EDA - MIREX Mood Classification

Anggota Kelompok

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In [1]:
```
from google.colab import drive
drive.mount('/content/drive')

DATASET_ROOT = "/content/drive/MyDrive/dataset-multimodal"
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call dri
ve.mount("/content/drive", force_remount=True).
```

Import Library

In [2]:
```
!pip install -q panns-inference transformers pretty_midi mido librosa seaborn

import os
import numpy as np
import pandas as pd
from tqdm import tqdm

import librosa
import pretty_midi
from mido import MidiFile

import torch
import torch.nn as nn

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.manifold import TSNE

# Audio model (PANNs)
from panns_inference import AudioTagging

# Lyrics model (BERT)
from transformers import BertTokenizer, BertModel

# MIDI model (ResNet18)
import torchvision.models as models
import torchvision.transforms as T

sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (8, 5)
```

```
device = "cuda" if torch.cuda.is_available() else "cpu"
print("Using device:", device)
```

```
Using device: cuda
```

In [3]:
```
def read_label_file(path_no_ext):
    """Coba baca <path_no_ext> atau <path_no_ext>.txt."""
    if os.path.exists(path_no_ext):
        path = path_no_ext
    elif os.path.exists(path_no_ext + ".txt"):
        path = path_no_ext + ".txt"
    else:
        raise FileNotFoundError(f"File label tidak ditemukan: {path_no_ext}(.txt
    with open(path, "r", encoding="utf-8") as f:
        lines = [line.strip() for line in f.readlines()]
    return lines

categories = read_label_file(os.path.join(DATASET_ROOT, "categories"))
clusters   = read_label_file(os.path.join(DATASET_ROOT, "clusters"))

print("Jumlah baris categories:", len(categories))
print("Jumlah baris clusters  :", len(clusters))

assert len(categories) == len(clusters), "Panjang categories dan clusters harus

# pakai daftar audio sebagai acuan urutan
audio_dir = os.path.join(DATASET_ROOT, "Audio")
audio_files = sorted([f for f in os.listdir(audio_dir) if f.lower().endswith(".m
audio_ids = [os.path.splitext(f)[0] for f in audio_files]

print("Jumlah file audio:", len(audio_ids))
assert len(audio_ids) == len(categories), "Jumlah audio != jumlah baris label"

labels_df = pd.DataFrame({
    "file_id": audio_ids,
    "category": categories,
    "cluster": clusters
})

display(labels_df.head())

print("\nDistribusi kategori:")
display(labels_df["category"].value_counts())

print("\nDistribusi cluster:")
display(labels_df["cluster"].value_counts())

plt.figure(figsize=(12, 4))
labels_df["category"].value_counts().plot(kind="bar")
plt.title("Distribusi Kategori (Target)")
plt.xlabel("Category")
plt.ylabel("Count")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
```

```
Jumlah baris categories: 903
Jumlah baris clusters  : 903
Jumlah file audio: 903
```

	file_id	category	cluster
0	001	Boisterous	Cluster 1
1	002	Boisterous	Cluster 1
2	003	Boisterous	Cluster 1
3	004	Boisterous	Cluster 1
4	005	Boisterous	Cluster 1

```
Distribusi kategori:
```

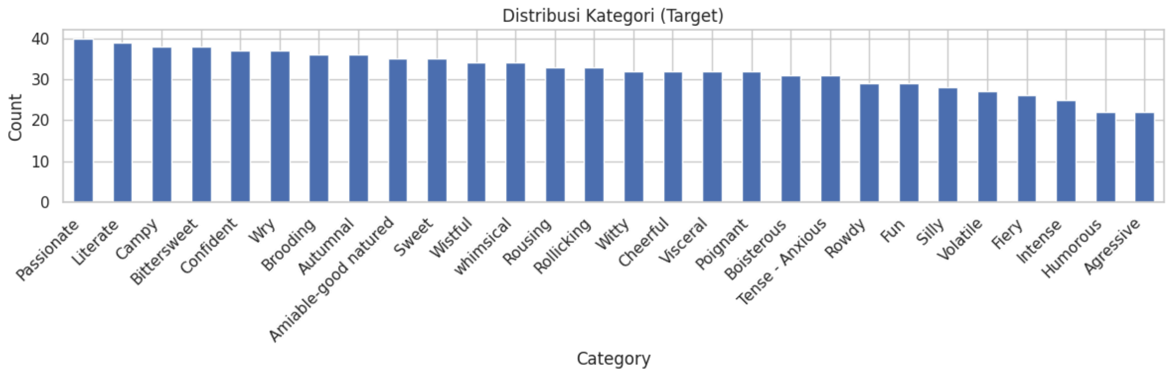
category	count
Passionate	40
Literate	39
Campy	38
Bittersweet	38
Confident	37
Wry	37
Brooding	36
Autumnal	36
Amiable-good natured	35
Sweet	35
Wistful	34
whimsical	34
Rousing	33
Rollicking	33
Witty	32
Cheerful	32
Visceral	32
Poignant	32
Boisterous	31
Tense - Anxious	31
Rowdy	29
Fun	29
Silly	28
Volatile	27
Fiery	26
Intense	25
Humorous	22
Agressive	22

dtype: int64

```
Distribusi cluster:
```

	count
cluster	
Cluster 3	215
Cluster 4	191
Cluster 1	170
Cluster 2	164
Cluster 5	163

dtype: int64



Helper Function

In [4]:
```python
def plot_hist(df, col, title, xlabel):
    plt.figure()
    plt.hist(df[col].dropna(), bins=30, edgecolor="black", alpha=0.8)
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel("Frequency")
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()

def tsne_and_scatter(X, labels, title, random_state=42):
    """
    X      : np.array [N, D]
    labels : list / Series panjang N
    """
    if X.shape[0] < 5:
        print("Data terlalu sedikit untuk t-SNE.")
        return None

    perplexity = min(30, max(5, X.shape[0] // 4))
    print(f"Running t-SNE: n_samples={X.shape[0]}, dim={X.shape[1]}, perplexity=

    tsne = TSNE(
        n_components=2,
        random_state=random_state,
        perplexity=perplexity,
        max_iter=1000
    )
    X_2d = tsne.fit_transform(X)

    labels = pd.Series(labels).astype(str)
    uniq = labels.unique()
    cmap = plt.cm.get_cmap("tab20", len(uniq))

    plt.figure(figsize=(8, 6))
    for i, lab in enumerate(uniq):
        mask = (labels == lab).values
        plt.scatter(
            X_2d[mask, 0],
            X_2d[mask, 1],
            s=40,
            alpha=0.7,
            label=lab,
            color=cmap(i)
        )
    plt.title(title)
    plt.xlabel("t-SNE dim 1")
    plt.ylabel("t-SNE dim 2")
    plt.legend(bbox_to_anchor=(1.05, 1), loc="upper left", fontsize=8)
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()
    return X_2d

# cek file korup
def check_audio_ok(path):
    try:
        _y, _sr = librosa.load(path, sr=None, mono=True)
        return True
    except Exception:
        return False

def check_lyrics_ok(path):
    try:
        with open(path, "r", encoding="utf-8") as f:
            _ = f.read()
        return True
    except Exception:
        return False

def check_midi_ok(path):
    try:
        _ = MidiFile(path)
        return True
    except Exception:
        return False

def zscore_np(x):
    m = x.mean(axis=0, keepdims=True)
    s = x.std(axis=0, keepdims=True) + 1e-8
    return (x - m) / s
```

AUDIO

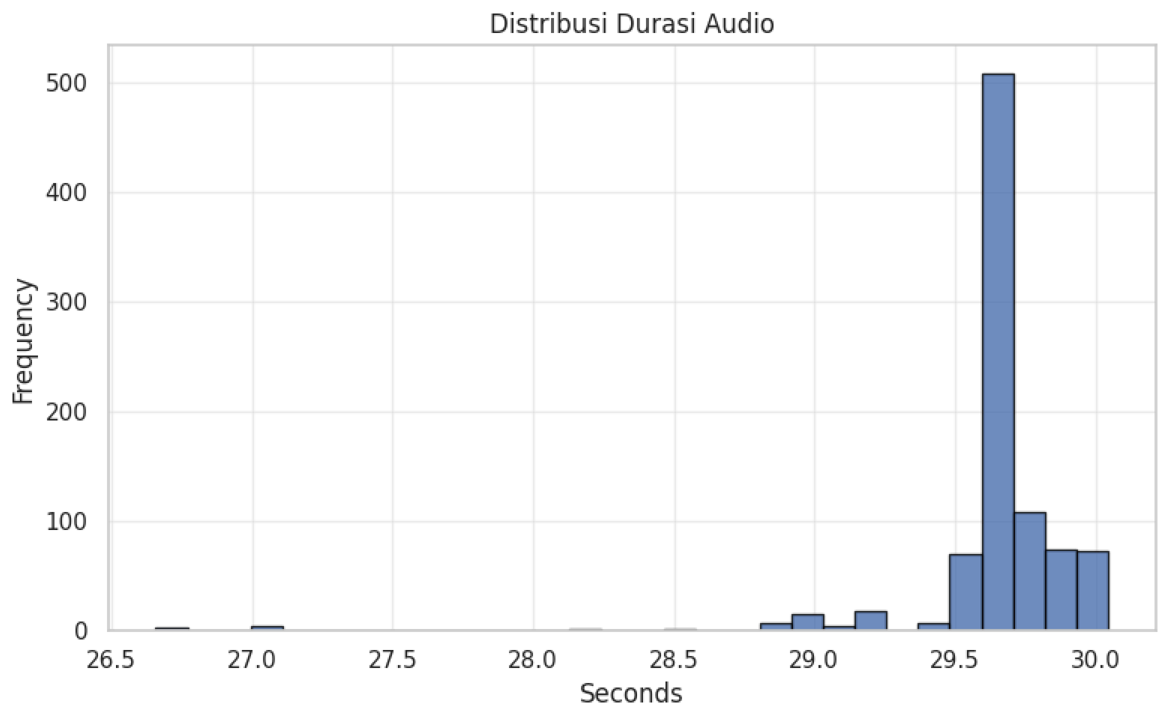
Dataset audio berisi 903 file .mp3 berdurasi ±30 detik, masing-masing merepresentasikan potongan lagu dalam bentuk sinyal suara asli.

