

Musical Genre Classification



AutoML 연구실
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22.01.18

To Do List

➤ Last Week

- Comparison result
- Dataset transform
- Dataset Integrity

➤ This Week

- Comparison result
- Dataset transform
- Dataset Integrity

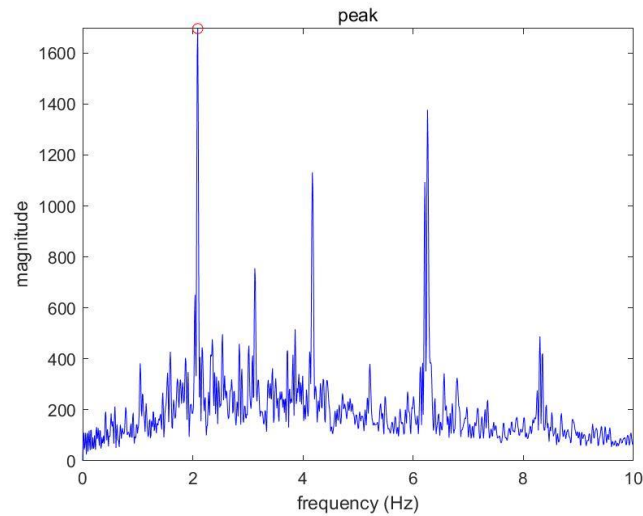
The standard statistics of the datasets

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]
Li	2021	CNN	4	FMA, GTZAN5, GTZAN10, EMA	STFT Spectrogram	Accuracy	[14]

MIRToolbox

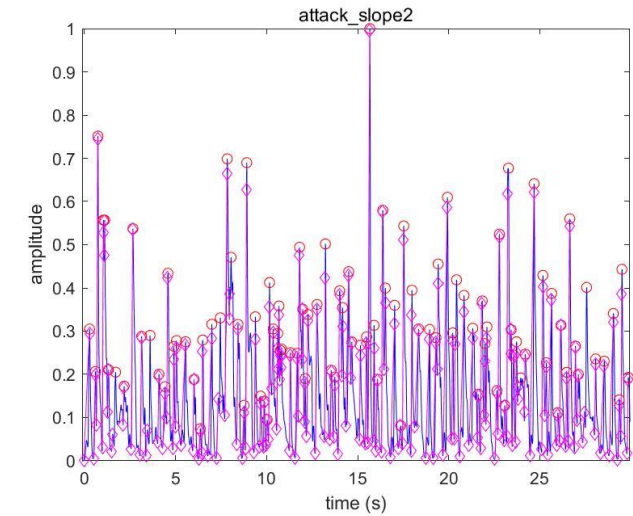
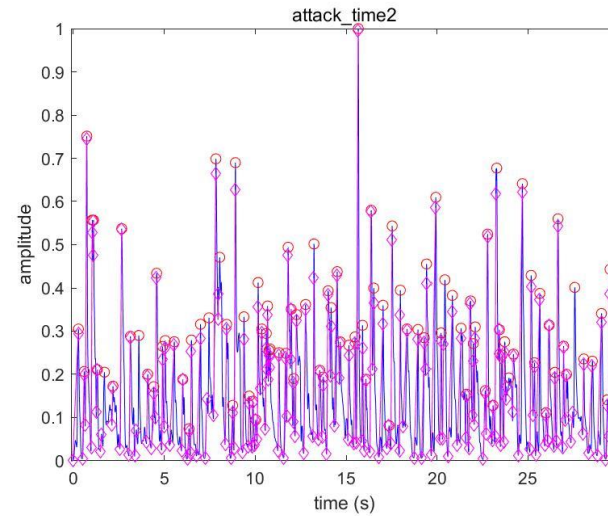
X_axis = frequency

