

Musical Genre Classification



AutoML 연구실
석사 과정 조성현
21.12.28

To Do List

➤ Last Week

- Evaluation metrics

➤ This Week

- 코드 분석

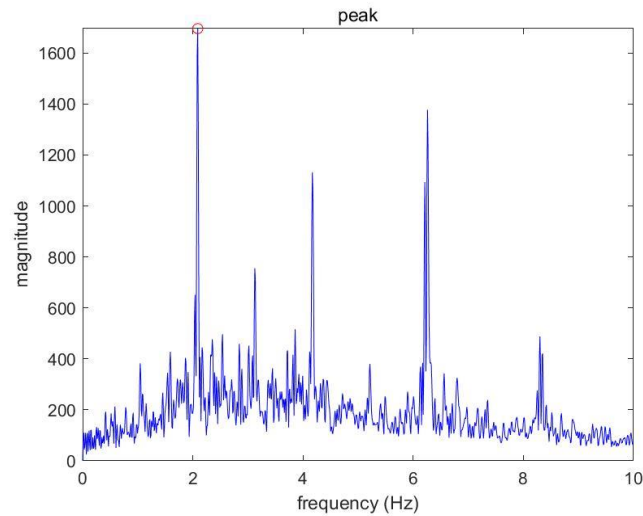
The standard statistics of the datasets

Author	Year	Neural Network	# of employed datasets	Employed Dataset	Input Type	Evaluation Metric	Ref.
Massoudi	2021	CNN	1	Urban Sound Classification Challenge	MFCC	Accuracy	[1]
Ghildiyal	2020	CNN	1	GTZAN	Mel-Spectrogram	Accuracy	[2]
Palanisamy	2020	CNN	3	ESC-50, GTZAN, UrbanSound8K	Log Mel-Spectrogram	Accuracy	[3]
Yu	2019	CNN	2	GTZAN, Extended Ballroom	STFT Spectrogram	Accuracy	[4]
Won	2020	CNN	3	MagnaTagATune, Million Song Dataset, MTG-Jamendo	Mel-Spectrogram	ROC-AUC, PR-AUC	[5]
Bisharad	2019	CNN	1	GTZAN	Mel-Spectrogram	Precision, Recall, F1 score	[6]
Zhang	2019	RNN	1	GTZAN	MFCC, chromagram	Accuracy	[7]
Chillara	2019	CNN	1	FMA-SMALL	Spectrogram	Accuracy	[8]
Zhang	2016	CNN	1	GTZAN	STFT Spectrogram	Accuracy	[9]
Choi	2017	CRNN	1	Million Song Dataset	Log Mel-Spectrogram	ROC-AUC	[10]
Su	2019	CNN	1	UrbanSound8k	Log Mel-Spectrogram, MFCC	Accuracy	[11]
Choi	2016	CNN	2	MagnaTagATune, Million Song Dataset	Mel-Spectrogram, MFCC, STFT	ROC-AUC	[12]
Li	2018	CNN	3	ESC-10, ESC-50, UrbanSound8k	Log Mel-Spectrogram	Accuracy	[13]

MIRToolbox

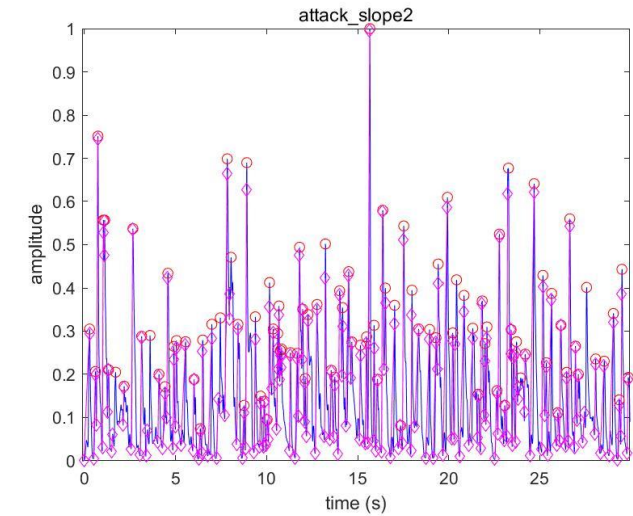
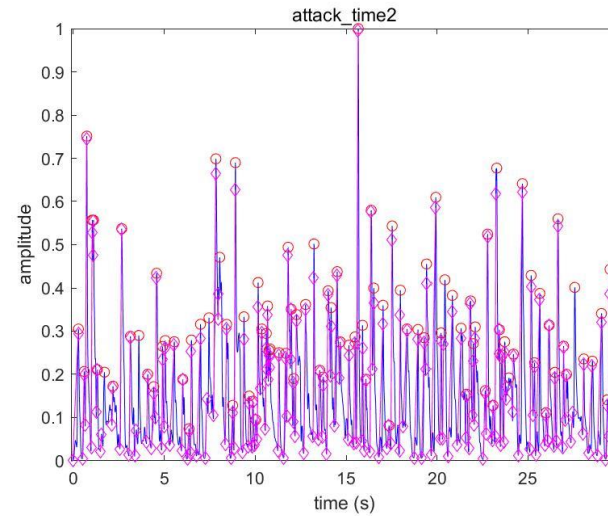
X_axis = frequency