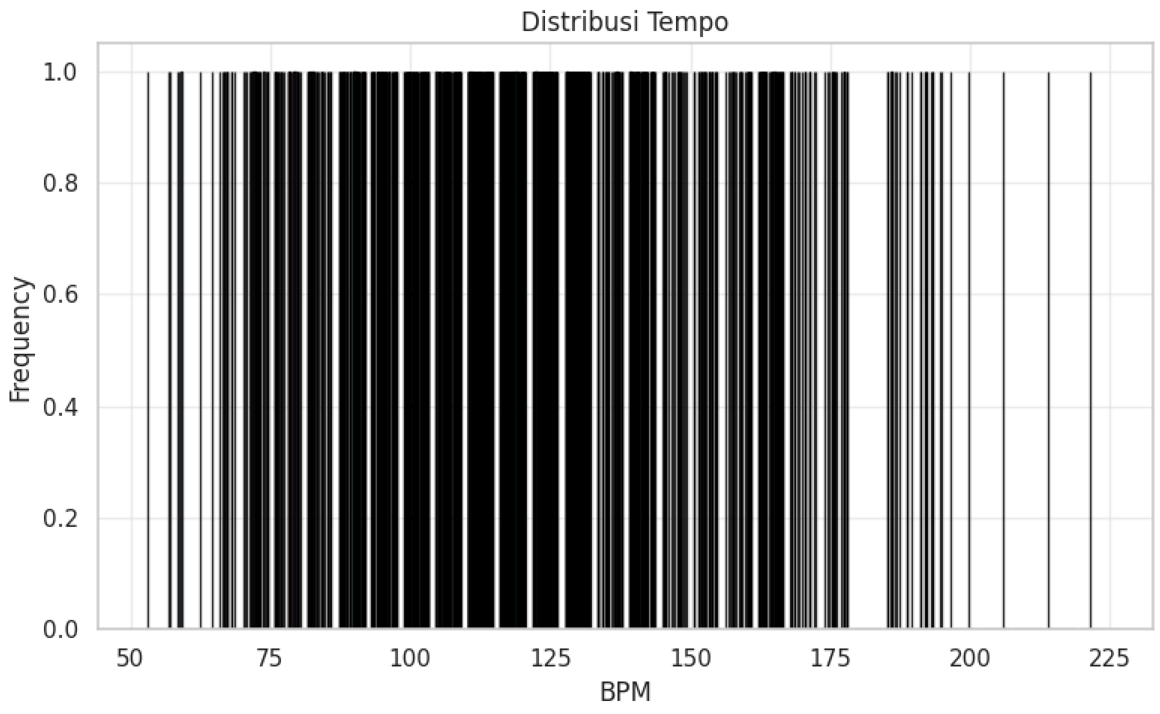
Cek File dan Fitur Mentah

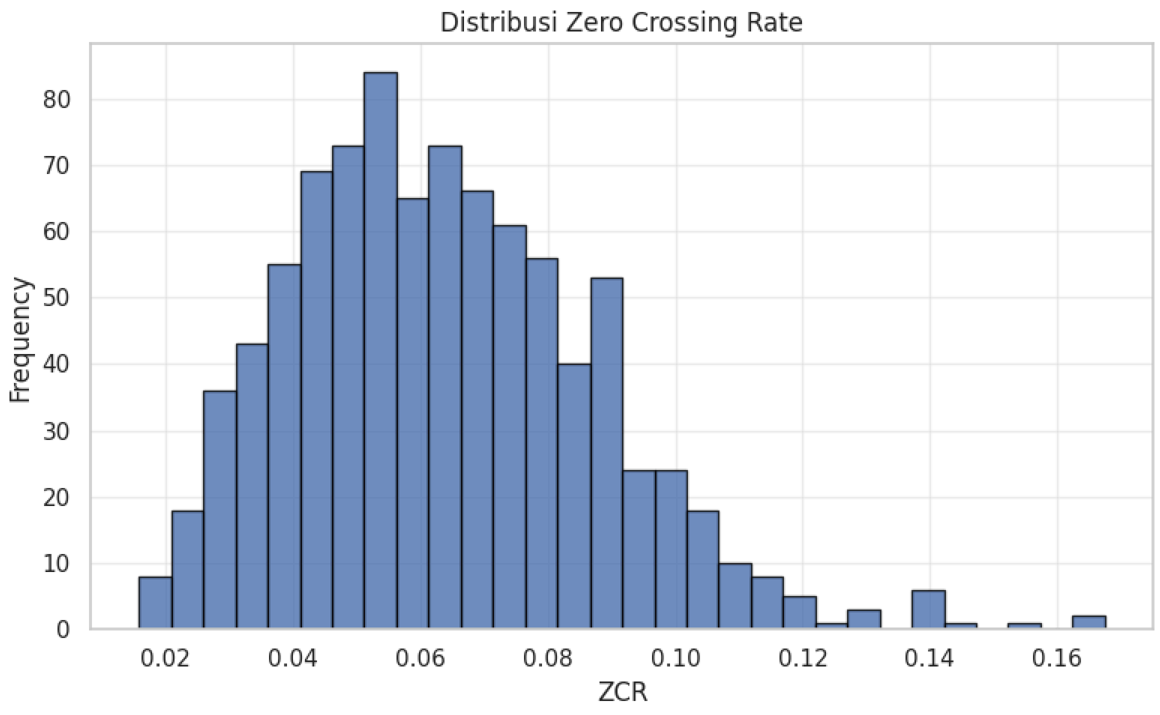
In [5]:
```
audio_dir = os.path.join(DATASET_ROOT, "Audio")
audio_files = sorted([f for f in os.listdir(audio_dir) if f.lower().endswith(".m
print("Total audio files found:", len(audio_files))

audio_meta = []
corrupt_audio = []

for f in tqdm(audio_files, desc="Checking audio files"):
    path = os.path.join(audio_dir, f)
    file_id = os.path.splitext(f)[0]
    ok = check_audio_ok(path)
    if not ok:
        corrupt_audio.append(file_id)
    audio_meta.append({
        "file_id": file_id,
        "file_name": f,
        "audio_ok": ok
    })

audio_df = pd.DataFrame(audio_meta)
print("Corrupt audio files:", len(corrupt_audio))
if corrupt_audio:
    print("Example corrupt:", corrupt_audio[:10])

# fitur: durasi, tempo, zcr, spectral centroid, rms
audio_stats = []
for f in tqdm(audio_files, desc="Extracting audio stats"):
    file_id = os.path.splitext(f)[0]
    if file_id in corrupt_audio:
        continue
    path = os.path.join(audio_dir, f)
    try:
        y, sr = librosa.load(path, sr=None, mono=True)
        duration = librosa.get_duration(y=y, sr=sr)
        tempo, _ = librosa.beat.beat_track(y=y, sr=sr)
        zcr = librosa.feature.zero_crossing_rate(y)[0].mean()
        centroid = librosa.feature.spectral_centroid(y=y, sr=sr)[0].mean()
        rms = librosa.feature.rms(y=y)[0].mean()

        audio_stats.append({
            "file_id": file_id,
            "duration_audio": duration,
            "tempo": tempo,
            "zcr": zcr,
            "spectral_centroid": centroid,
            "rms_energy": rms
        })
    except Exception:
        corrupt_audio.append(file_id)

audio_stats_df = pd.DataFrame(audio_stats)
print("Audio stats shape:", audio_stats_df.shape)
display(audio_stats_df.head())

plot_hist(audio_stats_df, "duration_audio", "Distribusi Durasi Audio", "Seconds"
plot_hist(audio_stats_df, "tempo", "Distribusi Tempo", "BPM")
plot_hist(audio_stats_df, "zcr", "Distribusi Zero Crossing Rate", "ZCR")
plot_hist(audio_stats_df, "spectral_centroid", "Distribusi Spectral Centroid", "
plot_hist(audio_stats_df, "rms_energy", "Distribusi RMS Energy", "Amplitude")
```

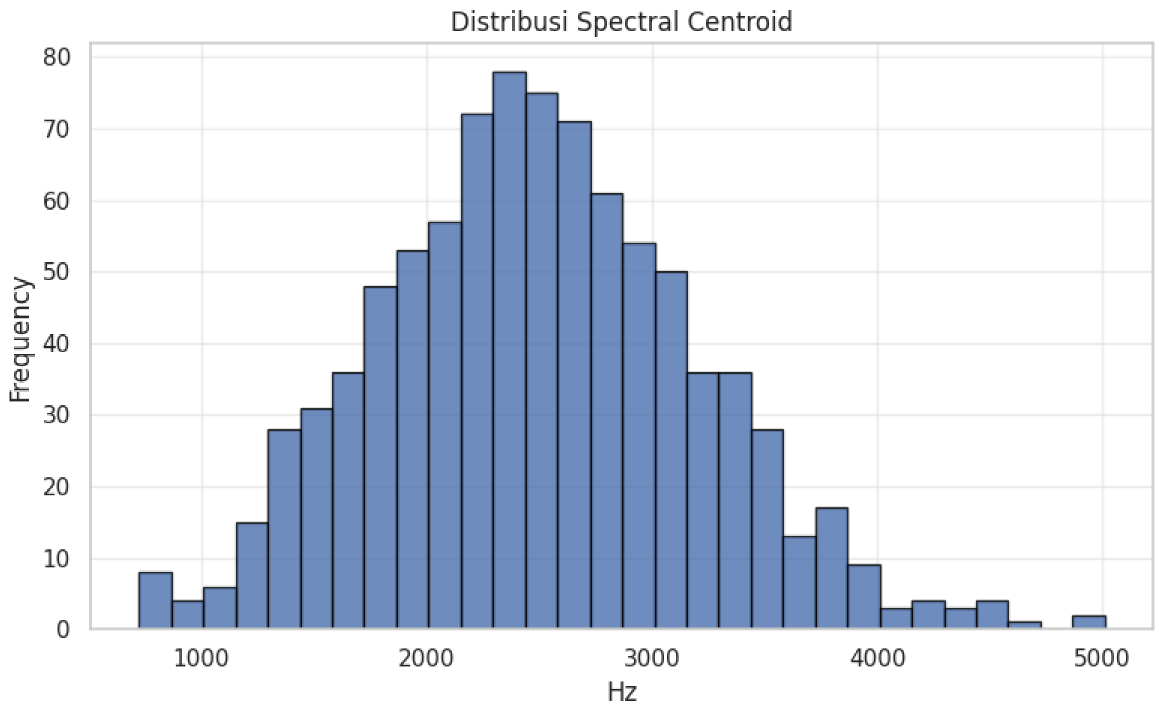
```
Total audio files found: 903
Checking audio files: 100%|██████████| 903/903 [03:48<00:00,  3.95it/s]
Corrupt audio files: 0
Extracting audio stats: 100%|██████████| 903/903 [06:21<00:00,  2.37it/s]
Audio stats shape: (903, 6)
```

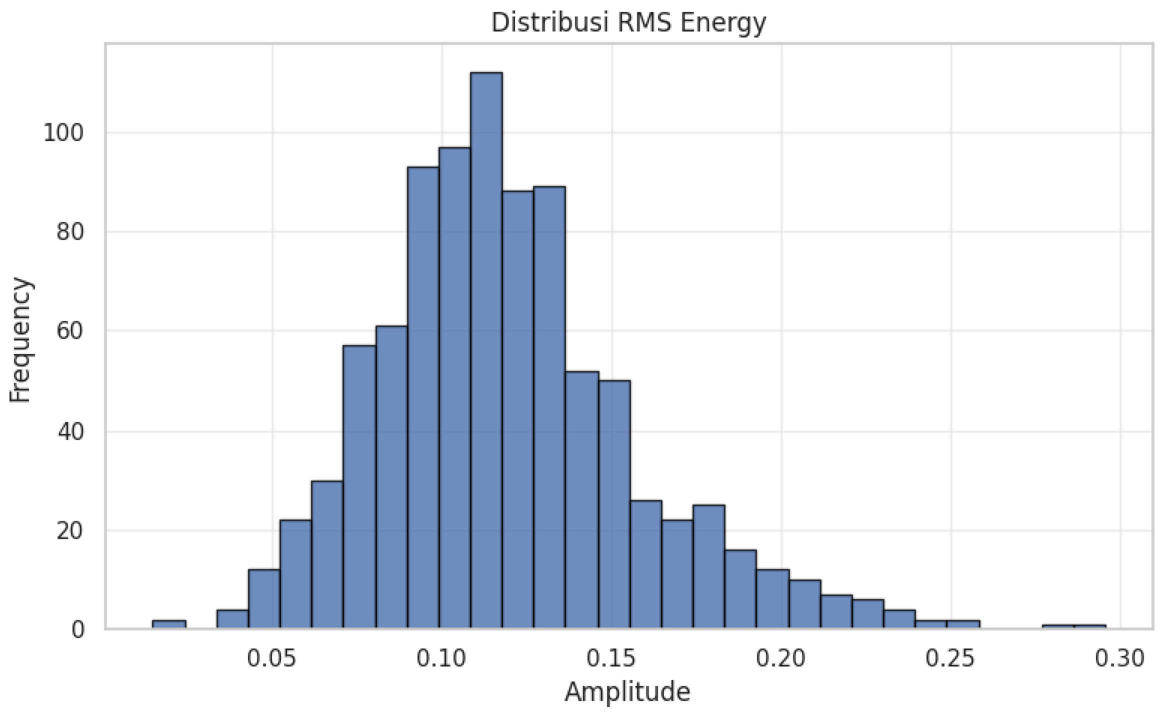
	file_id	duration_audio	tempo	zcr	spectral_centroid	rms_energy
0	001	29.628662	[60.799632352941174]	0.096978	3591.478661	0.124067
1	002	29.582222	[156.60511363636363]	0.024919	1726.221489	0.093081
2	003	29.767982	[105.46875]	0.058417	2591.292266	0.135723
3	004	29.675102	[95.703125]	0.088290	2967.550972	0.173973
4	005	28.885624	[101.33272058823529]	0.066502	2675.267259	0.117730




Distribusi Tempo
Frequency
BPM
1.0
0.8
0.6
0.4
0.2
0.0
50
75
100
125
150
175
200
225


Distribusi Zero Crossing Rate
Frequency
ZCR
80
70
60
50
40
30
20
10
0
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16





Distribusi Durasi

Histogram durasi audio menunjukkan bahwa hampir seluruh file memiliki panjang yang sangat konsisten di kisaran 29.5–30 detik. Hal ini sangat menguntungkan karena proses standardisasi panjang sinyal menjadi sederhana: pad/trim ke 30 detik.

