Unsupervised Learning with Variational Autoencoders for Hybrid Music Clustering

Updated Report with Experimental Results

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Course: Neural Networks (CSE425)

Date: January 2026

Abstract

We describe a thorough investigation on unsupervised clustering of songs employing the concept of Variational AutoEncoders (VAE) on the Free Music Archive (FMA) corpus. In this study, we assess a variety of VAE models, such as the basic VAE model, Convolutional VAE (Conv-VAE), Beta-VAE, and Conditional VAE (CVAE), for their ability to learn feature representation in musical audio and texts. In our implementation, we test multi-modal learning approaches by merging the learned audio spectral information with the learned text representation obtained by automatic speech-to-text processing. Results on a set of 3,081 songs show the superiority of the Beta-VAE model in clustering, yielding a high Silhouette Score value of 0.5264 and Calinski Harabasz Index value of 12,275.12.

1. Introduction

1.1 Motivation

Music Information Retrieval (MIR) or music organization is a difficult task in the field of machine learning due to the complexity of music data. In traditional music classification or organization tasks, feature extraction is done by humans through dimensionality reduction techniques such as PCA. In music data, such features might not represent the complexity in music data adequately. Additionally, Variational Autoencoders can handle this problem.

1.2 Problem Statement

This project addresses the challenge of unsupervised music clustering using hybrid features derived from both audio content and lyrical information. Specifically, we aim to:

1. Extract meaningful latent representations from music using VAE architectures

2. Combine audio spectral features (MFCCs) with lyrics embeddings for multi-modal learning
3. Compare multiple VAE variants (standard, convolutional, Beta-VAE, CVAE) for clustering performance
4. Evaluate against baseline methods using comprehensive clustering metrics

1.3 Contributions

- Implementation of four VAE architectures optimized for music feature learning
- Multi-modal fusion framework combining audio and lyrics using Whisper and Sentence-BERT
- Comprehensive evaluation using six clustering quality metrics
- Comparative analysis with baseline methods (PCA, standard autoencoder, direct K-Means)
- Detailed ablation studies on fusion strategies and architectural choices

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2. Experimental Setup

2.1 Hardware & Software Configuration

Component	Specification
GPU	NVIDIA Tesla T4 (15.83 GB VRAM)
CUDA Version	12.6
PyTorch	2. 9.0+cu126
Python	3.10
Key Libraries	scikit-learn, librosa, OpenAI Whisper, Sentence-Transformers

2.2 Dataset Overview

Free Music Archive (FMA) - Small Subset:

- Total tracks processed: 3,081
- Unique genres identified: 8 primary genres
- Audio features extracted: 20-dimensional MFCCs + 140-dimensional spectral features
- Lyrics extracted via Whisper speech-to-text transcription
- Text embeddings: 384-dimensional vectors from Sentence-BERT (all-MiniLM-L6-v2)

2.3 Genre Distribution (Initial Dataset: 106,574 tracks)

Genre	Count
Rock	14,182
Experimental	10,608
Electronic	9,372
Hip-Hop	3,552
Folk	2,803
Pop	2,332
Instrumental	2,079
International	1,389
Classical	1,230
Jazz	571
Other	1,476

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3. Feature Engineering Pipeline

3.1 Audio Processing

- 20 Mel-Frequency Cepstral Coefficients (MFCCs): Primary low-level audio features

- 140-dimensional spectral features: Extended representation for convolutional architectures
- Standardization: Z-score normalization applied to all audio features
- Processing time: 9 minutes 8 seconds for 3,081 tracks across 70 audio folders

3.2 Lyrics Extraction & Embedding

- Speech-to-Text: OpenAI Whisper (base model) for audio transcription
- Text Embedding: Sentence-BERT encodes lyrics to 384-dimensional vectors
- Normalization: L2 normalization applied to all embeddings
- Hybrid subset (493 tracks): Only 9 vocal tracks identified; 484 tracks are instrumental/minimal

Lyrics Quality Statistics:

Statistic	Value
Vocal tracks	9 (1.8%)
Instrumental/minimal	484 (98.2%)
Mean embedding value	-0.0001
Standard deviation	0.0510
Min value	-0.2029
Max value	0.4062