Fluctuation



X_axis = time

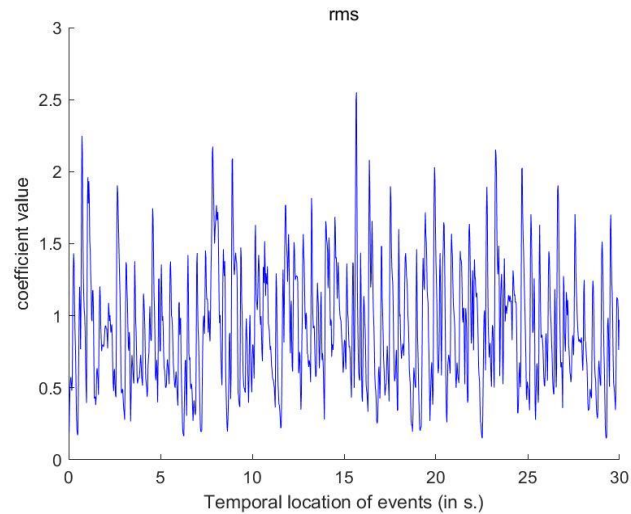
Rhythm



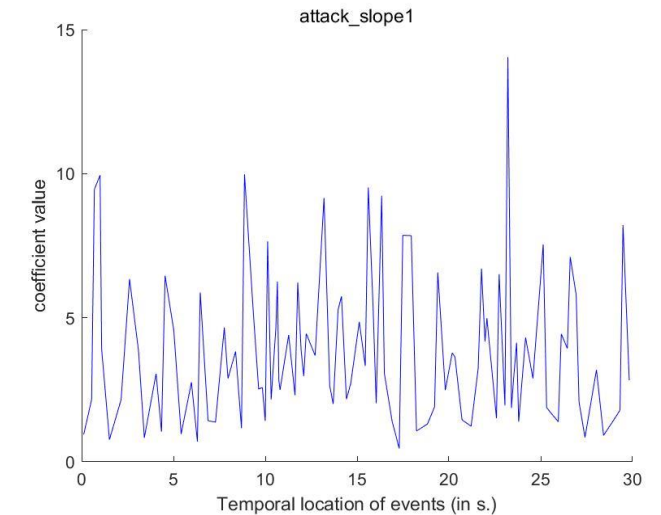
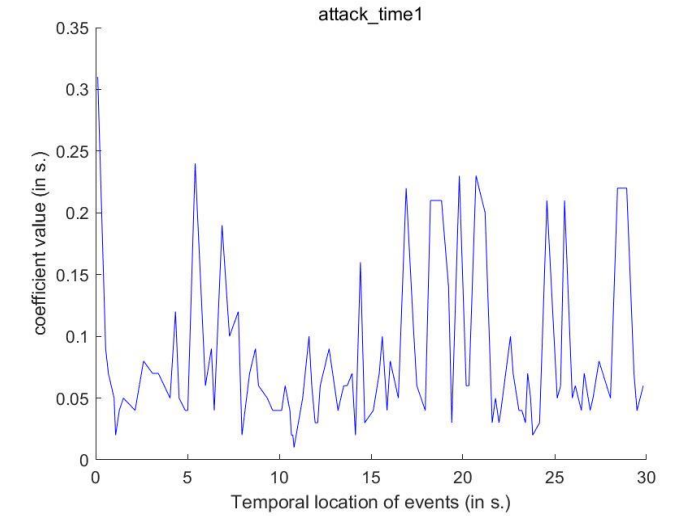
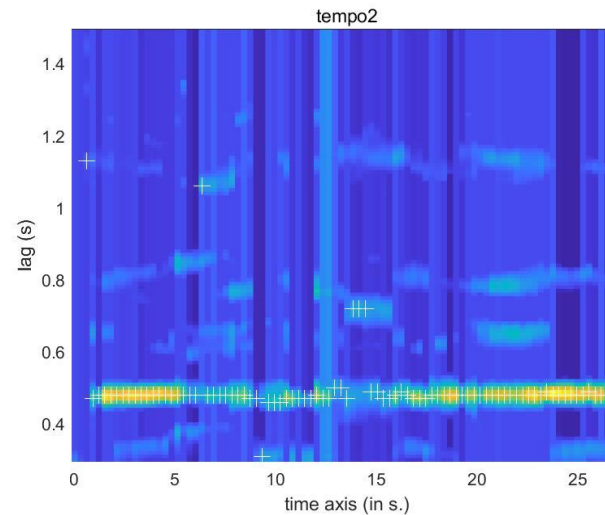
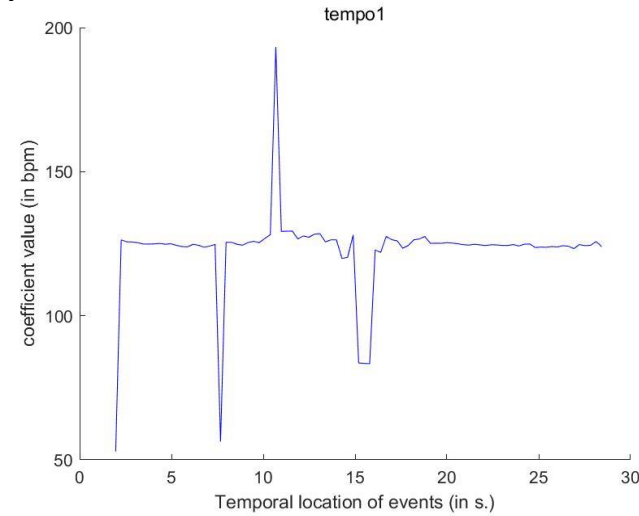
MIRToolbox

X_axis = Temporal location of events (in s.)

Dynamics



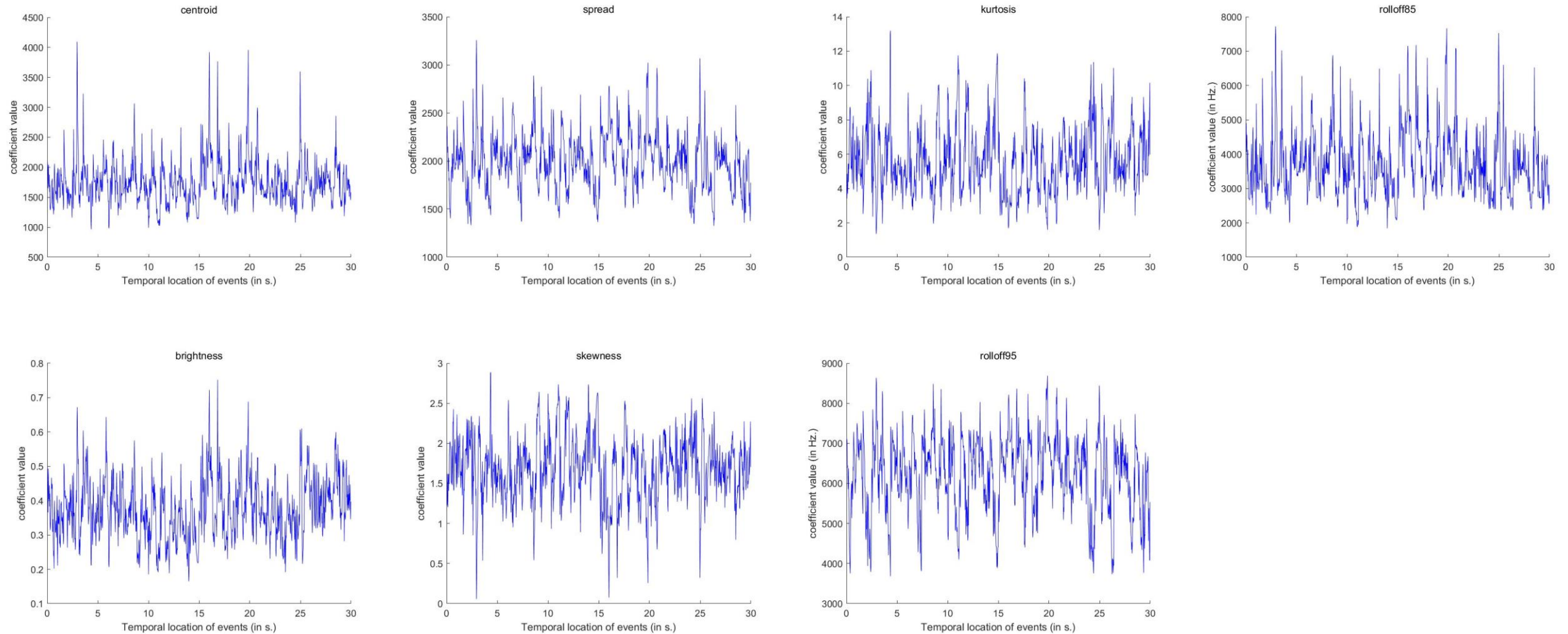
Rhythm



MIRToolbox

X_axis = Temporal location of events (in s.)