Fitur Spektral (ZCR, Spectral Centroid, RMS)

Distribusi ZCR, centroid, dan RMS menunjukkan pola yang normal tanpa outlier ekstrem. Hal ini mengindikasikan kualitas audio yang stabil dan tidak terdapat file dengan karakteristik spektral yang menyimpang.

Estimasi Tempo

Plot tempo menunjukkan hasil yang sangat noisy dan acak. Estimasi tempo dari librosa.beat_track tidak dapat diandalkan pada dataset multi-genre ini, sehingga EDA menyimpulkan bahwa tempo tidak digunakan sebagai fitur eksplisit.

PANNs CNN14 + t-SNE

In [13]:
```python
from panns_inference import AudioTagging

# 1) Load model PANNs CNN14 (pretrained)
at_model = AudioTagging(checkpoint_path=None, device=device)
print("✓ PANNs CNN14 loaded")

def extract_audio_embedding(path, model, target_sr=32000, seconds=30):
    """
    Ekstrak embedding CNN14 untuk 1 file audio full.
    - Resample ke target_sr (default 32 kHz)
    - Trim/pad ke 'seconds' detik
    - Kembalikan vektor embedding (2048-dim)
    """
    y, sr = librosa.load(path, sr=target_sr, mono=True)
    max_len = target_sr * seconds

    if len(y) < max_len:
        y = np.pad(y, (0, max_len - len(y)))
    else:
        y = y[:max_len]

    x = y[None, :]  # shape: (1, n_samples)
    with torch.no_grad():
        _, embedding = model.inference(x)  # embedding: [1, 2048]
    return embedding[0]  # (2048,)


# 2) Ekstrak embedding untuk semua audio yang tidak korup
audio_emb_records = []

for f in tqdm(audio_files, desc="Extracting audio embeddings (CNN14)"):
    file_id = os.path.splitext(f)[0]
    if file_id in corrupt_audio:
        continue

    path = os.path.join(audio_dir, f)
    try:
        emb = extract_audio_embedding(path, at_model)
        row = {"file_id": file_id}
        for i, v in enumerate(emb):
            row[f"audio_emb_{i}"] = float(v)
        audio_emb_records.append(row)
    except Exception as e:
        print("Error embedding", f, ":", e)

audio_emb_df = pd.DataFrame(audio_emb_records)
print("Audio embeddings (CNN14) shape:", audio_emb_df.shape)
display(audio_emb_df.head())

# 3) Gabung dengan fitur mentah + label
audio_full = (
    audio_stats_df
```

```
        .merge(audio_emb_df, on="file_id", how="inner")
        .merge(labels_df,    on="file_id", how="left")
)

print("Audio + labels:", audio_full.shape)
display(audio_full.head())

# 4) t-SNE embedding audio per kategori
audio_emb_cols = [c for c in audio_full.columns if c.startswith("audio_emb_")]
X_audio = audio_full[audio_emb_cols].values
y_audio = audio_full["category"].fillna("Unknown")

audio_tsne = tsne_and_scatter(
    X_audio,
    y_audio,
    title="t-SNE Audio Embeddings (PANNs CNN14) by Category"
)
```

```
Checkpoint path: /root/panns_data/Cnn14_mAP=0.431.pth
GPU number: 1
✓ PANNs CNN14 loaded
Extracting audio embeddings (CNN14): 100%|██████████| 903/903 [02:08<00:00,  7.05
it/s]
Audio embeddings (CNN14) shape: (903, 2049)
```

	file_id	audio_emb_0	audio_emb_1	audio_emb_2	audio_emb_3	audio_emb_4	audio_e
0	001	0.0	0.000000	0.0	0.0	0.0	
1	002	0.0	0.000000	0.0	0.0	0.0	
2	003	0.0	0.000000	0.0	0.0	0.0	
3	004	0.0	0.000000	0.0	0.0	0.0	
4	005	0.0	0.387401	0.0	0.0	0.0	

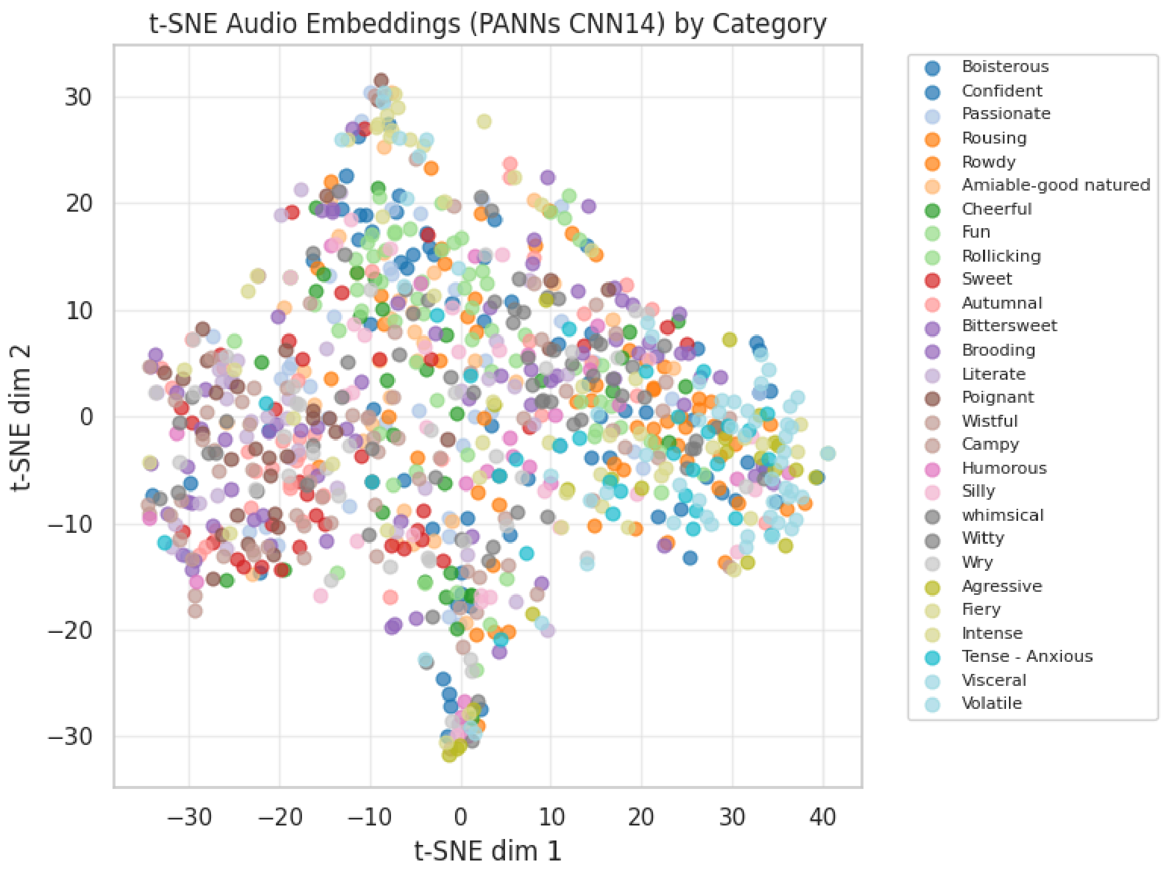
5 rows × 2049 columns

```
Audio + labels: (903, 2056)
```

	file_id	duration_audio	tempo	zcr	spectral_centroid	rms_energy
0	001	29.628662	[60.799632352941174]	0.096978	3591.478661	0.124067
1	002	29.582222	[156.60511363636363]	0.024919	1726.221489	0.093081
2	003	29.767982	[105.46875]	0.058417	2591.292266	0.135723
3	004	29.675102	[95.703125]	0.088290	2967.550972	0.173973
4	005	28.885624	[101.33272058823529]	0.066502	2675.267259	0.117730

5 rows × 2056 columns

```
Running t-SNE: n_samples=903, dim=2048, perplexity=30
/tmp/ipython-input-782246349.py:35: MatplotlibDeprecationWarning: The get_cmap fu
nction was deprecated in Matplotlib 3.7 and will be removed in 3.11. Use ``matplo
tlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or ``pyplot.get_cma
p()`` instead.
  cmap = plt.cm.get_cmap("tab20", len(uniq))
```



Hasil t-SNE pada embedding audio menunjukkan adanya pola penyebaran yang membentuk beberapa kelompok besar, namun kategori emosi masih saling tumpang-tindih. Hal ini menunjukkan bahwa representasi CNN14 berhasil menangkap karakter akustik secara umum, tetapi audio saja belum cukup kuat untuk memisahkan kategori emosi secara jelas pada ruang berdimensi rendah.

LIRIK

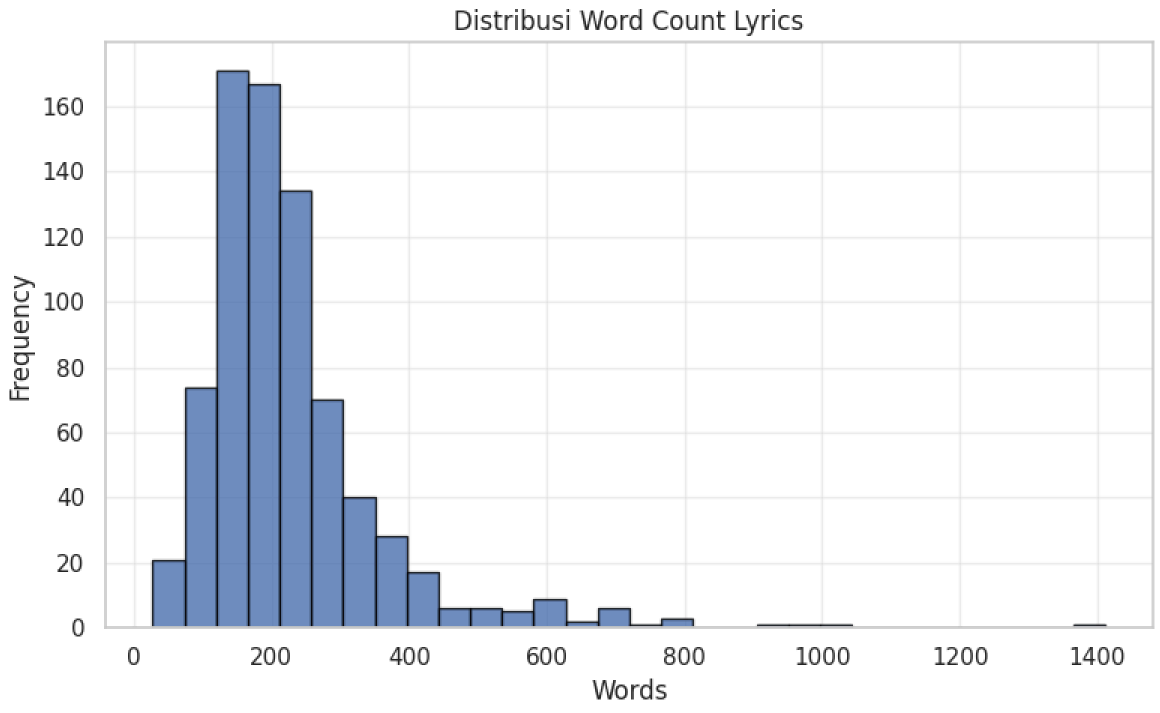
Dataset lirik terdiri dari 764 file .txt yang berisi teks lengkap dari lagu dengan nama file yang disesuaikan dengan ID audio. Lirik ini menyediakan informasi semantik yang tidak muncul pada sinyal audio.