Fluctuation



X_axis = time

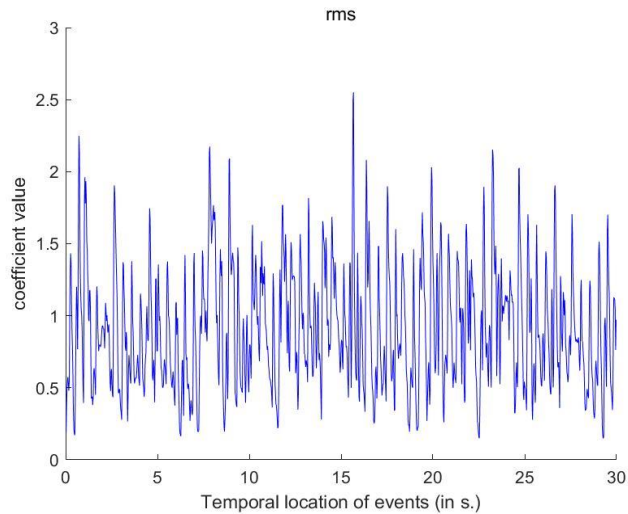
Rhythm



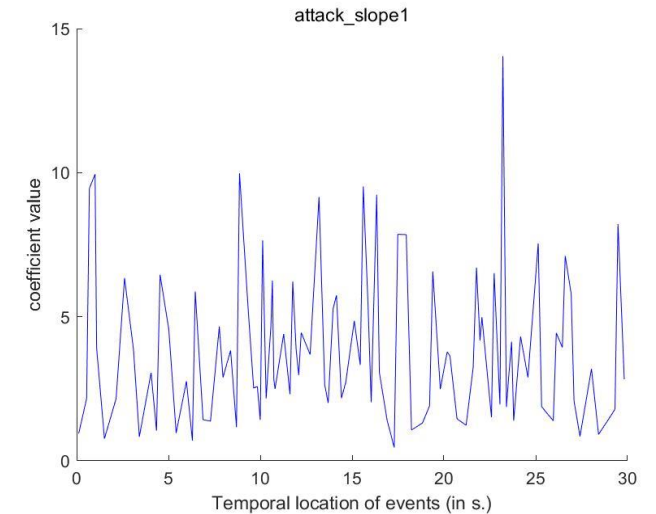
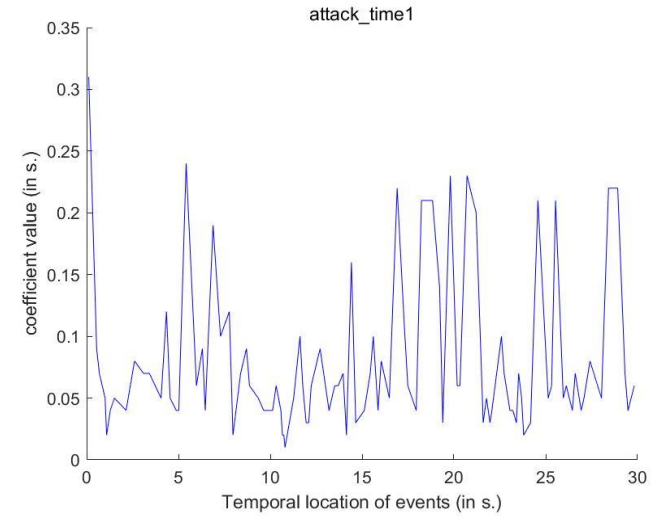
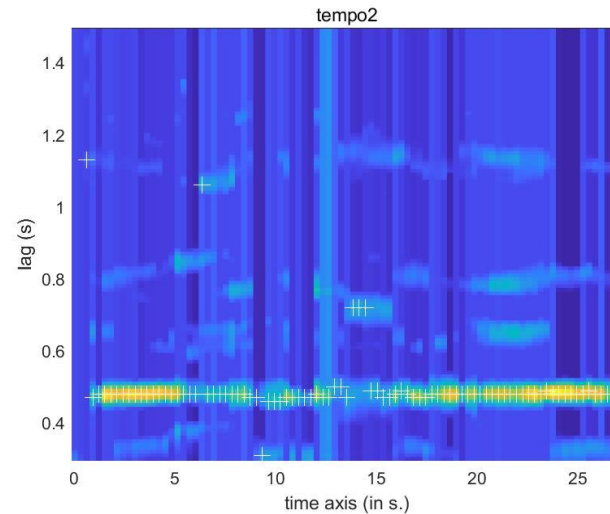
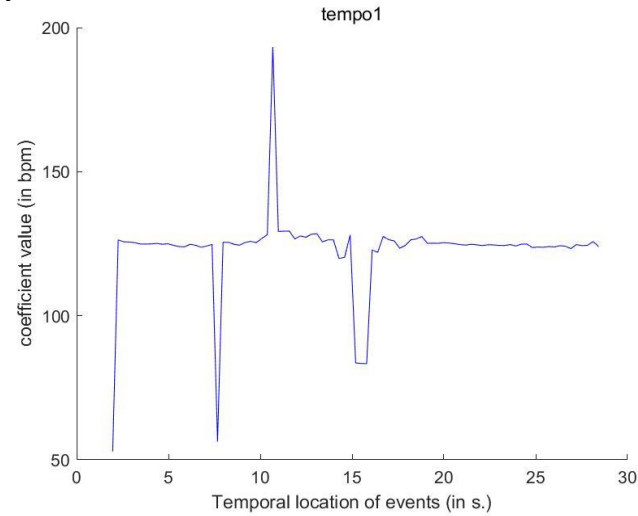
MIRToolbox

X_axis = Temporal location of events (in s.)