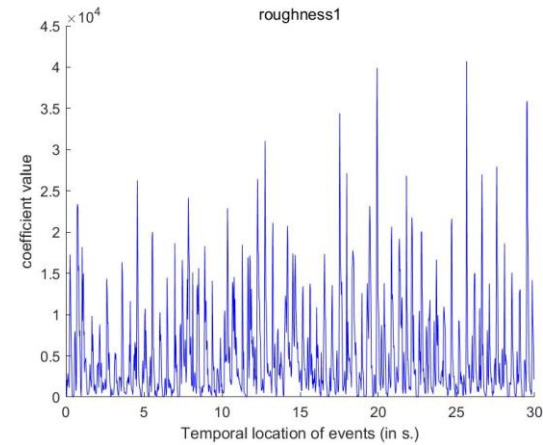
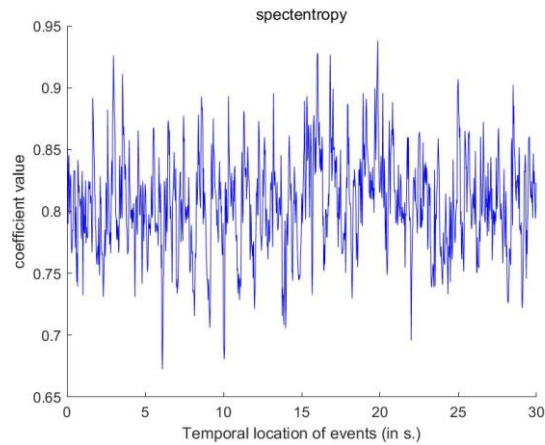
Spectral



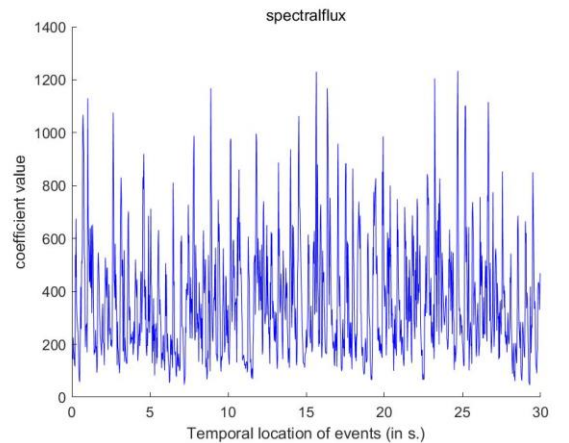
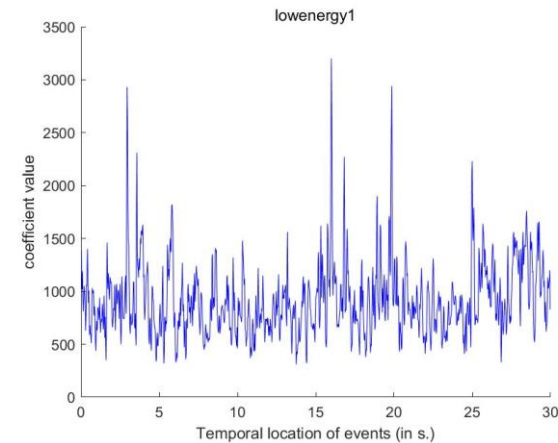
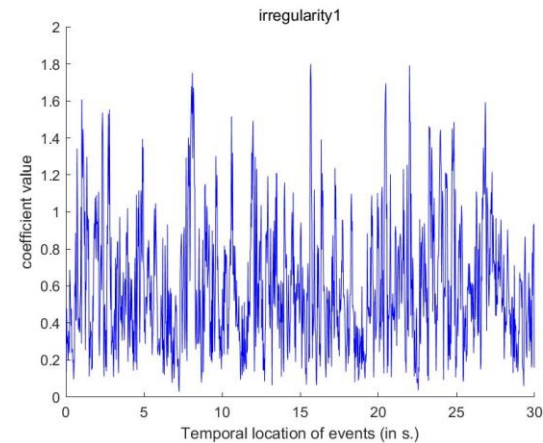
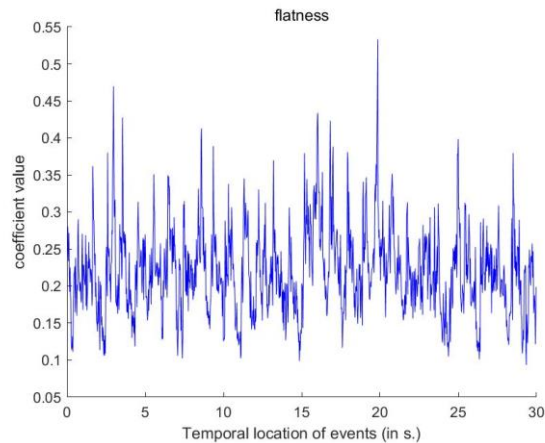
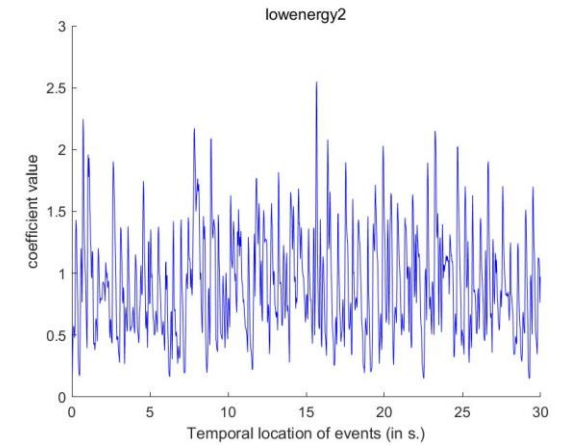
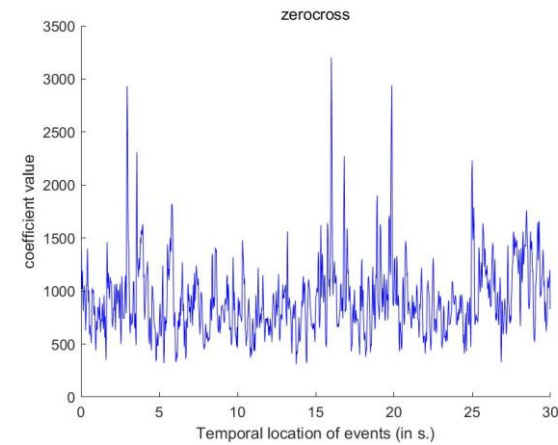
MIRToolbox