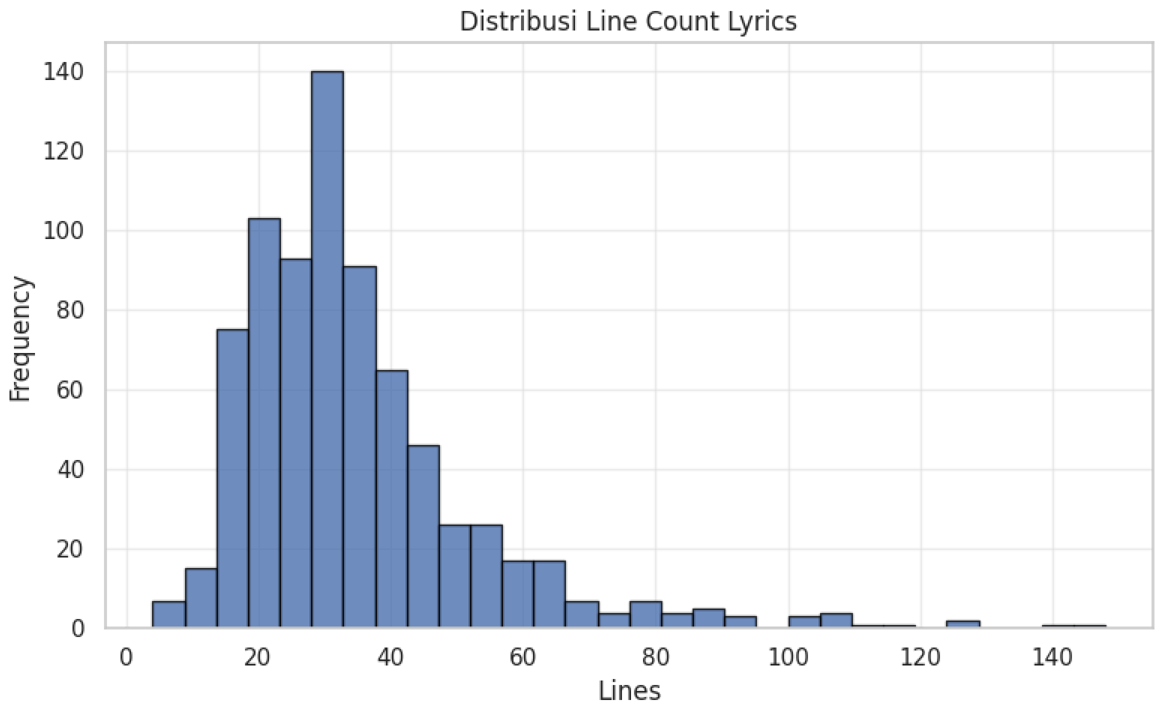
Cek File dan Fitur Mentah

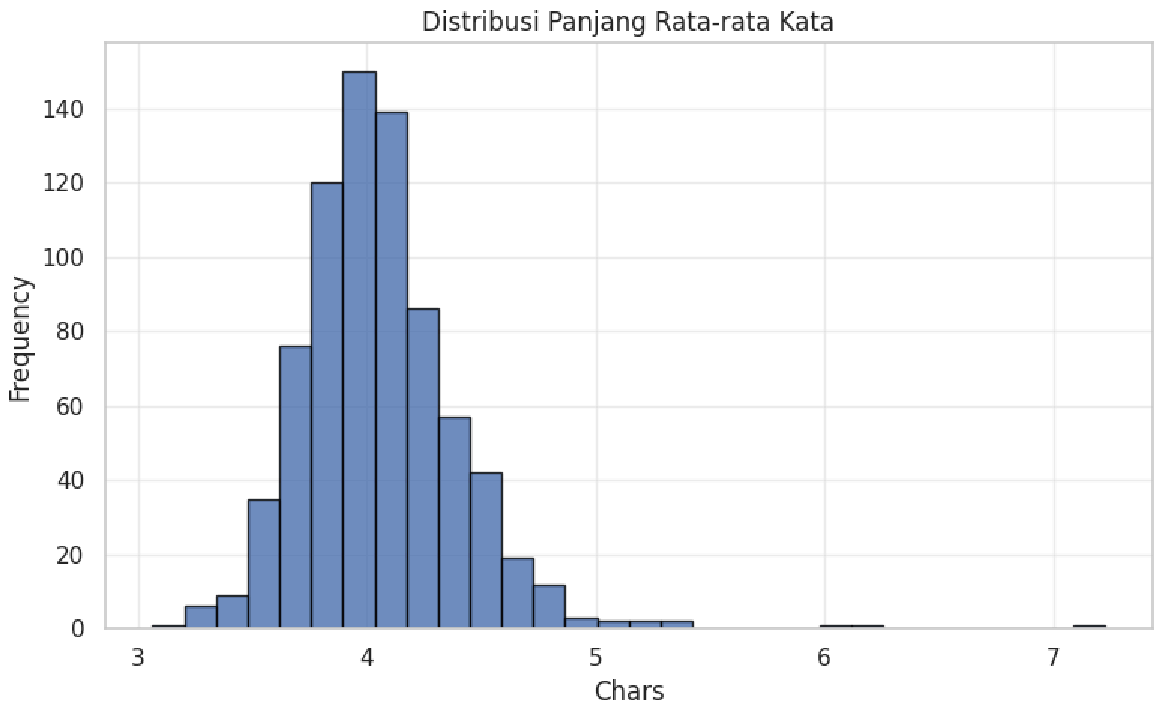
In [7]:
```
lyrics_dir = os.path.join(DATASET_ROOT, "Lyrics")
lyrics_files = sorted([f for f in os.listdir(lyrics_dir) if f.lower().endswith("
print("Total lyrics files found:", len(lyrics_files))

lyrics_meta = []
corrupt_lyrics = []

for f in tqdm(lyrics_files, desc="Checking lyrics files"):
    path = os.path.join(lyrics_dir, f)
    file_id = os.path.splitext(f)[0]
    ok = check_lyrics_ok(path)
    if not ok:
        corrupt_lyrics.append(file_id)
    lyrics_meta.append({
        "file_id": file_id,
        "file_name": f,
        "lyrics_ok": ok
    })

lyrics_df = pd.DataFrame(lyrics_meta)
print("Corrupt lyrics files:", len(corrupt_lyrics))

lyrics_stats = []
for f in tqdm(lyrics_files, desc="Extracting lyrics stats"):
    file_id = os.path.splitext(f)[0]
    if file_id in corrupt_lyrics:
        continue
    path = os.path.join(lyrics_dir, f)
    try:
        with open(path, "r", encoding="utf-8") as fh:
            text = fh.read().strip()
        if not text:
            continue
        words = text.split()
        lines = text.split("\n")
        word_count = len(words)
        char_count = len(text)
        line_count = len([ln for ln in lines if ln.strip()])
        avg_word_len = np.mean([len(w) for w in words]) if words else 0.0

        lyrics_stats.append({
            "file_id": file_id,
            "word_count": word_count,
            "char_count": char_count,
            "line_count": line_count,
            "avg_word_length": avg_word_len
        })
    except Exception:
        corrupt_lyrics.append(file_id)

lyrics_stats_df = pd.DataFrame(lyrics_stats)
print("Lyrics stats shape:", lyrics_stats_df.shape)
display(lyrics_stats_df.head())

plot_hist(lyrics_stats_df, "word_count", "Distribusi Word Count Lyrics", "Words"
plot_hist(lyrics_stats_df, "line_count", "Distribusi Line Count Lyrics", "Lines"
plot_hist(lyrics_stats_df, "avg_word_length", "Distribusi Panjang Rata-rata Kata
```

```
Total lyrics files found: 764
Checking lyrics files: 100%|██████████| 764/764 [00:12<00:00, 59.38it/s]
Corrupt lyrics files: 0
Extracting lyrics stats: 100%|██████████| 764/764 [00:01<00:00, 443.93it/s]
Lyrics stats shape: (764, 5)
```

	file_id	word_count	char_count	line_count	avg_word_length
0	001	167	907	28	4.239521
1	003	260	1321	33	4.065385
2	004	232	1157	52	3.758621
3	007	426	2073	65	3.819249
4	008	122	642	18	4.098361







Distribusi Word Count, Line Count, dan Panjang Kata

Mayoritas lirik memiliki sekitar 150–350 kata, dengan beberapa outlier sangat panjang hingga >1000 kata. Line count juga konsisten di kisaran 20–45 baris. Hal ini berarti:

- Lirik cukup panjang untuk memberikan konteks semantik
- Tetapi perlu ada pembatasan max_length saat menggunakan BERT untuk mencegah pemotongan berlebihan

Struktur lirik konsisten seperti lirik musik pada umumnya, sehingga tidak membutuhkan pembersihan mendalam atau normalisasi struktur.