Dynamics



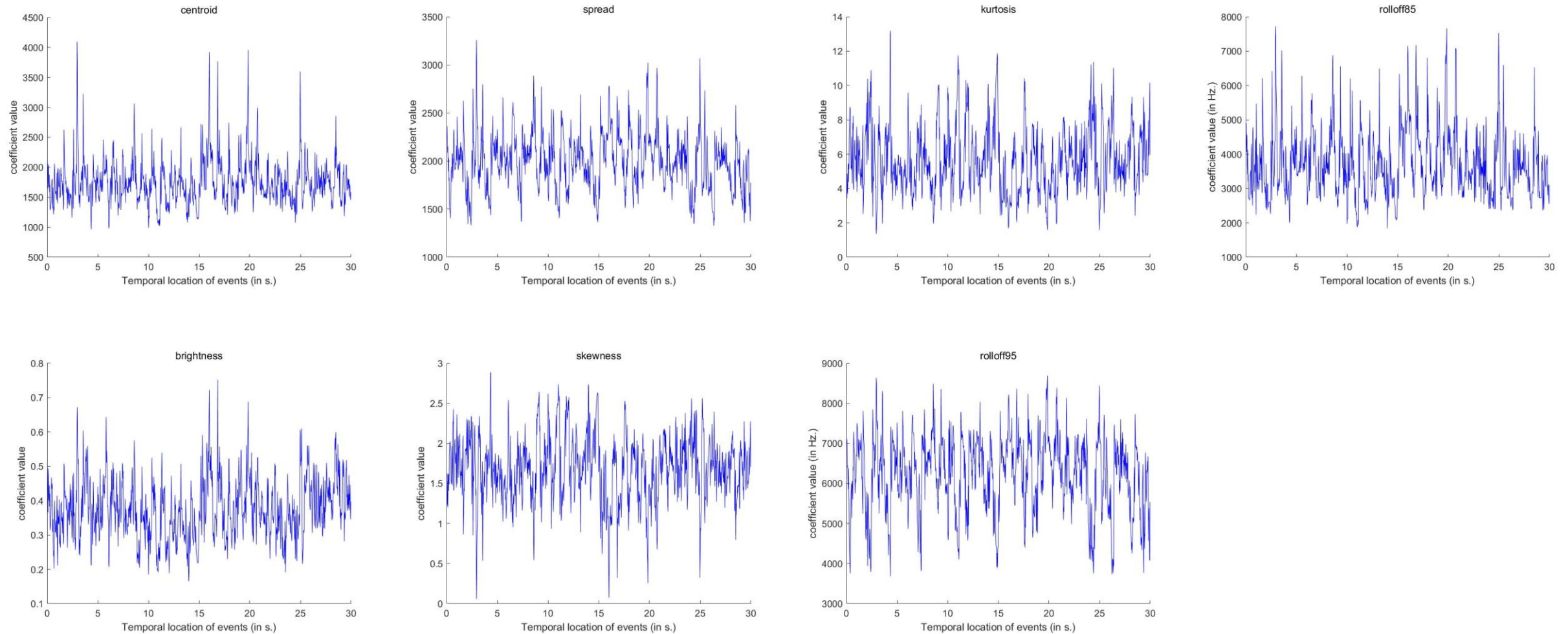
Rhythm



MIRToolbox

X_axis = Temporal location of events (in s.)

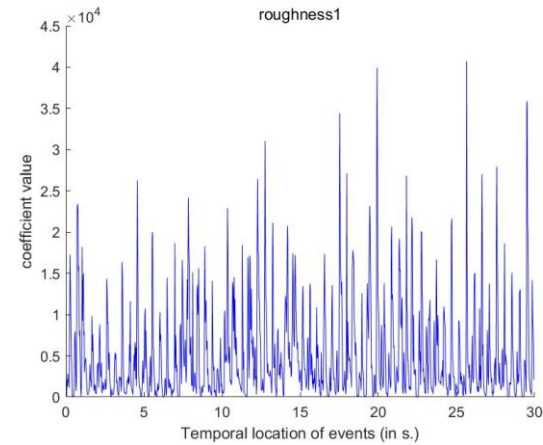
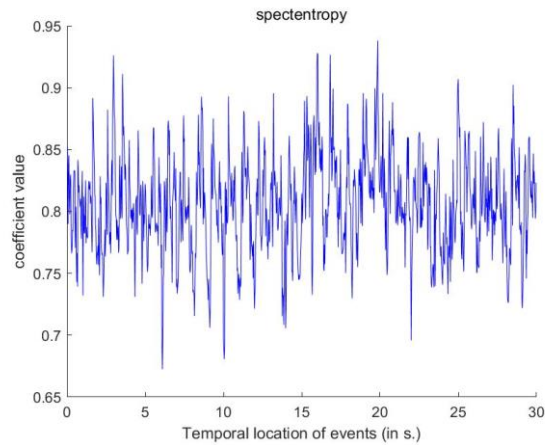
Spectral