X_axis = Temporal location of events (in s.)

Spectral



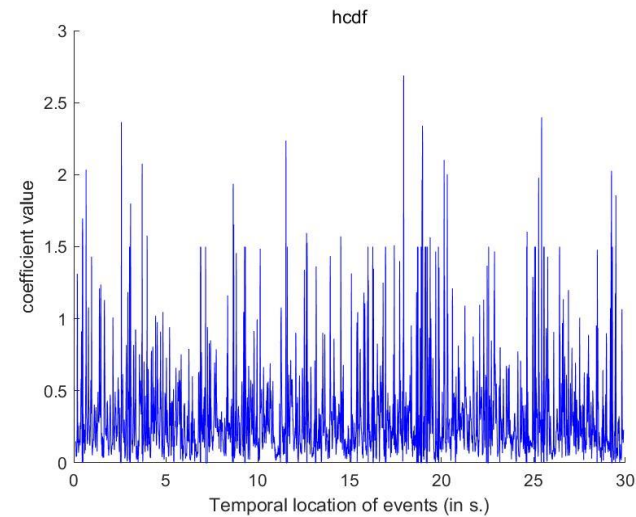
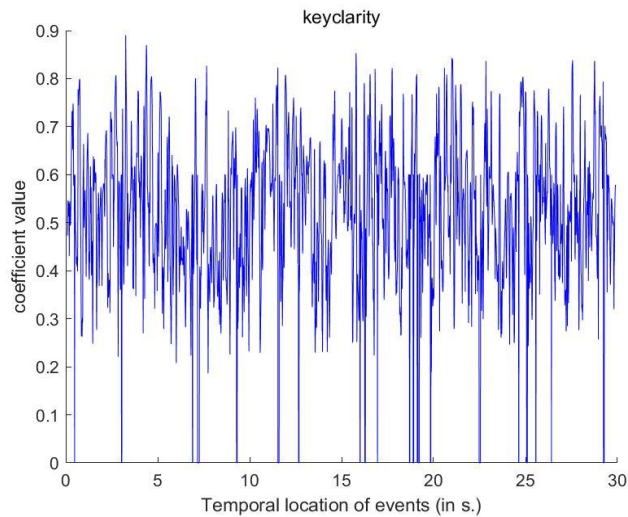
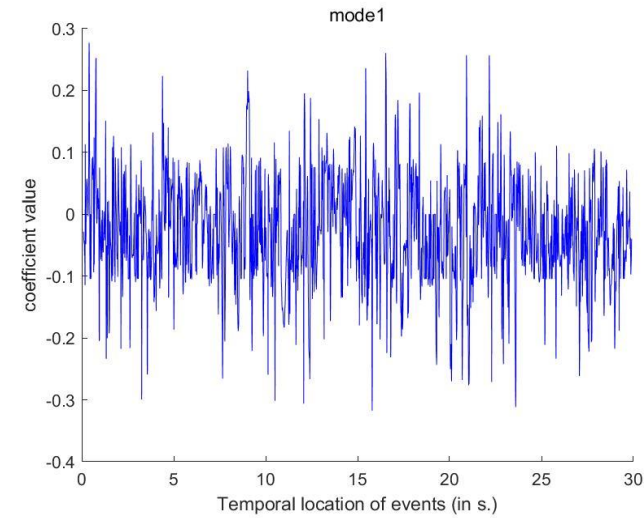
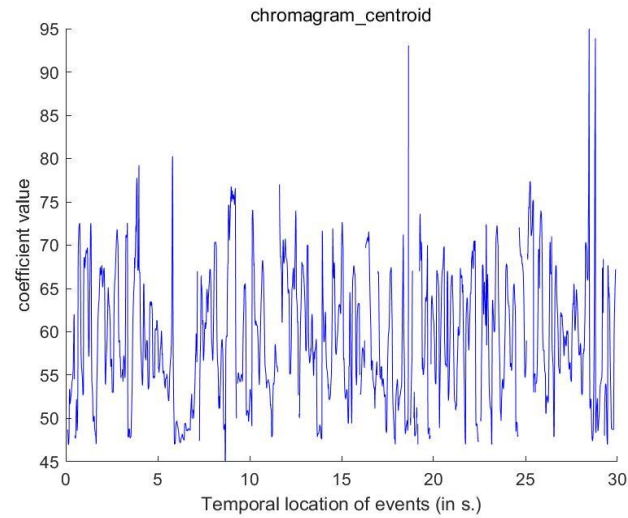
Timbre



MIRToolbox

X_axis = Temporal location of events (in s.)