BERT Embedding dan t-SNE

In [8]:
```
bert_model_name = "bert-base-uncased"   # ganti kalau mau IndoBERT
tokenizer = BertTokenizer.from_pretrained(bert_model_name)
bert_model = BertModel.from_pretrained(bert_model_name).to(device)
bert_model.eval()
print("✓ BERT loaded:", bert_model_name)

def get_bert_embedding(text, tokenizer, model, max_len=256):
    inputs = tokenizer(
        text,
        return_tensors="pt",
        truncation=True,
        padding="max_length",
        max_length=max_len
    )
    inputs = {k: v.to(device) for k, v in inputs.items()}
    with torch.no_grad():
        outputs = model(**inputs)
    hidden = outputs.last_hidden_state        # [1, L, H]
    mask = inputs["attention_mask"].unsqueeze(-1)
    masked = hidden * mask
    sum_hidden = masked.sum(dim=1)
    sum_mask = mask.sum(dim=1)
    mean_pooled = sum_hidden / sum_mask
    return mean_pooled.squeeze(0).cpu().numpy()   # (H,)

lyrics_emb_records = []
for f in tqdm(lyrics_files, desc="Extracting lyrics embeddings"):
    file_id = os.path.splitext(f)[0]
    if file_id in corrupt_lyrics:
        continue
    path = os.path.join(lyrics_dir, f)
    try:
        with open(path, "r", encoding="utf-8") as fh:
            text = fh.read().strip()
        if not text:
            continue
        emb = get_bert_embedding(text, tokenizer, bert_model)
        row = {"file_id": file_id}
        for i, v in enumerate(emb):
            row[f"lyrics_emb_{i}"] = float(v)
        lyrics_emb_records.append(row)
    except Exception as e:
        print("Error embedding lyrics", f, ":", e)

lyrics_emb_df = pd.DataFrame(lyrics_emb_records)
print("Lyrics embeddings shape:", lyrics_emb_df.shape)

lyrics_full = (
    lyrics_stats_df
      .merge(lyrics_emb_df, on="file_id", how="inner")
      .merge(labels_df, on="file_id", how="left")
)
print("Lyrics + labels:", lyrics_full.shape)
display(lyrics_full.head())

lyrics_emb_cols = [c for c in lyrics_full.columns if c.startswith("lyrics_emb_")
X_lyrics = lyrics_full[lyrics_emb_cols].values
y_lyrics = lyrics_full["category"].fillna("Unknown")

lyrics_tsne = tsne_and_scatter(
    X_lyrics, y_lyrics,
    title="t-SNE Lyrics Embeddings (BERT) by Category"
)
```

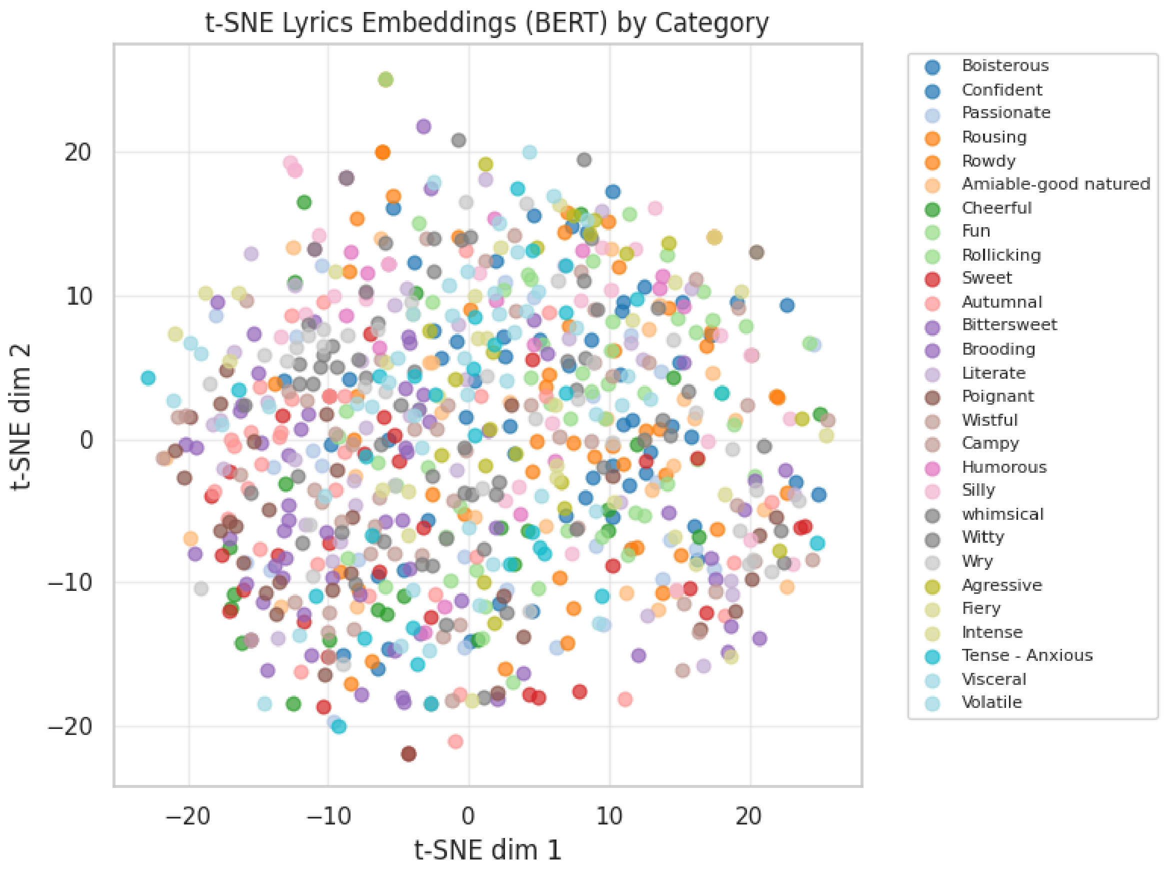
```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94: UserWa
rning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (h
ttps://huggingface.co/settings/tokens), set it as secret in your Google Colab and
restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access publi
c models or datasets.
  warnings.warn(
tokenizer_config.json:   0%|          | 0.00/48.0 [00:00<?, ?B/s]
vocab.txt:   0%|          | 0.00/232k [00:00<?, ?B/s]
tokenizer.json:   0%|          | 0.00/466k [00:00<?, ?B/s]
config.json:   0%|          | 0.00/570 [00:00<?, ?B/s]
model.safetensors:   0%|          | 0.00/440M [00:00<?, ?B/s]
✓ BERT loaded: bert-base-uncased
```

```
Extracting lyrics embeddings: 100%|██████████| 764/764 [00:16<00:00, 46.21it/s]
Lyrics embeddings shape: (764, 769)
Lyrics + labels: (764, 775)
```

	file_id	word_count	char_count	line_count	avg_word_length	lyrics_emb_0	lyrics_emb
0	001	167	907	28	4.239521	-0.091757	0.2224
1	003	260	1321	33	4.065385	-0.110028	-0.0086
2	004	232	1157	52	3.758621	0.257812	-0.1018
3	007	426	2073	65	3.819249	0.143314	-0.0734
4	008	122	642	18	4.098361	0.073305	0.1110

5 rows × 775 columns

```
Running t-SNE: n_samples=764, dim=768, perplexity=30
/tmp/ipython-input-782246349.py:35: MatplotlibDeprecationWarning: The get_cmap fu
nction was deprecated in Matplotlib 3.7 and will be removed in 3.11. Use ``matplo
tlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or ``pyplot.get_cma
p()`` instead.
  cmap = plt.cm.get_cmap("tab20", len(uniq))
```



Berdasarkan hasil t-SNE pada embedding BERT di dataset ini, representasi lirik tidak membentuk cluster yang selaras dengan kategori emosi yang digunakan. Hal ini disebabkan karena kategori emosi dalam dataset lebih bersifat akustik (berdasarkan karakter suara dan mood musikal) daripada semantik, sehingga lirik tidak menjadi penentu utama. Selain itu, reduksi dimensi melalui t-SNE menyebabkan informasi semantik halus tidak tampak secara visual.

MIDI

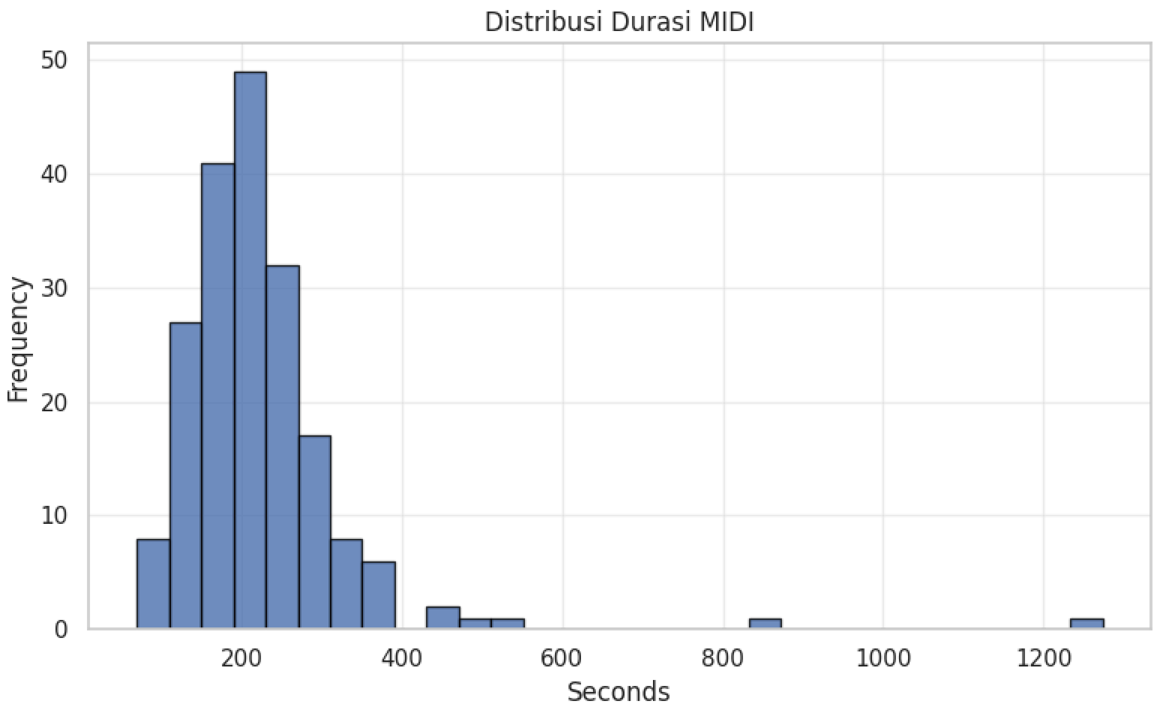
Dataset MIDI mencakup 196 file .mid yang merepresentasikan struktur musik secara simbolis, seperti nada dan ritme.