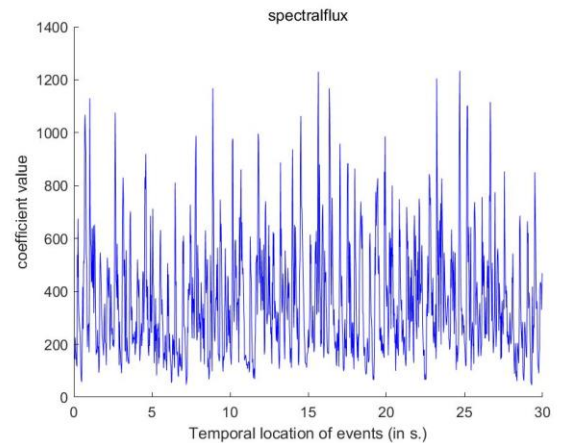
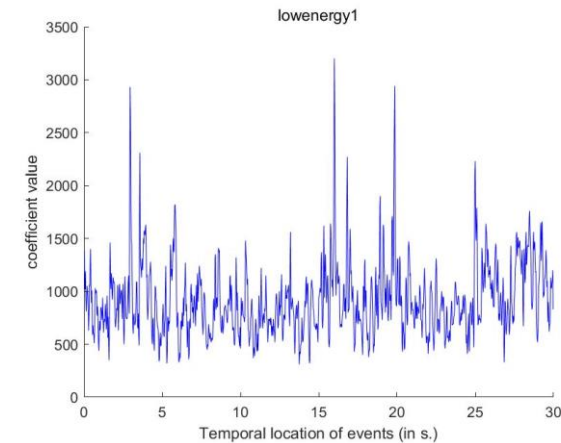
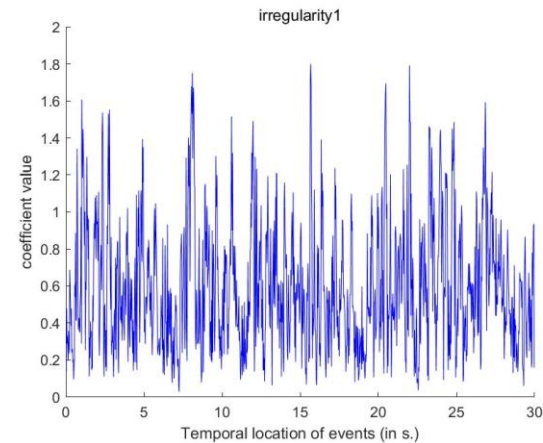
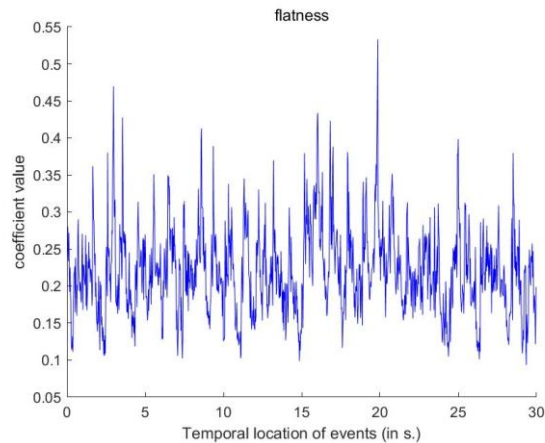
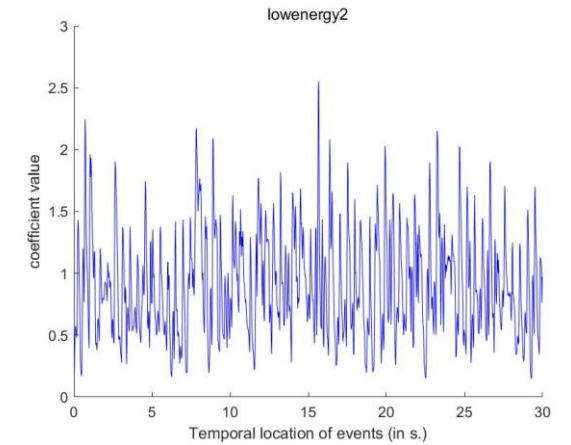
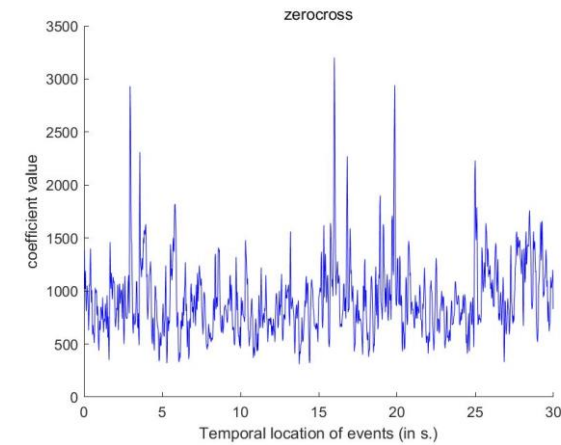
MIRToolbox

X_axis = Temporal location of events (in s.)