3.3 Multi-Modal Feature Fusion Strategies

Strategy	Description	Dimensions
Concatenation	Direct audio + lyrics concatenation	404
Weighted Fusion	PCA-reduced audio (0.6) + lyrics (0.4)	64
PCA-Reduced	Dimensionality reduction on concatenation (99.99% variance)	64

4. VAE Architectures & Training Results

4.1 Standard VAE (Easy Task) - Hybrid

Features Architecture:

- Input: 404 dimensions (audio + lyrics)
- Encoder: [404 → 512 → 256 → 32]
- Decoder: [32 → 256 → 512 → 404]
- Total parameters: 759,508

Training Configuration:

- Optimizer: Adam (lr=0.001)
- Batch size: 256
- Epochs: 100
- Learning rate schedule: Step decay (γ=0.5 every 20 epochs)
- Training time: 46.33 seconds

Training Loss Progression:

Epoch	Loss	Learning Rate
10	32.8423	0.001000
20	20.3699	0.001000
30	17.7039	0.001000
50	16.4313	0.001000
70	16.2909	0.000500
90	15.7844	0.000125
100	16.1627	0.000063

4.2 Convolutional VAE (Medium

Task) Architecture:

- Input: 140-dimensional spectral features
- Encoder: Conv1D [1 → 32 → 64 → 128 → 256]
- Decoder: ConvTranspose1D [256 → 128 → 64 → 32 → 1]
- Latent dimension: 32 (reshaped from 16)
- Total parameters: 534,849
- Regularization: Batch Normalization + Dropout (0.2)

4.3 Beta-VAE (Hard

Task) Architecture:

- Input: 20 dimensions (audio MFCCs only)
- Encoder: [20 → 512 → 256 → 128 → 32]
- Decoder: [32 → 128 → 256 → 512 → 20]
- Beta parameter: $\beta = 4.0$
- Total parameters:

365,908 Training Results:

Metric	Value
Total Loss	17.9625
Reconstruction Loss	15.7037
KL Divergence Loss	0.5647
Loss Reduction	42.64%
Training Time	35.08 seconds

4.4 Conditional VAE (Hard Task) Architecture:

- Encoder input: 21 (20 audio features + 1 genre condition)
- Decoder input: 33 (32 latent + 1 genre condition)
- Hidden layers: [512, 256, 128]
- Total parameters: 312,660
- Conditioning: One-hot encoded genre labels

Training Results:

Metric	Value
Total Loss	12.9078
Reconstruction Loss	9.3730
KL Divergence Loss	3.5348
Loss Reduction	40.20%
Training Time	38.08 seconds

5. Experimental Results

5.1 Task 1: Standard VAE with Hybrid Features (493 tracks) Clustering Method: K-Means (k=8)

Method	Silhouette ↑	CH Index ↑	DB Index ↓
VAE + K-Means	0.0717	39.80	—
PCA + K-Means (Baseline)	0.0707	46.51	—
Improvement	+1.52%	-14.42%	—

Cluster Distribution (VAE + K-Means):

Cluster	Tracks	Percentage
Cluster 0	6	1.2%
Cluster 1	127	25.8%
Cluster 2	34	6.9%
Cluster 3	23	4.7%
Cluster 4	78	15.8%
Cluster 5	146	29.6%
Cluster 6	57	11.6%
Cluster 7	22	4.5%

5.2 Task 2: Conv-VAE with Multiple Algorithms (3,081 tracks) Algorithm Comparison:

Algorithm	Silhouette ↑	CH Index ↑	DB Index ↓	ARI ↑
K-Means	0.1031	374.91	1.8782	0.0000
Agglomerative	0.0408	295.07	2.3264	0.0000
DBSCAN	0.4862	30.74	0.5893	0.0000

Key Findings:

- DBSCAN achieved highest Silhouette Score (0.4862) but identified only 2 clusters with 210 noise points (6.8%)
- K-Means provides best balanced performance
- Agglomerative clustering shows poorest metrics

Baseline Comparison:

Method	Silhouette ↑	CH Index ↑	DB Index ↓	ARI ↑
Conv-VAE + K-Means	0.1031	374.91	1.8782	0.0000
PCA + K-Means	0.0534	288.07	2.4417	0.0000
Autoencoder + K-Means	0.0296	168.61	2.6522	0.0000
Direct K-Means	0.0490	281.21	2.4904	0.0000

Performance Gains:

- Conv-VAE vs PCA: +93.1% Silhouette, +30.1% CH Index
- Conv-VAE vs Autoencoder: +248.3% Silhouette, +122.4% CH Index
- Conv-VAE vs Direct: +110.4% Silhouette, +33.3% CH Index

5.3 Task 3: Beta-VAE, CVAE, and Multi-Modal Fusion (3,081 tracks)

5.3.1 Individual VAE Architecture Performance

Method	Silhouette ↑	CH Index ↑	DB Index ↓	ARI ↑	NMI ↑	Purity ↑
Beta-VAE	0.5264	12,275.12	0.5314	-0.0003	0.0032	0.1477
CVAE	0.1122	325.73	1.7007	-0.0002	0.0036	0.1457
Conv-VAE	0.1031	374.91	1.8782	-0.0002	0.0035	0.1470

Beta-VAE Dominance:

- Silhouette Score: 5.11× better than ConvVAE
- CH Index: 32.7× better than Conv-VAE
- DB Index: 3.54× better (lower is better)
- Wins 3 out of 6 primary metrics

5.3.2 Multi-Modal Fusion Strategy Results

Method	Silhouette ↑	CH Index ↑	DB Index ↓	ARI ↑	NMI ↑	Purity ↑
Beta-VAE	0.5264	12,275.12	0.5314	-0.0003	0.0032	0.1477
Weighted Avg	0.1186	466.16	1.6994	-0.0004	0.0034	0.1506
Concat (H+B+C)	0.0954	273.21	1.8452	0.0005	0.0045	0.1496
PCA Reduced	0.0954	273.24	1.8450	0.0005	0.0045	0.1506
With Genre Info	0.0954	273.24	1.8450	0.0005	0.0045	0.1506

Multi-Modal Fusion Analysis:

- Single-modality Beta-VAE outperforms all fusion strategies
- Multi-modal concatenation shows slight improvements in ARI (0.0005) and NMI (0.0045)
- Weighted averaging provides second-best overall performance (Silhouette: 0.1186)
- Genre information does not improve clustering—only one dominant genre in subset

5.3.3 Best Performing Methods Summary

Metric	Best Method	Score
Silhouette Score	Beta-VAE	0.5264
Calinski-Harabasz Index	Beta-VAE	12,275.12
Davies-Bouldin Index	Beta-VAE	0.5314
Adjusted Rand Index	MM-Concat	0.0005
Normalized Mutual Information	MM-Concat	0.0045
Cluster Purity	MM-Weighted Avg	0.1506
Overall Winner	Beta-VAE	(3/6 metrics)

Training Efficiency Analysis

Model	Parameters	Training Time	Epochs	Loss Reduction
Standard VAE	759,508	46.33s	100	—
Conv-VAE	534,849	—	—	—
Beta-VAE	365,908	35.08s	100	42.64%
CVAE	312,660	38.08s	100	40.20%

GPU Optimization Strategies Applied:

- Batch size 256 (3-4× faster than batch size 64)
- Batch normalization for better gradient flow
- Memory pinning (15% speedup in data loading)
- Non-blocking GPU transfers
- Learning rate scheduling with step decay

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6. Discussion & Analysis

6.1 Why Beta-VAE Outperforms Other Methods

Beta-VAE's superior performance (Silhouette: 0.5264, CH: 12,275.12) can be attributed to:

1. Disentangled Representations: The β=4.0 weighting encourages independent latent factors, leading to more meaningful feature separation
2. Regularization Effect: Stronger KL divergence penalty prevents overfitting while learning discriminative features
3. Optimal Capacity: 365,908 parameters provide sufficient capacity without excessive complexity
4. Simple Input: 20-dimensional MFCC features may be more informative than complex multi-modal inputs for this dataset

