Uncertainty-Aware Medical Image Synthesis Using Diffusion Transformer for Imbalanced Classification

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1) The Problem: Class Imbalance in Medical Imaging

Rare but critical — minority classes are the hardest to classify, yet the most important.

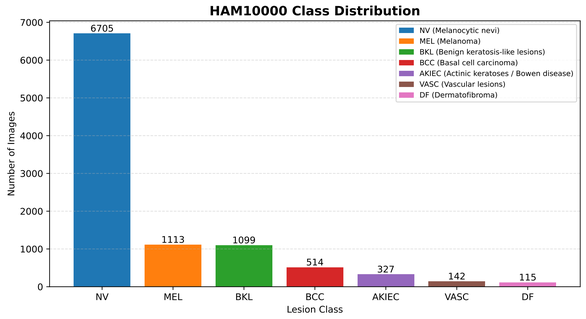


Figure 1. Class distribution of HAM10000 dataset [3] — severe imbalance across 7 skin lesion categories.

Models trained on such data become biased toward majority classes — failing on rare but critical conditions.

2) Existing Approaches & Baseline

Method	Approach	Limitation
Re-weighting	Loss re-weighting	Ignores feature distribution
Oversampling (SMOTE)	Feature interpolation	Low quality samples
GAN-based Aug	Image synthesis	Training instability
Diffusion Models	High quality synthesis	No uncertainty control
IOIS (Baseline) [2]	Online synthesis + AAS	Standard Diffusion Models, Accuracy-based sampling

Table 1. Comparison of existing approaches and baseline.

We extend IOIS with DiT-RAE and uncertainty-aware adaptive sampling for robust imbalanced classification.

3) Research Gap & Motivation

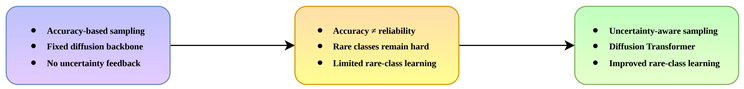


Figure 2. From existing methods to our proposed approach.

4) Proposed Framework

How can we synthesize high-quality, uncertainty-guided samples to address class imbalance in medical imaging?

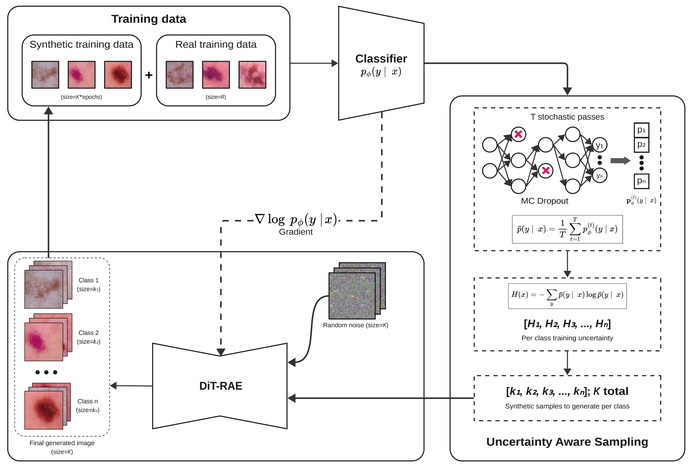


Figure 3. This is the proposed DiT-RAE and uncertainty aware sampling based framework. It comprises three components, which are iteratively performed: training classifier, entropy-guided sampling, and generating images via DiT-RAE in an online fashion.

5) Key Contributions & Results

- Diffusion Transformers with Representation Autoencoders (DiT-RAE) the generative backbone for high-quality medical image synthesis.
- Uncertainty-aware adaptive sampling prioritizes informative samples using entropy feedback.
- Classes with higher uncertainty (entropy) receive more synthetic samples, while well-learned classes receive fewer — outperforming accuracy-based sampling in imbalanced settings.
- Unified framework integrating DiT-RAE synthesis with uncertainty-aware sampling.

Visualization Results

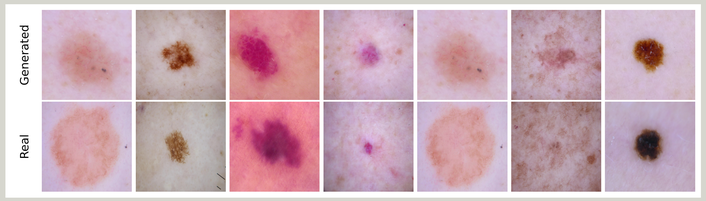


Figure 4. Visualization of synthetic images generated from proposed framework vs real images from HAM10000 dataset.

Quantitative Results

Method	Macro-F1	B-ACC	MCC
StyleGAN2-ADA [1]	80.03	80.14	78.82
IOIS (Baseline) [2]	81.97	81.50	80.64
Mamba-DDPM-BSA [4]	82.71	82.14	81.03
Ours	86.00	84.04	84.30

Table 2. Comparison with state-of-the-art methods on HAM10000 dataset.

6) Future Work

- *Evaluate framework generalizability across diverse medical imaging domains.*
- *Incorporate quality-based filtering of synthetic samples before classifier training.*

References

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