Spectral



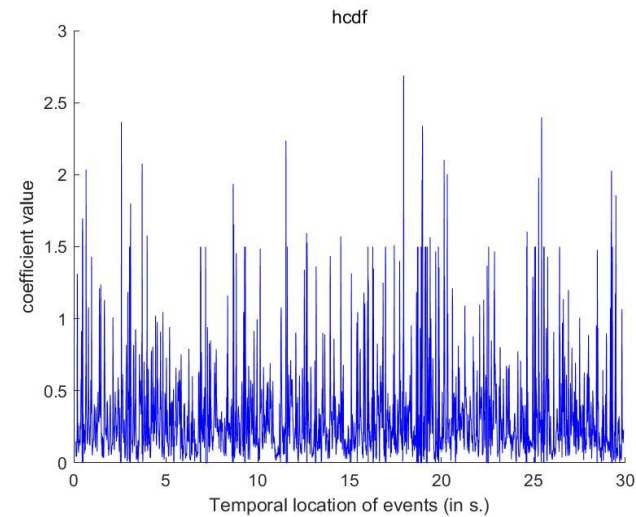
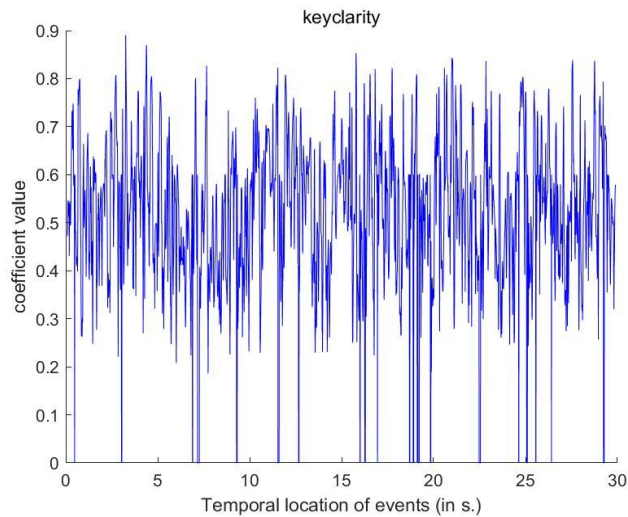
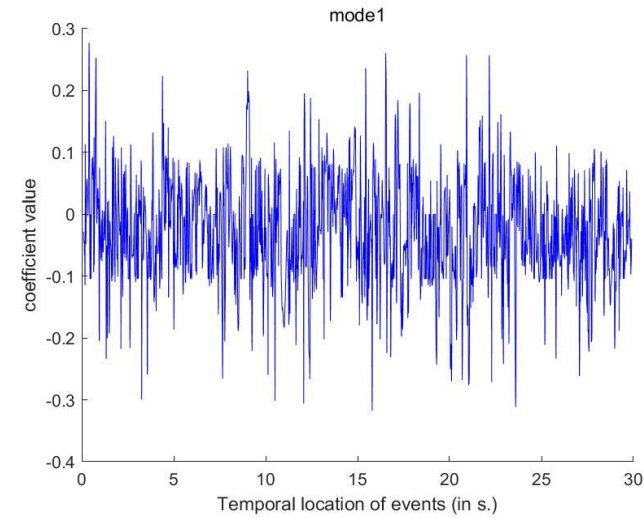
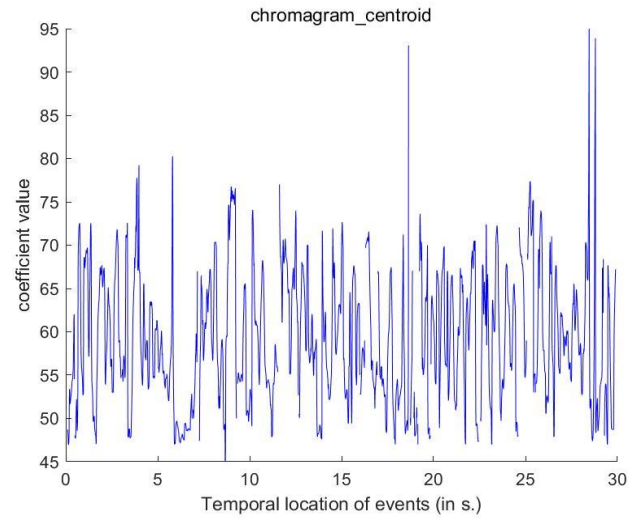
Timbre



MIRToolbox

X_axis = Temporal location of events (in s.)