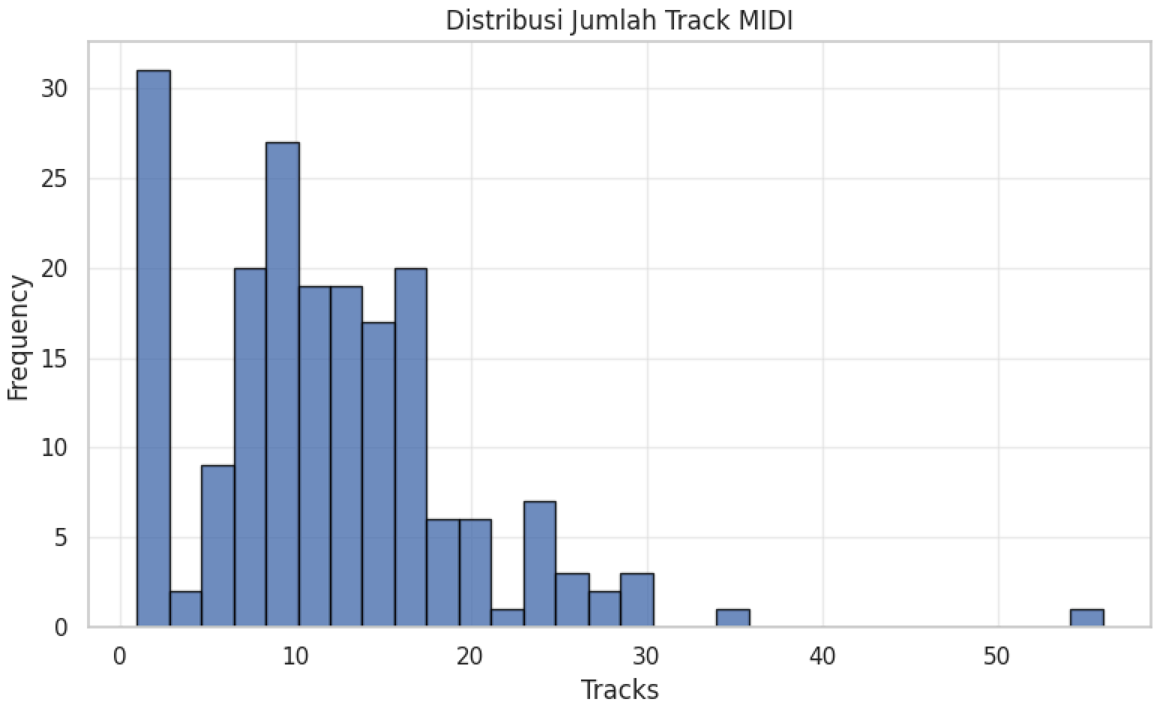
Cek File dan Fitur Mentah

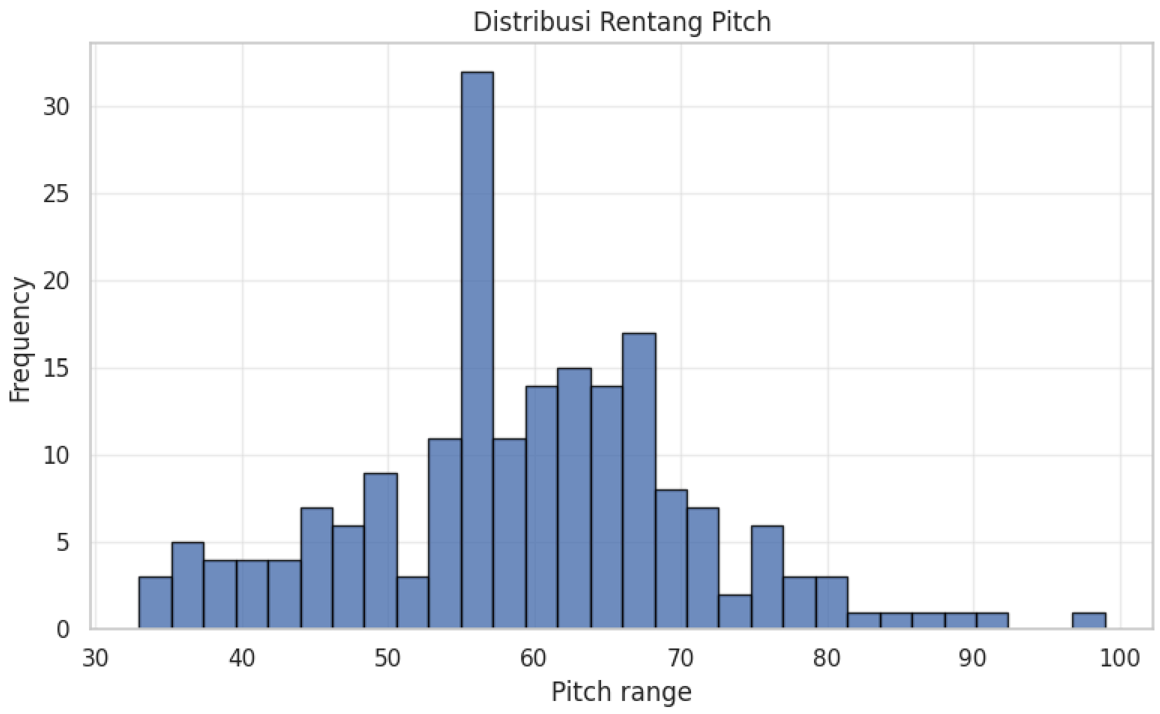
In [9]:
```
midi_dir = os.path.join(DATASET_ROOT, "MIDIs")
midi_files = sorted([f for f in os.listdir(midi_dir) if f.lower().endswith(".mid
print("Total MIDI files found:", len(midi_files))

midi_meta = []
corrupt_midi = []

for f in tqdm(midi_files, desc="Checking MIDI files"):
    path = os.path.join(midi_dir, f)
    file_id = os.path.splitext(f)[0]
    ok = check_midi_ok(path)
    if not ok:
        corrupt_midi.append(file_id)
    midi_meta.append({
        "file_id": file_id,
        "file_name": f,
        "midi_ok": ok
    })

midi_df = pd.DataFrame(midi_meta)
print("Corrupt MIDI files:", len(corrupt_midi))

midi_stats = []
for f in tqdm(midi_files, desc="Extracting MIDI stats"):
    file_id = os.path.splitext(f)[0]
    if file_id in corrupt_midi:
        continue
    path = os.path.join(midi_dir, f)
    try:
        mid = MidiFile(path)
        duration = mid.length
        n_tracks = len(mid.tracks)

        notes = []
        velocities = []
        for track in mid.tracks:
            for msg in track:
                if msg.type == "note_on" and msg.velocity > 0:
                    notes.append(msg.note)
                    velocities.append(msg.velocity)

        if len(notes) == 0:
            min_pitch = max_pitch = pitch_range = 0
        else:
            min_pitch = int(np.min(notes))
            max_pitch = int(np.max(notes))
            pitch_range = max_pitch - min_pitch

        avg_vel = float(np.mean(velocities)) if len(velocities) > 0 else 0.0

        midi_stats.append({
            "file_id": file_id,
            "duration_midi": duration,
            "n_tracks": n_tracks,
            "min_pitch": min_pitch,
            "max_pitch": max_pitch,
            "pitch_range": pitch_range,
            "avg_velocity": avg_vel
        })
    except Exception:
        corrupt_midi.append(file_id)

midi_stats_df = pd.DataFrame(midi_stats)
print("MIDI stats shape:", midi_stats_df.shape)
display(midi_stats_df.head())

plot_hist(midi_stats_df, "duration_midi", "Distribusi Durasi MIDI", "Seconds")
plot_hist(midi_stats_df, "n_tracks", "Distribusi Jumlah Track MIDI", "Tracks")
plot_hist(midi_stats_df, "pitch_range", "Distribusi Rentang Pitch", "Pitch range
plot_hist(midi_stats_df, "avg_velocity", "Distribusi Velocity Rata-rata", "Veloc
```

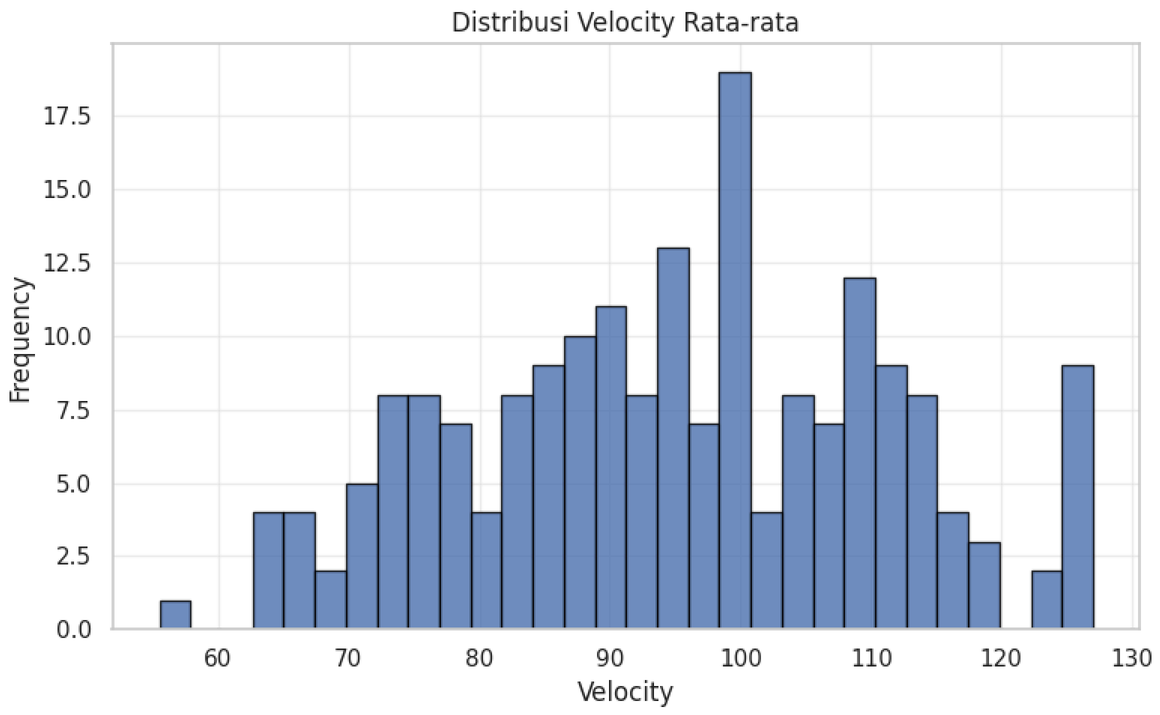
```
Total MIDI files found: 196
Checking MIDI files: 100%|██████████| 196/196 [00:22<00:00,  8.66it/s]
Corrupt MIDI files: 2
Extracting MIDI stats: 100%|██████████| 196/196 [00:58<00:00,  3.34it/s]
MIDI stats shape: (194, 7)
```

	file_id	duration_midi	n_tracks	min_pitch	max_pitch	pitch_range	avg_velocity
0	004	230.458718	22	28	91	63	117.386846
1	008	267.857000	3	40	73	33	126.945980
2	012	280.470035	8	28	84	56	91.172080
3	019	249.595000	7	31	91	60	113.399088
4	020	138.923494	13	11	103	92	105.848546


Distribusi Durasi MIDI
Frequency
Seconds
0
10
20
30
40
50
200
400
600
800
1000
1200


Distribusi Jumlah Track MIDI
Frequency
Tracks
0
5
10
15
20
25
30
0
10
20
30
40
50





Ditemukan bahwa terdapat 2 file MIDI yang corrupt. Untuk menjaga konsistensi data dan mencegah error pada tahap pemrosesan selanjutnya, file-file MIDI yang corrupt tersebut akan dikeluarkan (exclude) dari dataset.

Durasi MIDI

Durasi MIDI jauh lebih bervariasi dibandingkan audio, berkisar antara 150 hingga >1200 detik. Ini merupakan temuan penting, karena representasi MIDI (piano-roll) akan menjadi sangat panjang dan tidak sebanding antar sampel jika tidak distandardisasi.

Jumlah Track

Banyak file memiliki 5–20 track, tetapi terdapat juga MIDI kompleks dengan >50 track. Hal ini menunjukkan dataset MIDI sangat heterogen dari sisi instrumen dan aransemen.

Rentang Pitch & Velocity

Distribusi pitch range (50–70) dan average velocity (70–115) cukup konsisten, menandakan perbedaan utama dari MIDI bukan terletak pada pitch/velocity, tetapi durasi dan kompleksitas.