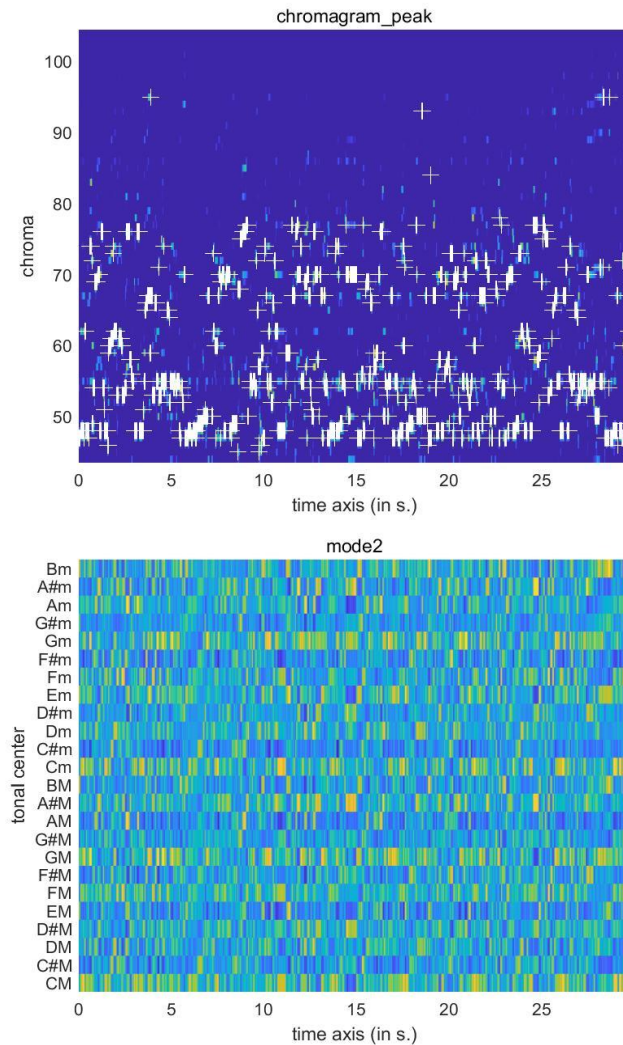
Tonal



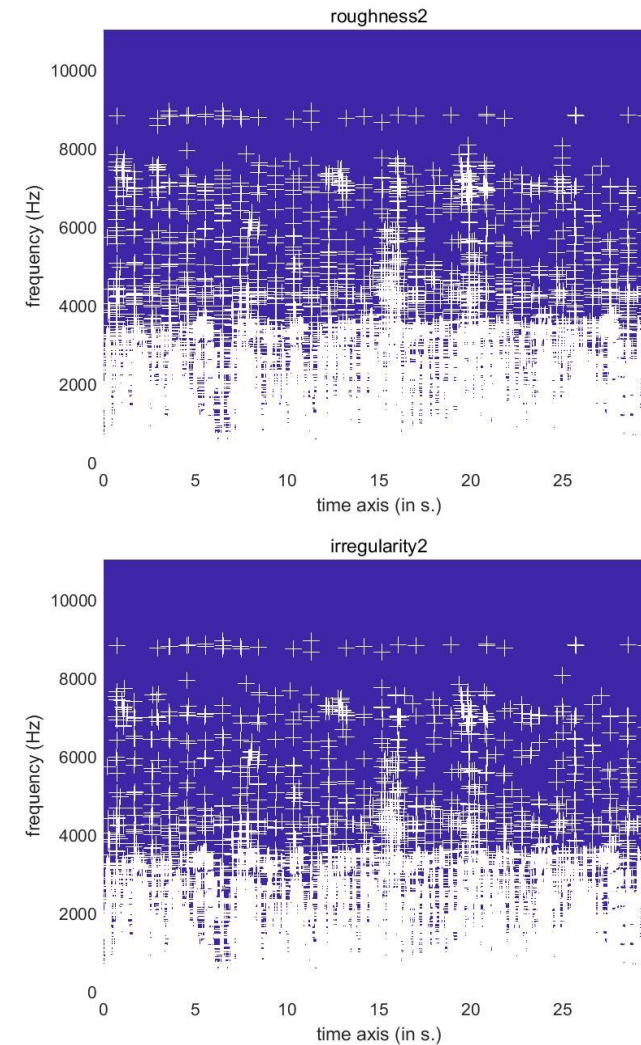
MIRToolbox

X_axis = time axis (in s.)