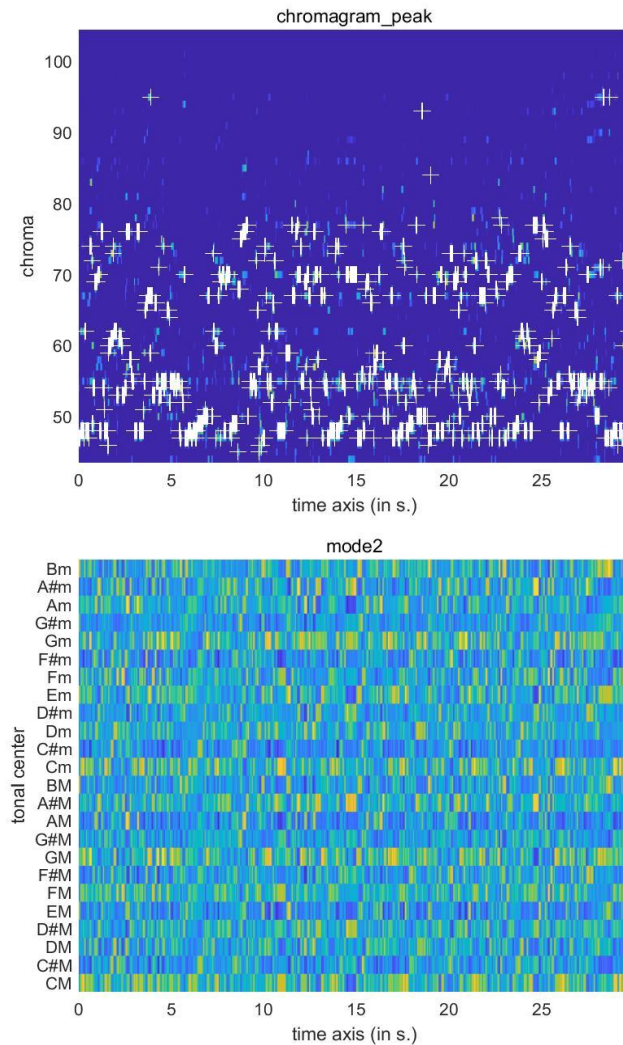
Tonal



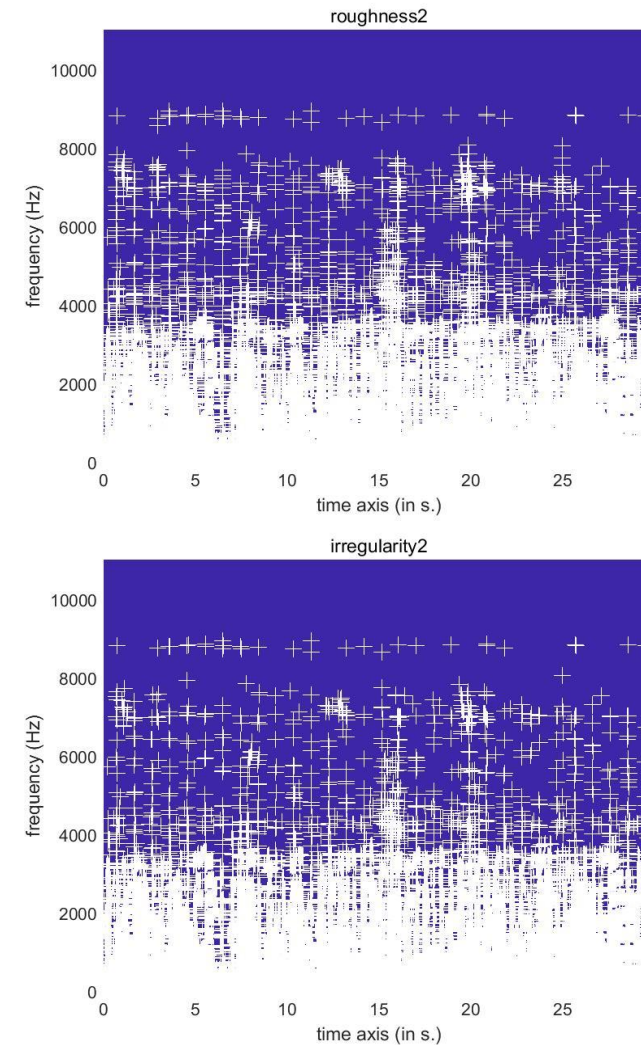
MIRToolbox

X_axis = time axis (in s.)

Tonal



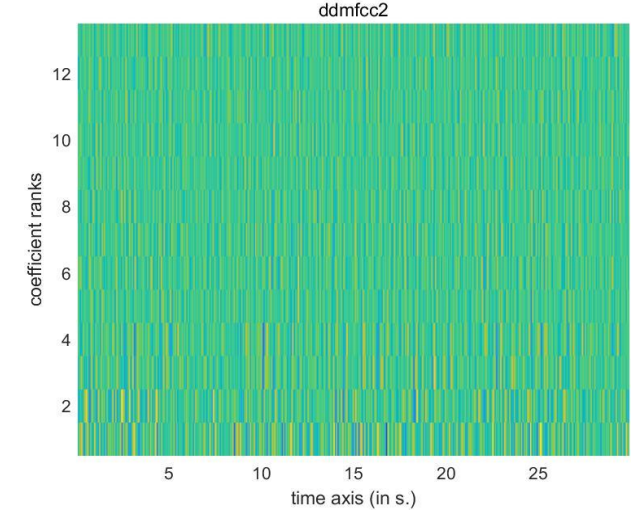
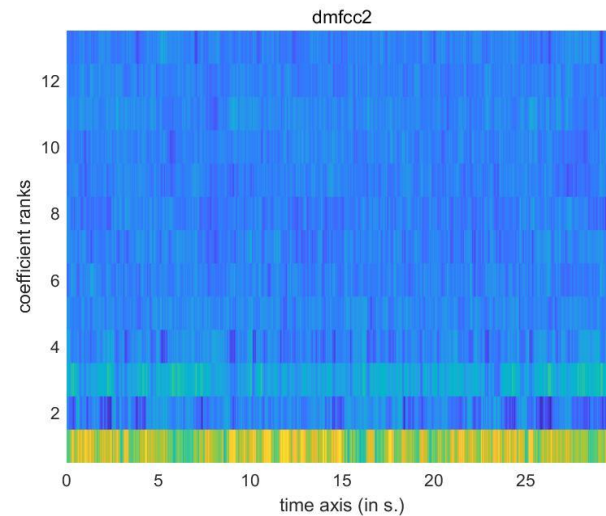
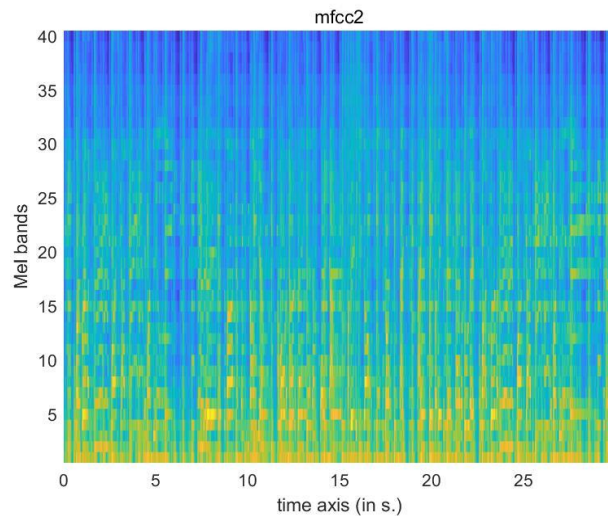
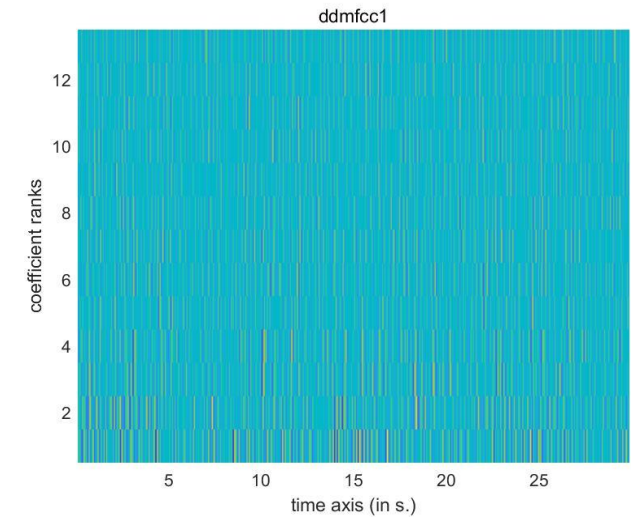
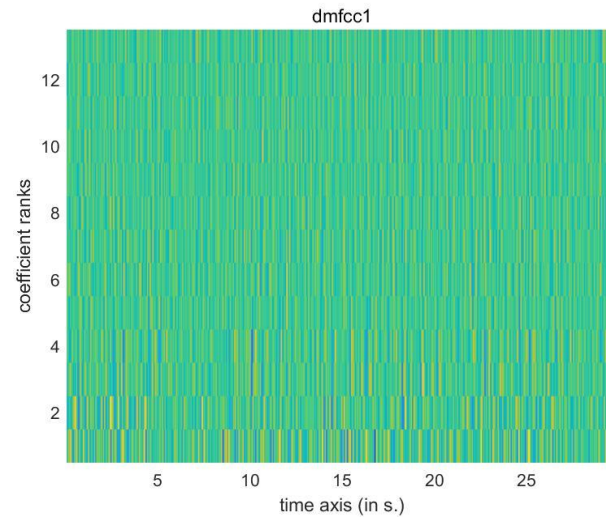
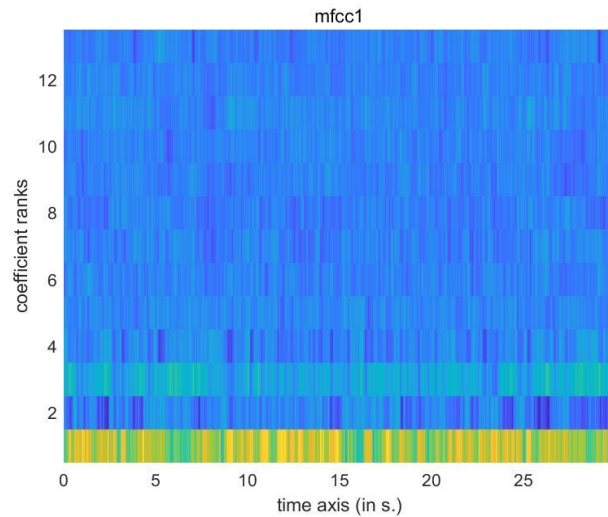
Spectral