Resnet Embedding dan t-SNE

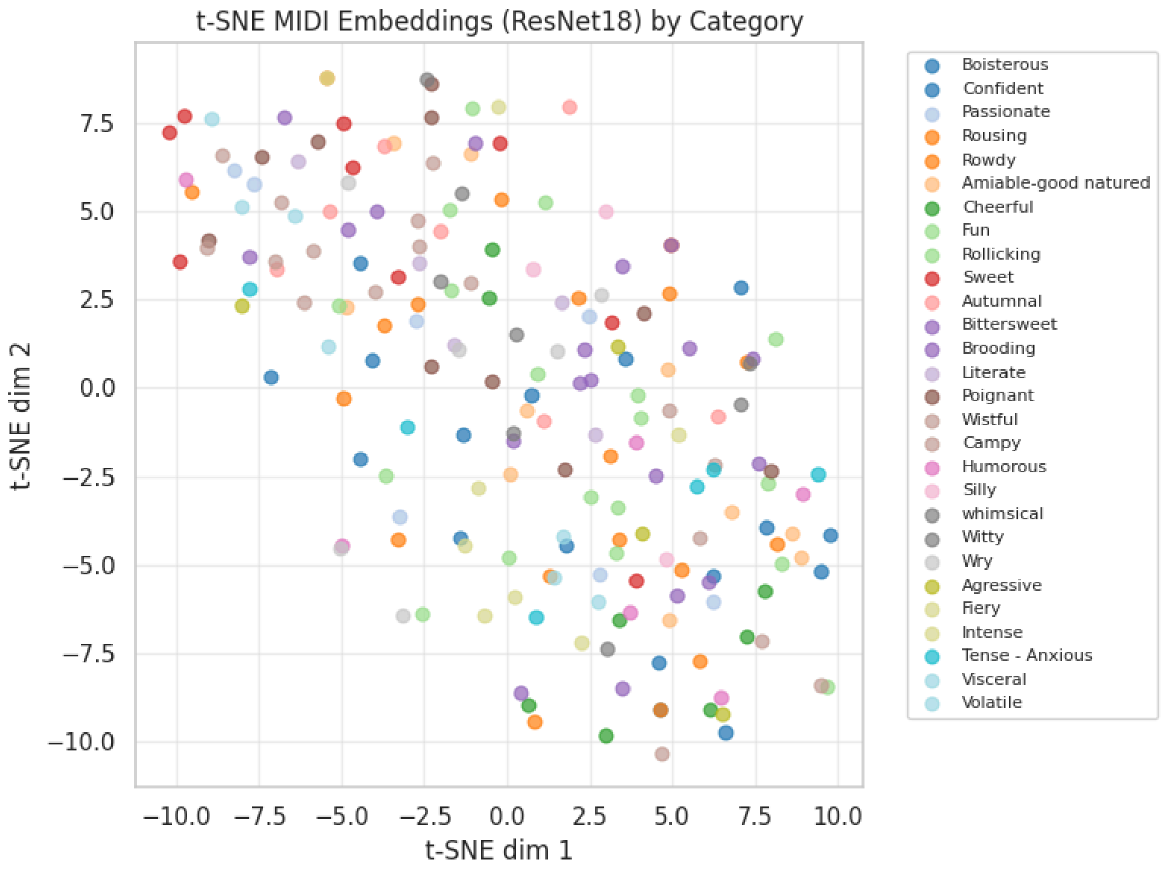
In [10]:
```
resnet18 = models.resnet18(weights=models.ResNet18_Weights.IMAGENET1K_V1)
resnet18.conv1 = nn.Conv2d(
    1,
    resnet18.conv1.out_channels,
    kernel_size=resnet18.conv1.kernel_size,
    stride=resnet18.conv1.stride,
    padding=resnet18.conv1.padding,
    bias=False
)
resnet18.fc = nn.Identity()
resnet18 = resnet18.to(device)
resnet18.eval()
print("✓ ResNet18 ready for MIDI embeddings")

midi_transform = T.Compose([
    T.ToTensor(),            # (H, W) → [1, H, W]
    T.Resize((224, 224)),
    T.Normalize(mean=[0.5], std=[0.5])
])

def midi_to_pianoroll(path, fs=10, max_length=1000):
    pm = pretty_midi.PrettyMIDI(path)
    roll = pm.get_piano_roll(fs=fs)       # [128, T]
    roll = (roll > 0).astype(np.float32)
    if roll.shape[1] > max_length:
        roll = roll[:, :max_length]
    else:
        pad = max_length - roll.shape[1]
        roll = np.pad(roll, ((0, 0), (0, pad)), mode="constant")
    return roll

def extract_midi_embedding(path):
    roll = midi_to_pianoroll(path)
    img = midi_transform(roll)            # [1, H, W]
    img = img.unsqueeze(0).to(device)     # [1, 1, H, W]
    with torch.no_grad():
        emb = resnet18(img)               # [1, 512]
    return emb.squeeze(0).cpu().numpy()

midi_emb_records = []
for f in tqdm(midi_files, desc="Extracting MIDI embeddings"):
    file_id = os.path.splitext(f)[0]
    if file_id in corrupt_midi:
        continue
    path = os.path.join(midi_dir, f)
    try:
        vec = extract_midi_embedding(path)
        row = {"file_id": file_id}
        for i, v in enumerate(vec):
            row[f"midi_emb_{i}"] = float(v)
        midi_emb_records.append(row)
    except Exception as e:
        print("Error embedding MIDI", f, ":", e)

midi_emb_df = pd.DataFrame(midi_emb_records)
print("MIDI embeddings shape:", midi_emb_df.shape)

midi_full = (
    midi_stats_df
      .merge(midi_emb_df, on="file_id", how="inner")
      .merge(labels_df, on="file_id", how="left")
)
print("MIDI + labels:", midi_full.shape)
display(midi_full.head())

midi_emb_cols = [c for c in midi_full.columns if c.startswith("midi_emb_")]
X_midi = midi_full[midi_emb_cols].values
y_midi = midi_full["category"].fillna("Unknown")

midi_tsne = tsne_and_scatter(
    X_midi, y_midi,
    title="t-SNE MIDI Embeddings (ResNet18) by Category"
)
```

```
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /roo
t/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:01<00:00, 30.9MB/s]
✓ ResNet18 ready for MIDI embeddings
Extracting MIDI embeddings:   0%|          | 0/196 [00:00<?, ?it/s]/usr/local/li
b/python3.12/dist-packages/pretty_midi/pretty_midi.py:122: RuntimeWarning: Tempo,
Key or Time signature change events found on non-zero tracks.  This is not a vali
d type 0 or type 1 MIDI file.  Tempo, Key or Time Signature may be wrong.
  warnings.warn(
Extracting MIDI embeddings: 100%|██████████| 196/196 [00:39<00:00,  4.92it/s]
MIDI embeddings shape: (194, 513)
MIDI + labels: (194, 521)
```

	file_id	duration_midi	n_tracks	min_pitch	max_pitch	pitch_range	avg_velocity	midi_
0	004	230.458718	22	28	91	63	117.386846	1.
1	008	267.857000	3	40	73	33	126.945980	1.
2	012	280.470035	8	28	84	56	91.172080	0.
3	019	249.595000	7	31	91	60	113.399088	1.
4	020	138.923494	13	11	103	92	105.848546	0.

5 rows × 521 columns

```
Running t-SNE: n_samples=194, dim=512, perplexity=30
/tmp/ipython-input-782246349.py:35: MatplotlibDeprecationWarning: The get_cmap fu
nction was deprecated in Matplotlib 3.7 and will be removed in 3.11. Use ``matplo
tlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or ``pyplot.get_cma
p()`` instead.
  cmap = plt.cm.get_cmap("tab20", len(uniq))
```



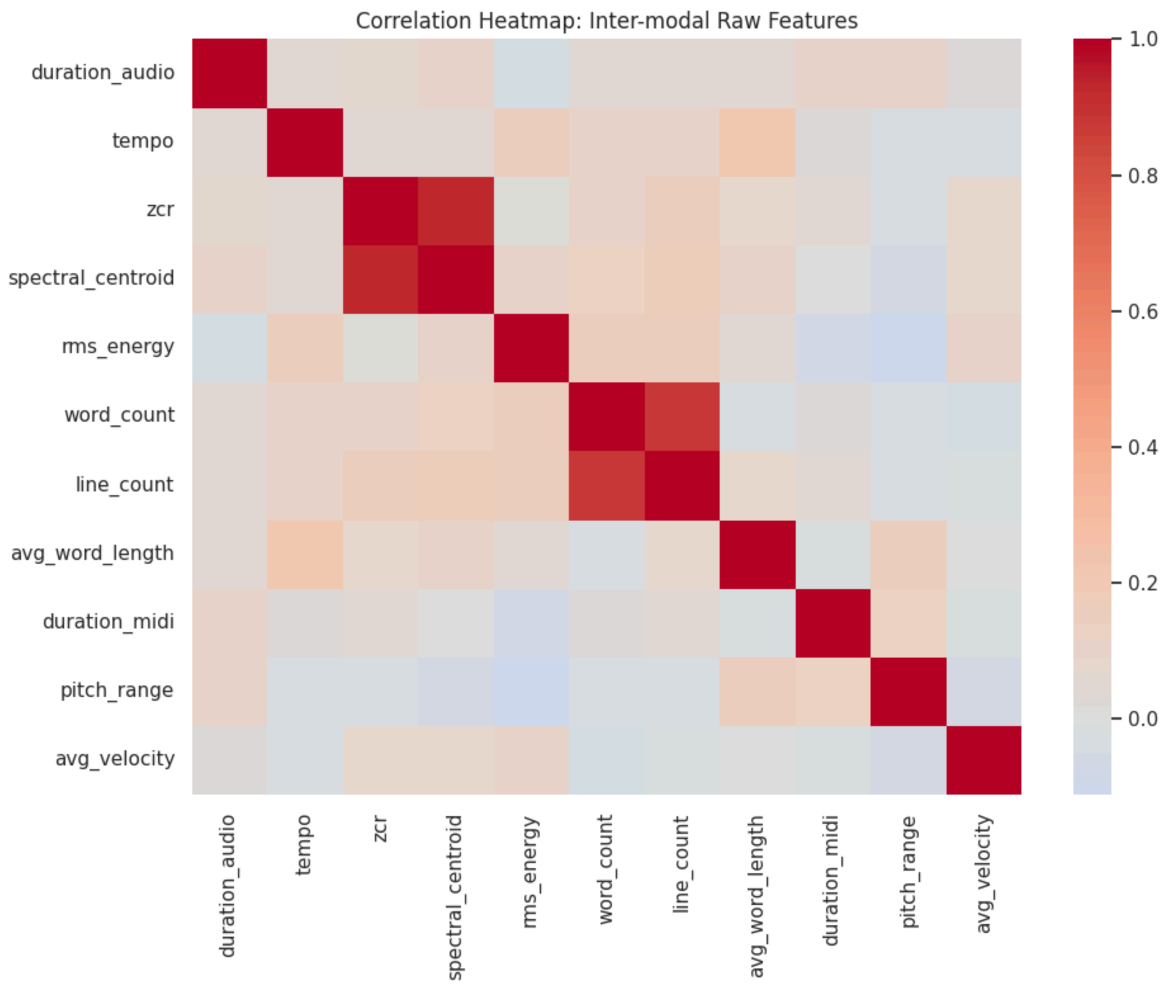
Visualisasi t-SNE pada embedding MIDI menunjukkan sebaran titik yang sangat acak tanpa pola clustering yang berarti. Variabilitas durasi dan jumlah track MIDI yang tinggi serta jumlah data yang lebih sedikit membuat modalitas ini kurang mampu menghasilkan representasi yang terpisah antar kategori.

