

.Portfolio Project

Manual Music Data Labeling & Critical Evaluation

Role: Music Data Annotator / AI Music Trainer (Manual Labeling)

Focus: Structured metadata annotation of a small set of AI-generated tracks (instrumental + vocal)

Duration: 1 week (Week 5 – Manual Data Labeling)

Project Overview

This project focuses on manual music data labeling, a core skill for training, evaluating, and curating AI-driven music systems. The objective was to create high-quality, human-verified metadata for a small but representative set of AI-generated tracks (instrumental + vocal), ensuring consistency, musical correctness, and job-ready formatting.

Each track was annotated using a structured template with the following columns:

- Title
- Genre
- BPM
- Key
- Instruments
- Mood
- Sections
- Source / Model
- Duration (mm:ss)
- Audio Link / File Path
- Notes

The annotations were compiled in a clean Excel/CSV format, designed to be immediately usable for AI training, evaluation, or content curation pipelines.

Annotation Methodology

All labels were produced manually, based on critical listening rather than automated extraction. My workflow followed three steps:

1. Focused Listening
 - Identification of tempo range and rhythmic feel
 - Tonal center and mode recognition
 - Instrumental layers and texture evolution
2. Musical Validation

- Cross-checking BPM and key against musical perception
- Avoiding over-specification (no speculative labels)
- Choosing industry-standard genre and mood terminology

3. Metadata Normalization

- Consistent vocabulary across tracks
- Objective (BPM, key, instruments) and subjective (mood) fields
- Readable, scalable structure suitable for larger datasets

Critical Commentary

Overall, the annotated tracks are fully compliant with their intended briefs in terms of tempo, tonality, instrumentation, structure, and mood. The metadata accurately reflects the musical content and is aligned with real-world expectations in AI music datasets.

A recurring observation is that several tracks rely on harmonic or textural looping, which is common in functional music (underscore, ambient, corporate).

From a data perspective, these tracks are coherent, predictable, and well-suited for training models focused on mood consistency, background usage, and adaptive scoring, even if they offer limited internal variation.

Strengths of the Dataset

- Clean, human-verified labels
- Musically accurate tempo and key identification
- Appropriate genre and mood granularity
- Consistent formatting, ready for ingestion
- Clear separation between descriptive and evaluative fields

Limitations & Improvement Areas

- Limited harmonic diversity in some tracks
- Minimal structural contrast in loop-based cues
- Potential future enhancement: confidence scoring per label

These limitations are typical of production-ready functional music and do not compromise dataset quality, but they should be acknowledged in model training and evaluation contexts.

Professional Relevance

This project simulates real AI music annotation tasks, such as:

- Training data preparation
- Dataset cleaning and validation
- Music content curation
- Human-in-the-loop evaluation workflows

The methodology prioritizes clarity, reproducibility, and musical correctness, making it suitable for roles in AI music training, audio QA, and content evaluation.