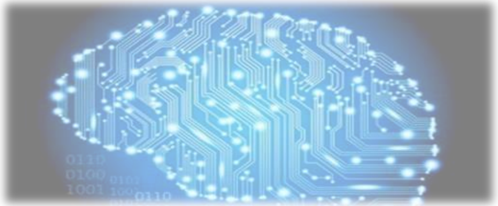
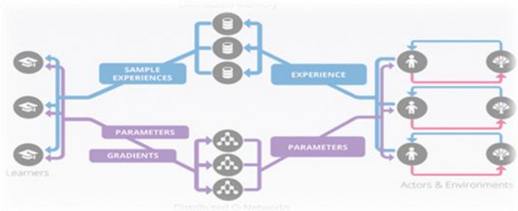




Musical Genre Classification

AutoML 연구실
석사 과정 조성현

22.02.08

To Do List

- Last Week
  - Comparison result
  - Dataset transform
  - Dataset Integrity

- This Week
  - Comparison result
  - Dataset Integrity

Related Work 1

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]

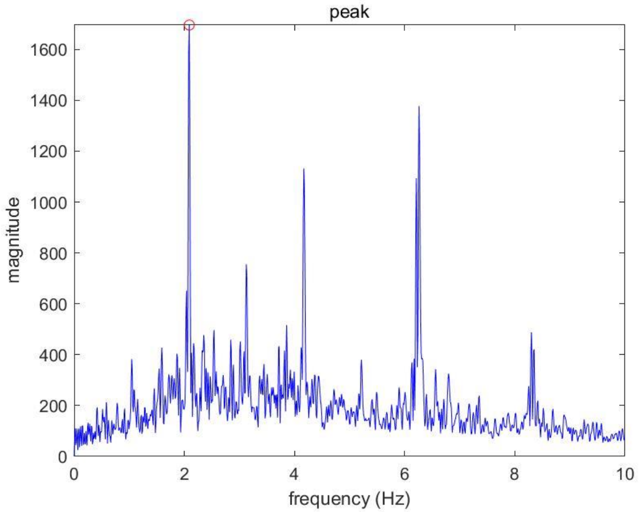
Related Work 2

Author	Year	Neural Network	# of employed datasets	Employed Dataset	Input Type	Evaluation Metric	Ref.
Li	2021	CNN	4	FMA, GTZAN5, GTZAN10, EMA	STFT Spectrogram	Accuracy	[14]
ASHRAF	2020	CNN-RNN	2	GTZAN, FMA-SMALL	Mel-Spectrogram	Accuracy, Precision, Recall, F1-Score	[15]
Elbir	2018	CNN	1	GTZAN	Raw Audio, STFT Spectrogram, MFCC	Accuracy, Precision, Recall, F1-Score	[16]

