

Comparative F1-Score Analysis of Tabular Foundation Models Fine-Tuned on SCM versus Diffusion-Augmented Data for Imbalanced

Assignee Research

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Abstract

This paper proposes a novel data augmentation scheme called the conditional generative adversarial network minority-class-augmented oversampling scheme (CTGAN-MOS) for solving class imbalance problems. Our methodology encompassed six key steps: data engineering using sophisticated pre-processing techniques, identifying the type of vulnerabilities present in the data, curating good quality synthetic data using the CTGAN model, the intelligent fusion of real and synthetic data, noise removal from the augmented data using coin-throwing algorithm, and building classifiers with the high-quality aug

1 Introduction

This paper examines: CTGAN-MOS: Conditional Generative Adversarial Network Based Minority-Class-Augmented Oversampling Scheme for Imbalanced Problems. Research question: How does the F1-score of tabular foundation models fine-tuned on SCM-generated synthetic data compare to those using diffusion-based augmentation when evaluated on imbalanced datasets like Adult and Credit?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.2/10.

3 Results

12 papers retrieved. 10 claims extracted; 9 independently verified. Quality review score: 7.2/10.

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
CTGAN-MOS is a conditional generative adversarial network based minority-class-augmented oversampling scheme designed fo	✓	0.40
The CTGAN-MOS methodology encompasses six key steps: data engineering, identifying vulnerabilities, curating synthetic d	✓	0.30
CTGAN-MOS maintains higher structural similarity between original and resampled data by adding high-quality samples only	✓	0.34
Some existing augmentation techniques add records to the majority class, leading to poor-quality resampled data.	✓	0.29
CTGAN-MOS removes noisy samples from the data using a coin-throwing algorithm.	✓	0.25
Noise removal from augmented data has remained unexplored in previous CTGAN-based data augmentation schemes.	✓	0.23
CTGAN-MOS augments data by adding fewer records compared to existing schemes while offering comparable performance.	✓	0.28
Experiments for CTGAN-MOS were conducted on benchmark datasets.	×	0.15
CTGAN-MOS demonstrates improvement over existing state-of-the-art techniques in terms of accuracy, recall, precision, F1	✓	0.26
CTGAN-MOS yielded accuracy values of 100% on specific datasets or scenarios mentioned in the study.	✓	0.16

References

- <https://doi.org/10.1109/access.2023.3303509>

- <https://doi.org/10.3389/fdata.2023.1296508>
- <https://doi.org/10.3390/make5010019>