Tonal



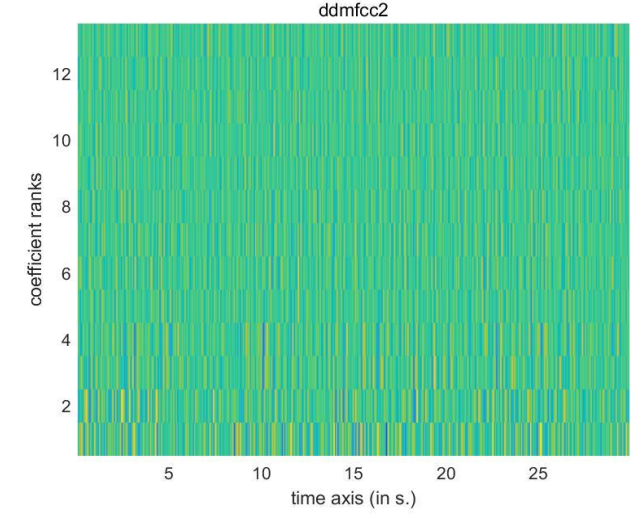
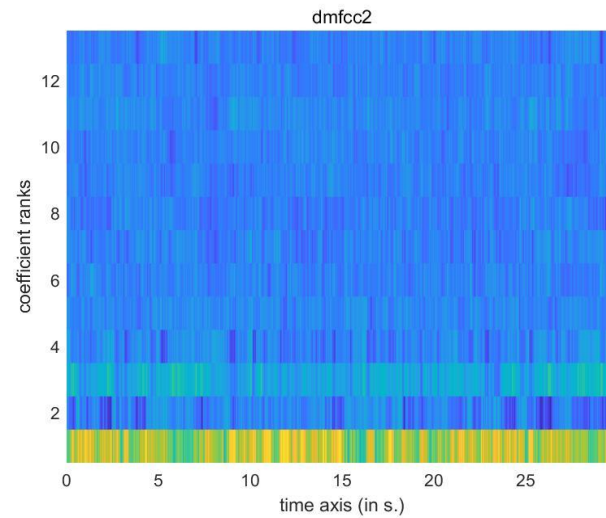
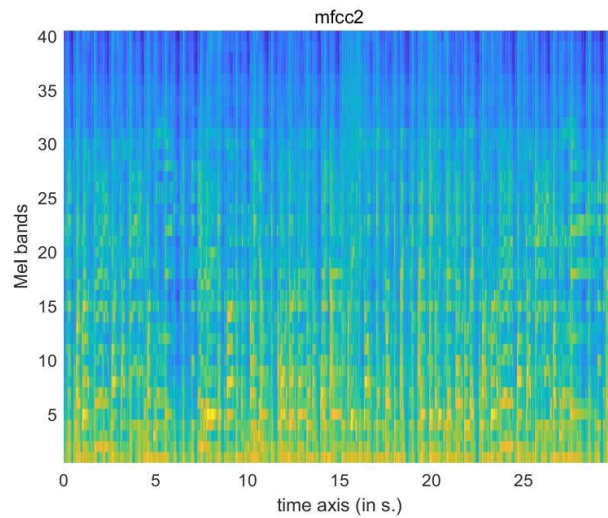
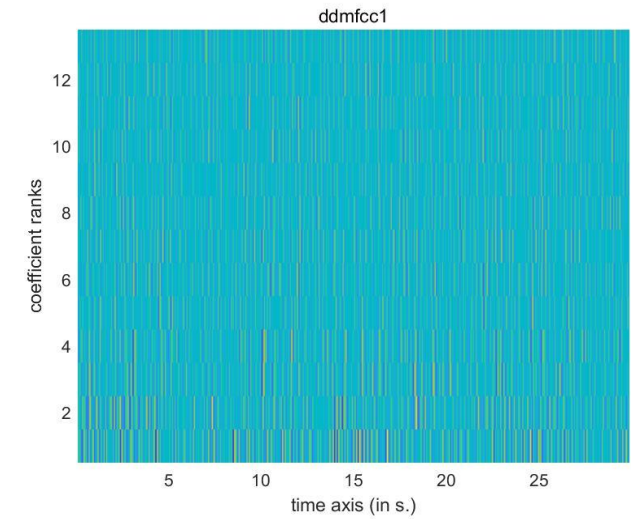
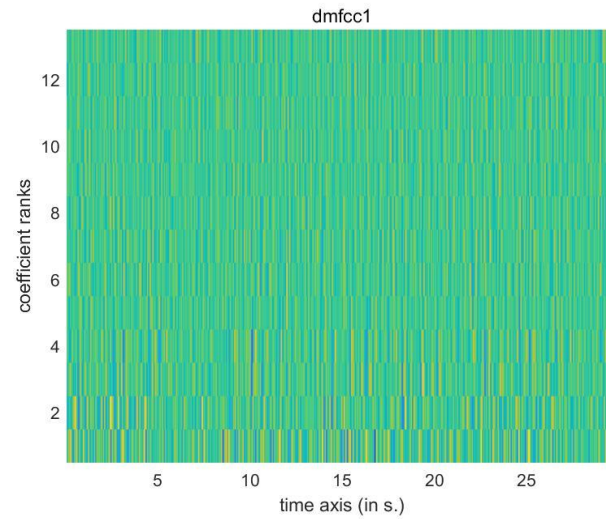
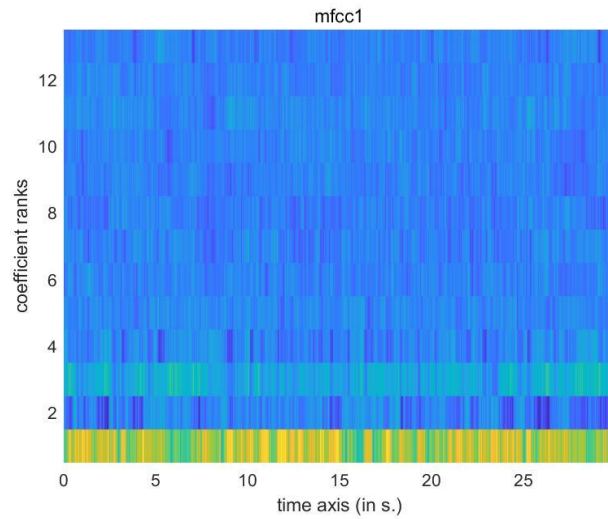
Spectral



MIRToolbox

X_axis = time axis (in s.)

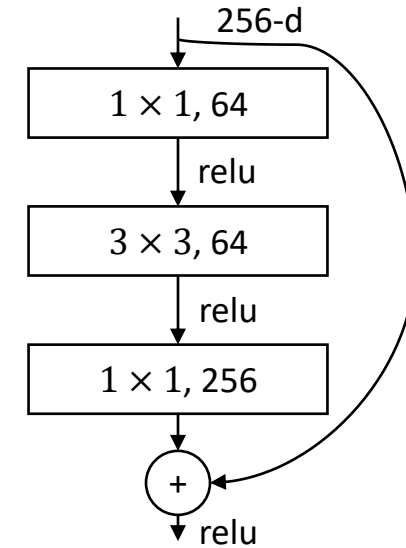
Spectral



Code Analysis(ResNet50_trust)