MIRToolbox

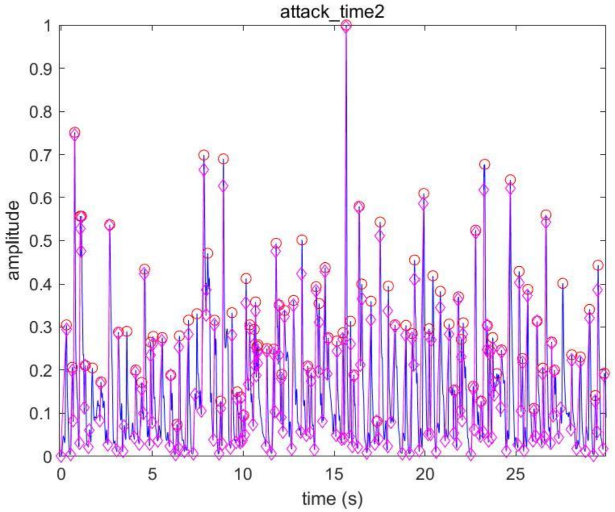
X_axis = frequency

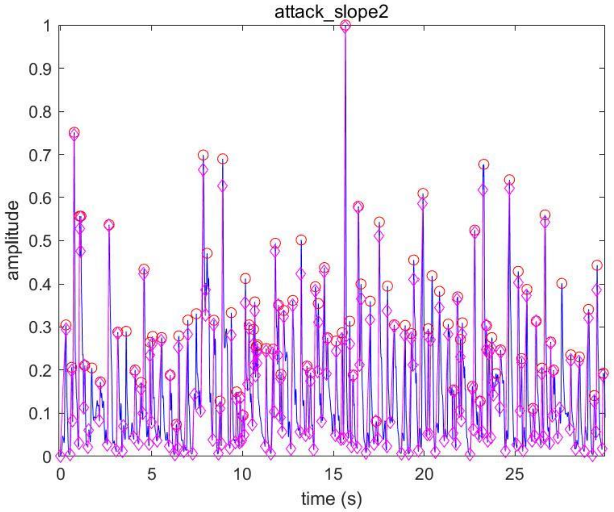
Fluctuation



X_axis = time

Rhythm

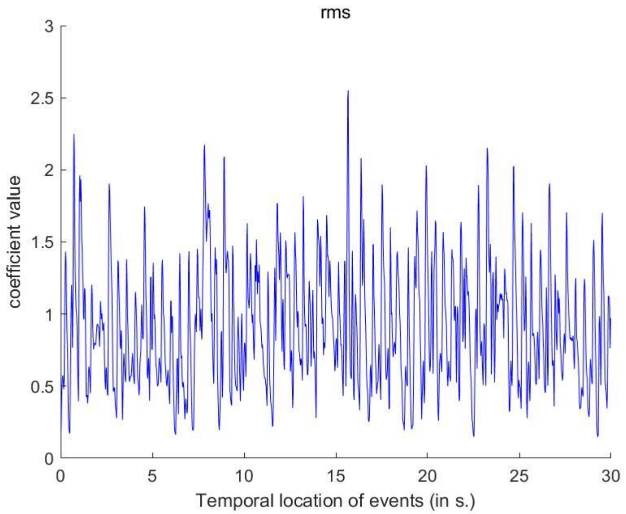




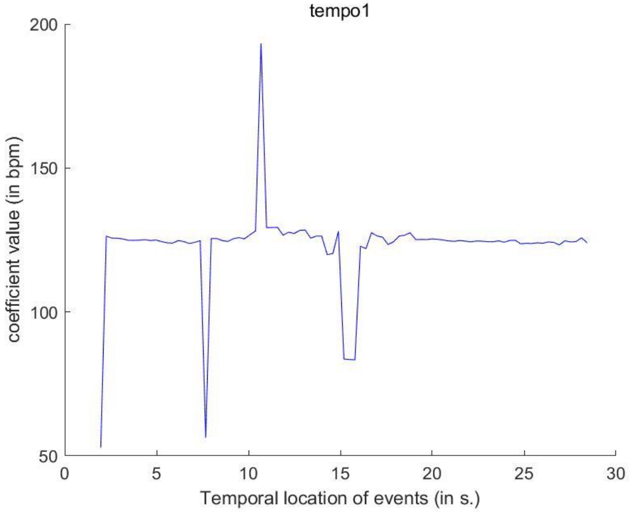
MIRToolbox

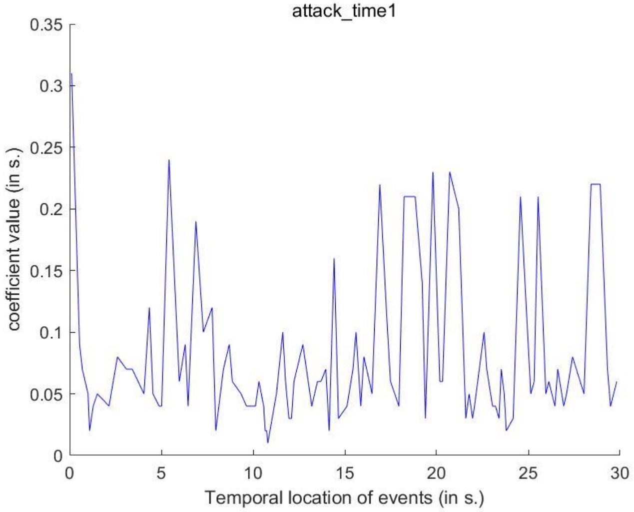
X_axis = Temporal location of events (in s.)

