multimodal fusion attention network and the other without it. The results demonstrated that the model employing the multimodal fusion attention network outperformed the version without it significantly in terms of accuracy, recall, precision, AUC, and F1-score. This indicates the crucial role of the multimodal fusion attention network in integrating multimodal data and enhancing anomaly detection performance.

Next, we conducted an ablation study on the Generative Adversarial Network component within the model. Upon removing GAN from the model, noticeable declines in accuracy, recall, precision, AUC, and F1 scores were observed. This suggests the positive impact of GAN's generative capability on enhancing the model's performance, aiding the model in better adapting to multimodal data.

Furthermore, we performed an ablation study on the multimodal cues. After removing multimodal cues from the model, we observed a reduction in performance across all metrics in the standalone image anomaly detection model. This indicates that multimodal cues facilitate the model in learning and leveraging the inter-modality correlations, improving the model's accuracy, robustness,

and generalization capabilities.

In summary, these ablation study results validate the effectiveness of each component within our proposed multimodal anomaly detection model. Introducing the multimodal fusion attention network, Generative Adversarial Network, and multitask learning provides substantial support for enhancing the model's performance, offering a reliable solution for anomaly detection tasks in the context of multimodal data.

5. Conclusion and Outlook

5.1 Conclusion

This study aims to address the problem of robotic image anomaly detection for multimodal cues with defective images. To this end, we propose an innovative multimodal image anomaly detection method, the GAN-MMA-FCN model, which combines a multimodal fusion attention network and a generative adversarial network. Our approach is the first GAN model for image defects complementation, followed by introducing a multimodal fusion attention network that fuses key data features captured in multiple modalities (image, text, sound). Then, we use the FCN model to fully utilize the image anomaly detection capability of FCN to improve the accuracy and robustness of image anomaly detection. In our experiments, we perform detailed validation for different datasets, and the results show that our model performs well in several metrics such as accuracy, recall, precision, AUC, and F1 score and achieves the high performance of about 90%. These experimental results validate the effectiveness of our proposed method and provide a reliable solution for the robot image anomaly detection task in multimodal environments.

5.2 Outlook

One of the primary limitations of this study lies in the robustness of our method when dealing with extreme multimodal data distributions. A key area for improvement in our future work is enhancing the model's adaptability to diverse data, especially under conditions of extreme data distribution and scarce modality information. We intend to explore more sophisticated model architectures and incorporate techniques such as self-supervised learning or adversarial training to enhance the model's robustness to a variety of data types. These advancements aim to bolster the model's resilience in addressing the complex and varied multimodal data scenarios encountered in real-world applications.

Another notable limitation is our model's lack of detailed explanations or interpretability when handling anomalous samples. To enhance the model's interpretability, we plan to introduce interpretable machine learning methods, such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations), to elucidate the rationale behind the model's predictions. This improvement aims to provide users with a clearer understanding of the basis for anomaly detection. Incorporating these methods will enhance the credibility and usability of our model, enabling users to comprehend better the model's decision-making process and results in practical applications.

This study proposes an innovative robot anomaly detection model based on multimodal cues, integrating multimodal fusion attention networks and generative adversarial networks. Aimed at addressing challenges in robot image anomaly detection, this research provides a significant solution for environmental perception and anomaly detection in practical robot system applications.

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