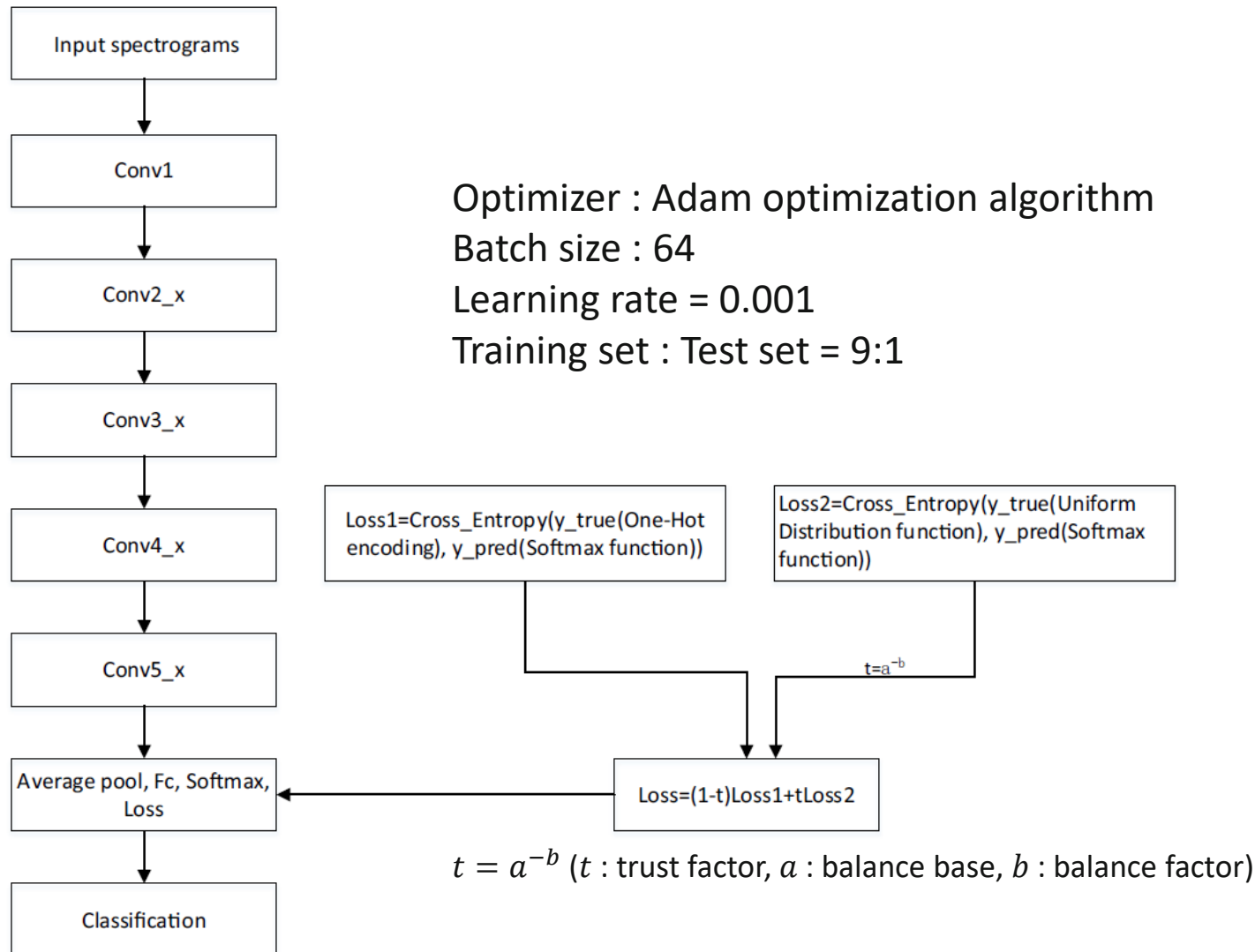
[14] Li, J., Han, L., Li, X., Zhu, J., Yuan, B., & Gou, Z. (2021). An evaluation of deep neural network models for music classification using spectrograms. *Multimedia Tools and Applications*, 1-27.

layer name	ouput size	50-layer
conv1	112×112	$7 \times 7, 64$, stride 2
conv2_x	56×56	3×3 max pool, stride 2
		$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$
conv4_x	14×14	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$
conv5_x	7×7	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax
FLOPs		3.8×10^9



A “bottleneck” building block for ResNet-50

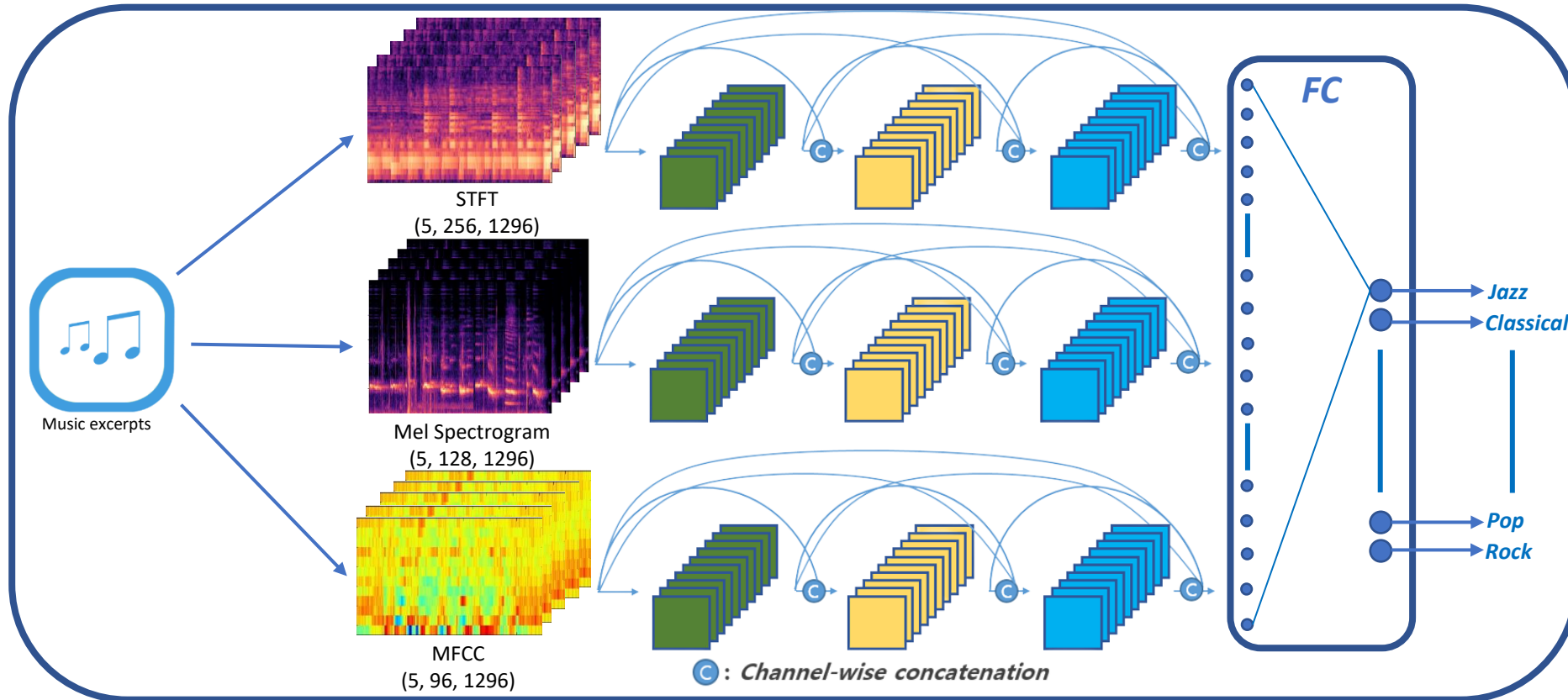
Code Analysis(ResNet50_trust)