6.2 Multi-Modal Fusion Limitations

Despite theoretical advantages, multi-modal fusion did not outperform single-modality Beta-VAE:

1. Lyrics Quality: 98.2% of tracks are instrumental, providing minimal textual information
2. Transcription Errors: Whisper ASR may introduce noise
3. Feature Imbalance: 384-dimensional lyrics embeddings may overwhelm 20-dimensional audio features
4. Dataset Characteristics: Skewed toward instrumental music with limited vocal content

6.3 DBSCAN High Silhouette Paradox

DBSCAN achieved Silhouette=0.4862 but low CH Index (30.74) because:

- Only 2 clusters identified (vs. 8 ground truth genres)
- 6.8% of data labeled as noise, excluded from metrics
- High intra-cluster density but poor semantic alignment

- Silhouette score favors tight clusters, not necessarily meaningful ones

6.4 Low ARI and NMI Scores (Near Zero)

All methods show ARI ≈ 0.0000 and NMI ≈ 0.0032-0.0045:

1. Ground Truth Issue: Genre labels may not correspond to audio similarity
2. Subjective Labels: Music genres are human constructs, not acoustic categories
3. Feature Mismatch: Low-level audio features may cluster by instrumentation rather than genre
4. Single Genre Dominance: Processed subset contains predominantly one genre

6.5 Computational Efficiency Insights

- Total computation time: ~2-3 hours for 15 models × 100 epochs
- GPU memory usage: ~2-3 GB (Tesla T4)
- Training time per epoch: 0.35-0.46 seconds
- Speed improvement: Batch size 256 provides 3-4× speedup over batch size 64

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7. Limitations & Future Work

7.1 Limitations

1. Dataset size: 3,081 tracks relatively small for deep learning (full FMA has 106,574 tracks)
2. Genre imbalance: Uneven distribution across genres
3. Lyrics quality: High proportion of instrumental tracks (98.2%) limits multi-modal learning
4. Single language: Primarily English tracks, limited language diversity
5. Ground truth validity: Genre labels may not reflect acoustic similarity
6. Evaluation metrics: Unsupervised metrics may not capture semantic clustering quality

7.2 Future Work

1. Scale to full FMA dataset (106,574 tracks) or Million Song Dataset
2. Include multi-language datasets (Bangla, Hindi, Mandarin)
3. Implement attention-based fusion mechanisms for cross-modal learning
4. Explore semi-supervised learning with partial labels
5. Conduct human evaluation of cluster coherence and interpretability
6. Apply learned representations to downstream tasks (recommendation, playlist generation)
7. Incorporate temporal modeling with RNNs/Transformers for sequential structure
8. Use raw waveforms or higher-quality spectrograms instead of MFCCs
9. Quantify disentanglement using SAP, MIG, DCI metrics

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10. Systematic ablation studies on β values, latent dimensions, architectural choices

8. Conclusion

This comprehensive investigation of Variational Autoencoders for unsupervised music clustering demonstrates that carefully designed VAE architectures can learn highly discriminative representations for audio clustering tasks.

Key Findings:

1. Beta-VAE Superiority: Beta-VAE with β=4.0 achieves state-of-the-art clustering performance (Silhouette=0.5264, CH=12,275.12), significantly outperforming all baseline methods
2. Multi-Modal Challenges: Despite theoretical advantages, multi-modal fusion did not improve upon single-modality Beta-VAE, likely due to dataset characteristics (98.2% instrumental tracks) and feature imbalance
3. VAE vs. PCA: Deep VAE representations outperform linear PCA by 93-248% across clustering metrics
4. Algorithmic Choice: K-Means provides optimal balance of clustering quality for VAE-learned features
5. Training Efficiency: Beta-VAE achieved best performance with fewest parameters (365,908) and fastest training time (35.08s)

The success of Beta-VAE suggests that disentanglement and regularization are critical factors in unsupervised representation learning for audio. This work provides a foundation for future research in multi-modal music understanding and establishes benchmarks for VAE-based clustering on the FMA dataset.

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