# Diffusion Models with Auxiliary Reconstruction for Tabular Data Generation and Classification

Assignee Research

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**Abstract**

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: How does integrating auxiliary reconstruction tasks affect the sample quality and downstream classification accuracy of diffusion models trained on the OpenML-CC18 tabular benchmark. 12 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: Guiding diffusion models to reconstruct flow fields from sparse data. Research question: How does integrating auxiliary reconstruction tasks affect the sample quality and downstream classification accuracy of diffusion models trained on the OpenML-CC18 tabular benchmark?.

## 2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.2/10.

## 3 Results

13 papers retrieved. 12 claims extracted; 0 independently verified. Quality review score: 4.2/10.

## 4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

## 5 Extracted Claims

| Claim | Verified | Confidence |
|---|---|---|
| The ConFIGu training method outperforms existing approaches in generating physically consistent samples for 2D Kolmogoro | × | 0.05 |
| The masked diffusion sampling method effectively reconstructs sparse data, preserving fine-grained details and structura | × | 0.13 |
| The 2D Kolmogorov flow dataset contains 4240 samples of size 256$\times$256, with 3000 samples used for training and 1240 for t | × | 0.03 |
| The Reynolds number Re for the 2D Kolmogorov flow is set to 1000. | × | 0.01 |
| The 3D isotropic turbulence dataset consists of 500 snapshots at a resolution of 1283, with 400 samples used for trainin | × | 0.03 |
| The divergence of the flow field $\nabla$$\cdot$u is used as the metric for physics consistency in the 3D turbulent scenario. | × | 0.06 |
| The masked diffusion method with N=100 outperforms other methods in the benchmark tables. | × | 0.06 |
| Dynamic Mode Decomposition (DMD) has been used to extract coherent structures and correlation features of fluid flow. | × | 0.03 |
| Callaham et al. used sparse representation to reconstruct target states from a dictionary of precomputed examples, showi | × | 0.04 |
| Loiseau et al. presented a sparse reduced-order modeling framework combining feature extraction, sparse nonlinear dynami | × | 0.03 |
| Zaki et al. proposed a hybrid approach bridging physics-based modeling and data-driven optimization for reconstructing t | × | 0.06 |
| Deng et al. tried reconstructing flows using discrete point measurements and non-time-resolved PIV measurements based on | × | 0.04 |

## References


- http://arxiv.org/abs/2510.19971v2

- http://arxiv.org/abs/2504.20900v1
- http://arxiv.org/abs/2502.17119v2