Code Analysis(ResNet50_trust)

Dataset	Types(the number of music audios)	Duration of each audio	Types(the number of music spectrograms)	Total number of music spectrograms
FMA	Classical(300) Electronic(300) Jazz(306) Rock(300)	30s	Classical(1800) Electronic(1800) Jazz(1836) Rock(1800)	7236
GTZAN_4	Classical(100) Disco(100) Jazz(100) Rock(100)	30s	Classical(600) Disco(600) Jazz(600) Rock(600)	2400
GTZAN_10	Blues(100) Classical(100) Country(100) Disco(100) Hiphop(100) Jazz(100) Metal(100) Pop(100) Reggae(100) Rock(100)	30s	Blues(600) Classical(600) Country(600) Disco(600) Hiphop(600) Jazz(600) Metal(600) Pop(600) Reggae(600) Rock(600)	6000
EMA	Angry(160) Happy(188) Quiet(160) Sad(133)	60s	Angry(1574) Happy(1833) Quiet(1536) Sad(1307)	6250

Code Analysis(proposed)



Optimizer : Adam optimization algorithm

Batch size : 32

Learning rate = 0.001

Training set : Test set = 9:1

Dataset statistics

Dataset (Genre)	Patterns	# of Classes	Average Patterns per Class $\pm$ Standard Deviation	Avg. Length(s)
Ballroom	698	8	87.250 ± 17.555	30
Ballroom-Extended	4180	13	321.538 ± 195.702	30
FMA-MEDIUM	24984	16	1561.500 ± 2069.356	30
FMA-SMALL	7996	8	999.500 ± 0.500	30
GTZAN	1000	10	100.000 ± 0.000	30
HOMBURG	1886	9	209.556 ± 134.866	10
ISMIR04	727	6	121.167 ± 95.602	120
MICM	1137	7	162.429 ± 119.717	360
Seyerlehner:Unique	3115	10	311.500 ± 248.349	30
Tropical Genres	1500	5	300.000 ± 0.000	30

Comparison Results

Dataset (Genre)	Proposed	ResNet50_trust($t=2$)	-	-	GA	Conventional
Ballroom	61.43	44.29	-	-	83.67	70.0
Ballroom-Extended	85.17	70.81	-	-	63.49	81.7
FMA-MEDIUM	-	-	-	-	51.98	-
FMA-SMALL	-	-	-	-	20.14	56.3
GTZAN	94.00	71.00	-	-	75.70	86.4
HOMBURG	56.61	50.26	-	-	31.17	-
ISMIR04	81.74	69.41	-	-	89.89	-
MICM	53.51	37.72	-	-	7.80	40.0
Seyerlehner:Unique	70.19	62.18	-	-	65.59	-
Tropical Genres	-	-	-	-	92.97	97.9
Avg . Rank	-	-	-	-	-	-

Dataset Transform

Dataset (Genre)	STFT	Mel Spectrogram	MFCC
Ballroom	0	0	0
Ballroom-Extended	0	0	0
FMA-MEDIUM	0	0	0
FMA-SMALL	0	0	0
GTZAN	0	0	0
HOMBURG	0	0	0
ISMIR04	0	0	0
MICM	0	0	0
Seyerlehner:Unique	0	0	0
Tropical Genres	0	0	0

Reference

- [1] Massoudi, M., Verma, S., & Jain, R. (2021, January). Urban Sound Classification using CNN. In *2021 6th International Conference on Inventive Computation Technologies (ICICT)* (pp. 583-589). IEEE.
- [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.
- [3] Palanisamy, K., Singhanian, D., & Yao, A. (2020). Rethinking cnn models for audio classification. *arXiv preprint arXiv:2007.11154*.
- [4] Yu, Y., Luo, S., Liu, S., Qiao, H., Liu, Y., & Feng, L. (2020). Deep attention based music genre classification. *Neurocomputing*, 372, 84-91.
- [5] Won, M., Ferraro, A., Bogdanov, D., & Serra, X. (2020). Evaluation of cnn-based automatic music tagging models. *arXiv preprint arXiv:2006.00751*.
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- [7] Zhang, S., Gu, H., & Li, R. (2019). MUSIC GENRE CLASSIFICATION: NEAR-REALTIME VS SEQUENTIAL APPROACH.
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- [9] Zhang, W., Lei, W., Xu, X., & Xing, X. (2016, September). Improved music genre classification with convolutional neural networks. In *Interspeech* (pp. 3304-3308).
- [10] Choi, K., Fazekas, G., Sandler, M., & Cho, K. (2017, March). Convolutional recurrent neural networks for music classification. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 2392-2396). IEEE.
- [11] Su, Y., Zhang, K., Wang, J., & Madani, K. (2019). Environment sound classification using a two-stream CNN based on decision-level fusion. *Sensors*, 19(7), 1733.
- [12] Choi, K., Fazekas, G., & Sandler, M. (2016). Automatic tagging using deep convolutional neural networks. *arXiv preprint arXiv:1606.00298*.
- [13] Li, S., Yao, Y., Hu, J., Liu, G., Yao, X., & Hu, J. (2018). An ensemble stacked convolutional neural network model for environmental event sound recognition. *Applied Sciences*, 8(7), 1152.
- [14] Li, J., Han, L., Li, X., Zhu, J., Yuan, B., & Gou, Z. (2021). An evaluation of deep neural network models for music classification using spectrograms. *Multimedia Tools and Applications*, 1-27.