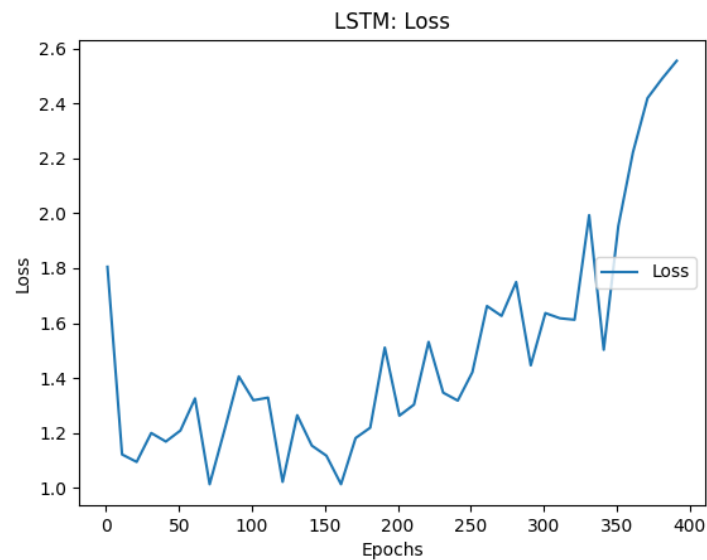
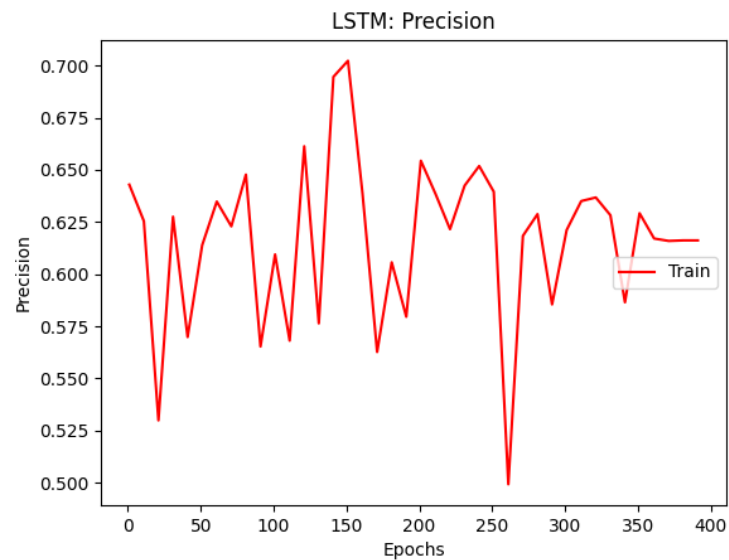
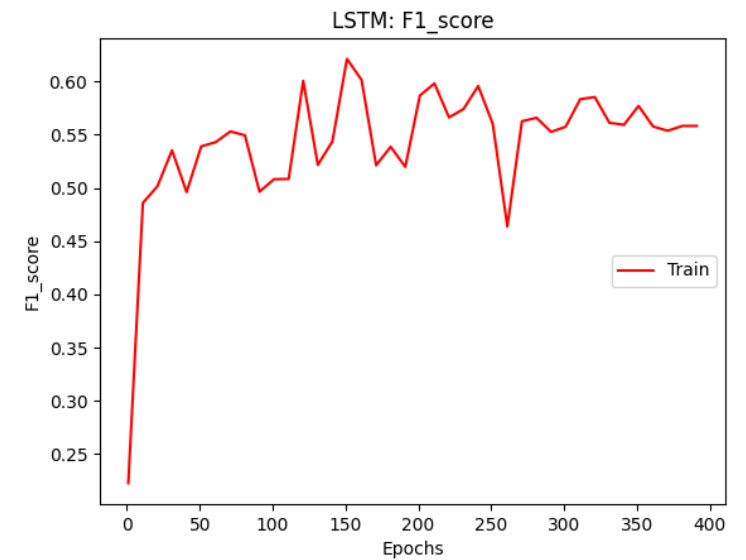
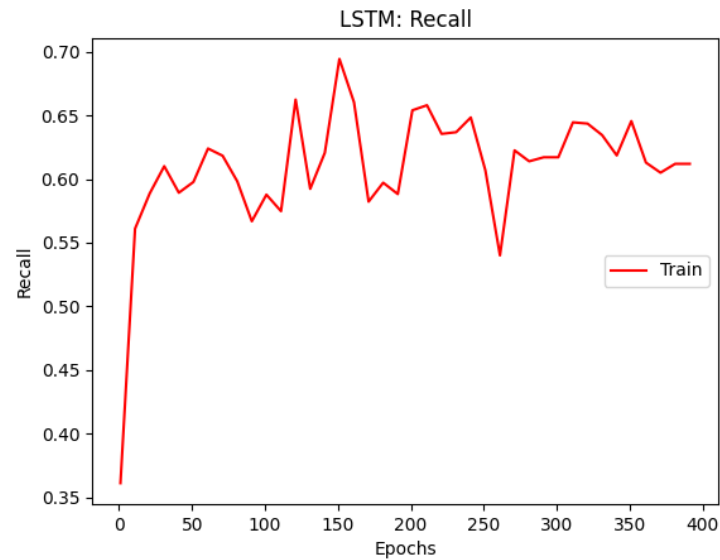
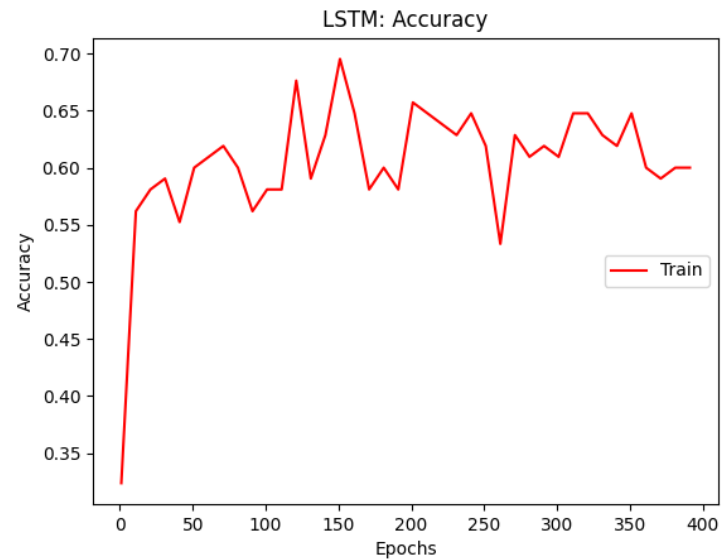
MIRToolbox