Inter-Modal (Korelasi Fitur Mentah)

In [15]:
```python
merged_raw = (
    audio_stats_df[["file_id", "duration_audio", "tempo", "zcr",
                    "spectral_centroid", "rms_energy"]]
      .merge(lyrics_stats_df[["file_id", "word_count", "line_count",
                              "avg_word_length"]], on="file_id", how="inner")
      .merge(midi_stats_df[["file_id", "duration_midi", "pitch_range",
                            "avg_velocity"]], on="file_id", how="inner")
      .merge(labels_df[["file_id", "category", "cluster"]], on="file_id", how="l
)

print("Merged raw features shape:", merged_raw.shape)
display(merged_raw.head())

feature_cols = [
    "duration_audio", "tempo", "zcr", "spectral_centroid", "rms_energy",
    "word_count", "line_count", "avg_word_length",
    "duration_midi", "pitch_range", "avg_velocity"
]

corr = merged_raw[feature_cols].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=False, cmap="coolwarm", center=0)
plt.title("Correlation Heatmap: Inter-modal Raw Features")
plt.tight_layout()
plt.show()

print("Rata-rata fitur per kategori:")
display(merged_raw.groupby("category")[feature_cols].mean())
```

```
Merged raw features shape: (191, 14)
```

	file_id	duration_audio	tempo	zcr	spectral_centroid	rms_energy
0	004	29.675102	[95.703125]	0.088290	2967.550972	0.173973
1	008	29.675102	[114.84375]	0.087663	3256.528882	0.279501
2	012	29.675102	[92.28515625]	0.115414	4149.681641	0.101903
3	019	29.767982	[139.6748310810811]	0.062891	2363.916372	0.113394
4	020	29.675102	[143.5546875]	0.078374	2703.798661	0.129200



```
Rata-rata fitur per kategori:
```

	duration_audio	tempo	zcr	spectral_centroid	rms_energy
category					
Agressive	29.535782	[126.58852025082237]	0.069666	2558.311877	0.105808
Amiable-good natured	29.331447	[116.53144013618153]	0.068020	2695.914878	0.129581
Autumnal	29.708273	[125.22210686273186]	0.049908	2045.174740	0.102691
Bittersweet	29.606498	[111.1428049521394]	0.050098	2062.446622	0.104438
Boisterous	29.693678	[117.21230996621621]	0.086527	3088.295306	0.159594
Brooding	29.650431	[127.38478630557768]	0.049753	2281.224215	0.156302
Campy	29.684390	[127.0932966239579]	0.065661	2488.613840	0.127535
Cheerful	29.605442	[103.80870015458156]	0.086243	3260.464828	0.106527
Confident	29.639305	[133.115053877699]	0.082025	2954.699400	0.146266
Fiery	29.767982	[162.9745523872679]	0.085413	2861.522015	0.129110
Fun	29.675102	[122.41609453554963]	0.071925	2783.544998	0.121902
Humorous	29.698322	[98.92034103731912]	0.068148	2746.196247	0.112655
Intense	29.712254	[115.32735461733424]	0.076888	2817.108135	0.114199
Literate	29.749406	[149.59370822192514]	0.044334	1980.018460	0.106879
Passionate	29.708273	[116.35150268916689]	0.053033	2268.579121	0.123182
Poignant	29.614730	[112.68401214134902]	0.041623	1829.658362	0.093400
Rollicking	29.675102	[119.47641372691838]	0.054565	2250.859338	0.118838
Rousing	29.393367	[112.08254664283658]	0.071163	2714.995689	0.120140
Rowdy	29.675102	[133.4742344241739]	0.069078	2657.660027	0.151889
Silly	29.380983	[113.6747542997543]	0.061210	2393.638885	0.143259
Sweet	29.534492	[125.75379427686049]	0.055512	2183.978186	0.104989
Tense - Anxious	29.760242	[123.89093906292561]	0.068807	2671.170240	0.113734
Visceral	29.698322	[142.31449994525633]	0.078698	2862.202167	0.116807
Volatile	29.860862	[95.47808520194134]	0.086607	2891.025098	0.122923
Wistful	29.580564	[124.65378365437445]	0.047692	2017.623201	0.107814
Witty	29.693678	[120.55216010518129]	0.097119	3474.854297	0.112090
Wry	29.760242	[131.1855628842213]	0.067645	2703.490375	0.095653
whimsical	29.690582	[132.25038109756096]	0.049931	2398.150280	0.125286

Visualisasi correlation heatmap menunjukkan bahwa korelasi antar fitur yang berbeda modalitas sangat rendah.

Fitur dalam modalitas yang sama menunjukkan korelasi cukup tinggi, seperti:

- word_count dan line_count,
- spectral_centroid dan ZCR,
- pitch_range dan duration_midi,

Namun korelasi lintas modalitas sebagian besar masih rendah, yang berarti hubungan hampir tidak ada.

t-SNE Gabungan 3 Modalitas

In [14]:

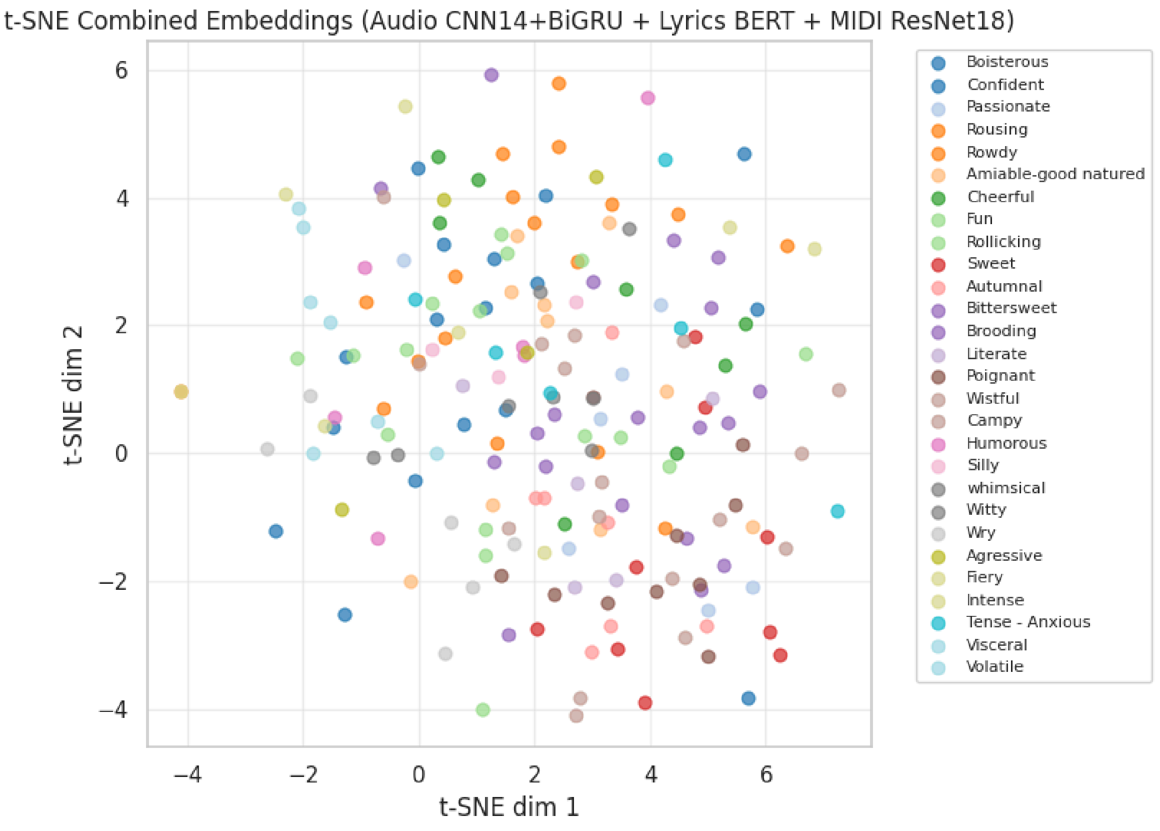
```
audio_emb_small  = audio_full[["file_id"] + [c for c in audio_full.columns if c.
lyrics_emb_small = lyrics_full[["file_id"] + [c for c in lyrics_full.columns if
midi_emb_small   = midi_full[["file_id"] + [c for c in midi_full.columns if c.st

combined = (
    audio_emb_small
      .merge(lyrics_emb_small, on="file_id", how="inner")
      .merge(midi_emb_small, on="file_id", how="inner")
      .merge(labels_df[["file_id", "category"]], on="file_id", how="left")
)

print("Combined embeddings shape:", combined.shape)
display(combined.head())

if combined.empty:
    print("Tidak ada sampel dengan tiga modalitas lengkap.")
else:
    audio_cols  = [c for c in combined.columns if c.startswith("audio_emb_")]
    lyrics_cols = [c for c in combined.columns if c.startswith("lyrics_emb_")]
    midi_cols   = [c for c in combined.columns if c.startswith("midi_emb_")]

    X_audio_z  = zscore_np(combined[audio_cols].values)
    X_lyrics_z = zscore_np(combined[lyrics_cols].values)
    X_midi_z   = zscore_np(combined[midi_cols].values)

    X_mm = np.concatenate([X_audio_z, X_lyrics_z, X_midi_z], axis=1)
    y_mm = combined["category"].fillna("Unknown")

    mm_tsne = tsne_and_scatter(
        X_mm, y_mm,
        title="t-SNE Combined Embeddings (Audio CNN14+BiGRU + Lyrics BERT + MIDI
    )
```

```
Combined embeddings shape: (191, 3330)
```

	file_id	audio_emb_0	audio_emb_1	audio_emb_2	audio_emb_3	audio_emb_4	audio_e
0	004	0.0	0.0	0.0	0.0	0.0	
1	008	0.0	0.0	0.0	0.0	0.0	
2	012	0.0	0.0	0.0	0.0	0.0	
3	019	0.0	0.0	0.0	0.0	0.0	
4	020	0.0	0.0	0.0	0.0	0.0	

5 rows × 3330 columns

```
Running t-SNE: n_samples=191, dim=3328, perplexity=30
/tmp/ipython-input-782246349.py:35: MatplotlibDeprecationWarning: The get_cmap fu
nction was deprecated in Matplotlib 3.7 and will be removed in 3.11. Use ``matplo
tlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or ``pyplot.get_cma
p()`` instead.
  cmap = plt.cm.get_cmap("tab20", len(uniq))
```



Ketika embedding dari ketiga modalitas digabungkan, t-SNE masih memperlihatkan tumpang-tindih antar kategori. Hal ini menegaskan bahwa tugas klasifikasi emosi musik memang kompleks dan tidak mudah dipisahkan secara linear.

Kesimpulan

Audio

Hasil EDA menunjukkan bahwa modalitas audio memiliki kualitas yang paling stabil, terutama karena seluruh file berdurasi hampir seragam di sekitar 30 detik. Oleh sebab itu, preprocessing audio dilakukan dengan men-standardisasi panjang sinyal menjadi tepat 30 detik melalui proses trim atau padding, lalu mengekstraknya menggunakan PANNs CNN14 pretrained. Fitur manual seperti tempo tidak digunakan karena terbukti sangat tidak stabil pada EDA, sedangkan CNN14 sudah mampu menangkap pola ritmis dan spektral secara otomatis dari waveform. Embedding 2048-dim dari CNN14 menjadi representasi akhir untuk modalitas audio.

Lirik

Pada modalitas lirik, variasi panjang teks cukup besar, namun struktur penulisan secara umum baik. Strategi preprocessing dilakukan dengan pembersihan ringan dan tokenisasi menggunakan BERT dengan batas panjang tertentu (256–384 token) untuk mengatasi lirik yang sangat panjang. Embedding diperoleh melalui mean pooling pada hidden state terakhir, menghasilkan representasi 768-dim yang telah mengandung informasi semantik tanpa perlu fitur manual tambahan.

Midi

Modalitas MIDI memiliki variabilitas paling besar, terutama dari sisi durasi dan jumlah track. Untuk menyejajarkan dengan audio, setiap file MIDI diambil window 30 detik kemudian dikonversi menjadi piano-roll biner. Piano-roll tersebut di-resize ke 224×224 agar sesuai dengan arsitektur ResNet18 pretrained yang digunakan sebagai feature extractor. Hasil ekstraksi berupa embedding 512-dim yang mewakili pola harmonis dan ritmis utama dari bagian lagu tersebut.

Late Fusion

Karena EDA menunjukkan bahwa ketiga modalitas tidak berkorelasi kuat dan tidak mampu memisahkan kategori secara individu (t-SNE menunjukkan overlap tinggi), digunakan pendekatan late fusion. Embedding dari setiap modalitas dinormalisasi menggunakan z-score, lalu digabungkan melalui late fusion sebelum dimasukkan ke MLP classifier. Pendekatan ini memungkinkan tiap modalitas berkontribusi sesuai kekuatannya, sekaligus memanfaatkan sifat komplementer antar-modalitas.