WORLD LAUREATES FORUM
世界顶尖科学家论坛
国际工程智能大会
2026 International Conference on AI for Engineering
World Laureates Foundation
上海世界顶尖科学家发展基金会
2026
工程智能研究院
INSTITUTE OF AI FOR ENGINEERING

Anomaly Detection and Generation with Diffusion Models: A Survey

IEEE Transactions on Pattern Analysis and Machine Intelligence (中科院一区TOP；CCF A)

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01 ABSTRACT

Anomaly detection suffers from scarce abnormal data and heterogeneous distributions. **Diffusion** models provide powerful distribution modeling and controllable generation, yet prior reviews often separate detection from generation. This survey presents a unified **ADGDM** perspective across **image, video, time series, tabular, and multimodal data,** establishing a taxonomy of scoring and **conditioning strategies** and revealing a synergistic **detection–generation cycle for practical applications.**

Research question

How can diffusion models unify anomaly detection and generation across heterogeneous modalities?

02 METHOD

ADGDM is organized around three anomaly-scoring paradigms—**reconstruction-, density-, and score-based methods**—and two conditioning strategies: **unconditional and conditional diffusion**. We examine advances across **image, video, time series, tabular, and multimodal AD,** followed by anomaly generation, evaluation resources, challenges, and future opportunities.

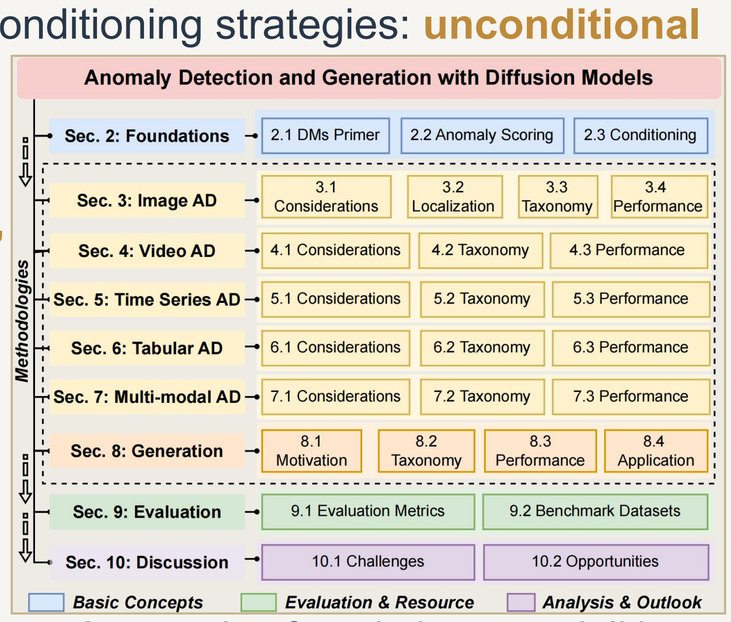


Figure 1. ADGDM framework spanning foundations, modalities, evaluation, and outlook

Survey Details

Scope: 5 AD modalities + anomaly generation
Taxonomy: 3 scoring paradigms + 2 conditioning strategies
Analysis: Methods, performance, datasets & metrics
Resources: Benchmarks, implementations & GitHub

03 RESULTS

Diffusion-based anomaly detection has grown rapidly from 2021–2025. Among surveyed AD papers, **TSAD accounts for 41%**, followed by **VAD (29%)** and **IAD (22%)**, highlighting strong momentum in sequential-data settings.

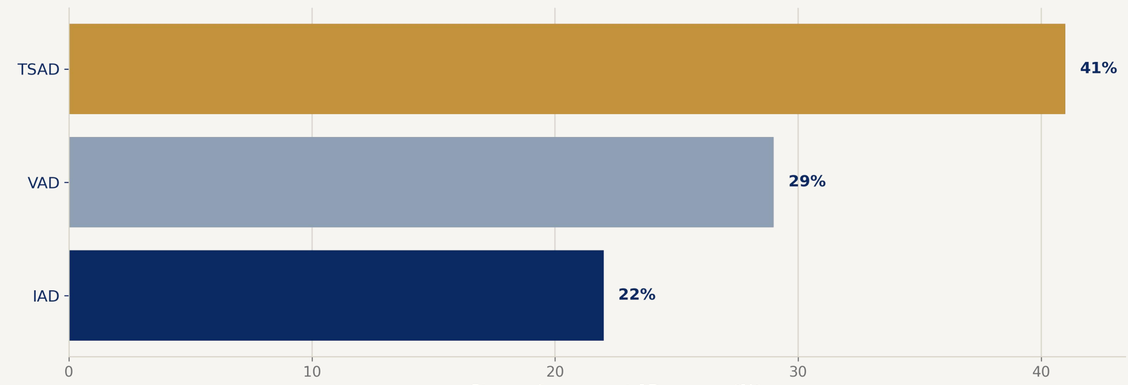


Figure 2. Modality distribution of surveyed AD papers.

Unlike modality-specific reviews, **ADGDM jointly covers detection and generation** within a unified cross-modal framework.

Table 1. Unified coverage of the ADGDM survey.

Dimension	Coverage
Modalities	IAD · VAD · TSAD · TAD · MAD
Tasks	Detection + Generation
Scoring	Reconstruction · Density · Score
Conditioning	Unconditional · Conditional

Key Insight

Detection ↔ Generation
Generation alleviates **anomaly scarcity**, while detection feedback enables **more targeted synthesis**.

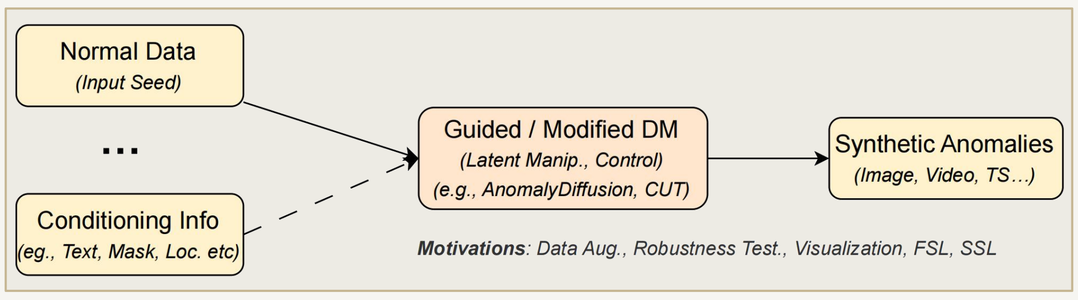


Figure 3. Guided diffusion for controllable anomaly generation.

Synthetic anomalies support **data augmentation, robustness testing, and self-supervised learning.**

04 DISCUSSION

Scalability & efficiency: iterative denoising remains costly for high-dimensional data.
Generalization & imbalance: domain shifts and rare anomalies limit robustness.
Identity shortcuts: reconstruction masks anomalies.

05 CONCLUSIONS

This survey unifies diffusion-based anomaly detection and generation across five modalities, connecting taxonomy, evaluation, and applications. It highlights **efficient architectures, adaptive conditioning, hybrid methods, and LLM/VLM integration** toward practical anomaly intelligence.

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