X_axis = time axis (in s.)

Spectral



Evaluation Metrics



Experimental Settings

❖ Input settings

- MFCC [0:13]
- Spectral_centroid [13:14]
- Chroma_stft [14:26]
- Spectral_contrast [26:33]

❖ Cross validation

- Train : Validation : Test = 7 : 2 : 1

❖ Timeseries_length = 128

Train = [420,128,33]

→ Validation = [120,128,33]

Test = [60,128,33]

❖ Experimental settings

- Optimizer = Adam
- Learning rate = 0.001
- Batch size = 35
- Epoch = 400
- Loss function = NLLLoss
- Stateful = False

Stateful vs Stateless

상호 작용 상태가 얼마나 오래 기록되는지, 해당 정보가 어떤 식으로 저장되는지를 기준으로 구별

	전달 여부
stateful	O
stateless	X

Functional

❖ NLLLoss (Negative Log Likelihood Loss)

- Classification에 유용
- Neural Network에서 log-probabilities를 얻으려면 마지막 layer에 Log Softmax layer를 추가

❖ Softmax

- Multiclass 분류에서 사용
- 분류될 클래스가 n 개라고 할 때, n 차원의 벡터를 입력 받아 각 클래스에 속할 확률 추정
- Log-Softmax = Softmax함수에 log를 취한 것
- Softmax에 의한 결과는 NLL Loss에 직접적으로 사용할 수 없어서 log-softmax 사용

❖ CrossEntropyLoss

- LogSoftmax + NLLLoss가 하나의 single class에 합쳐져 있음

Reference

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- [2] Ghildiyal, A., Singh, K., & Sharma, S. (2020, November). Music genre classification using machine learning. In *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 1368-1372). IEEE.
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