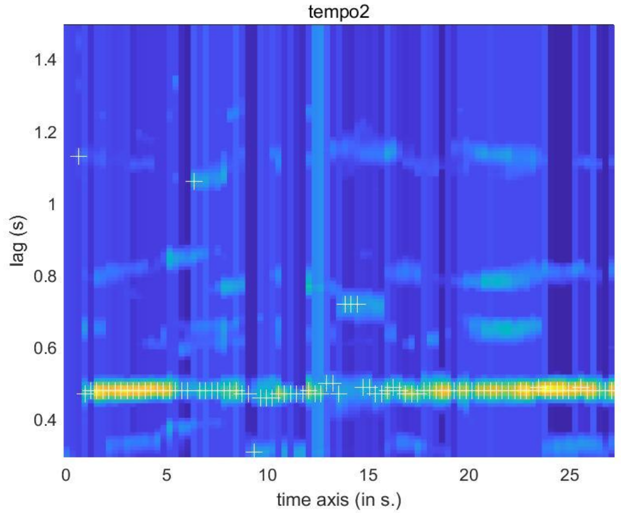
Dynamics

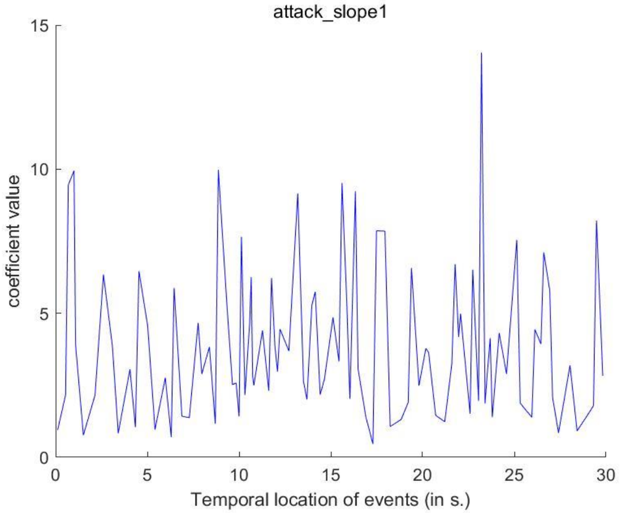


Rhythm





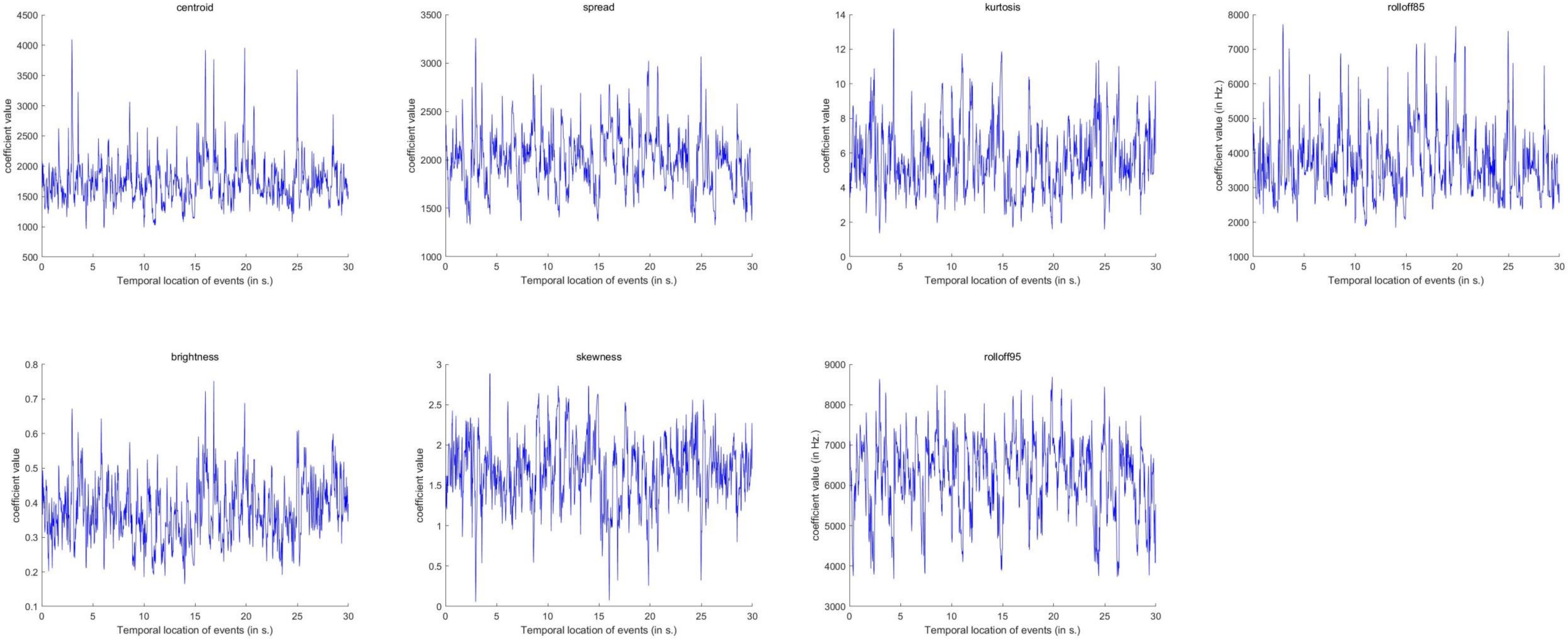




MIRToolbox

X_axis = Temporal location of events (in s.)

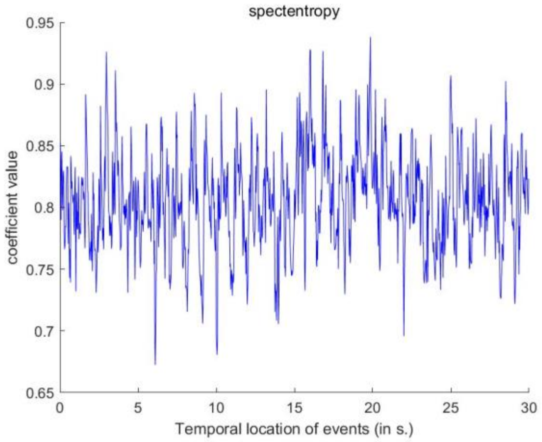
Spectral

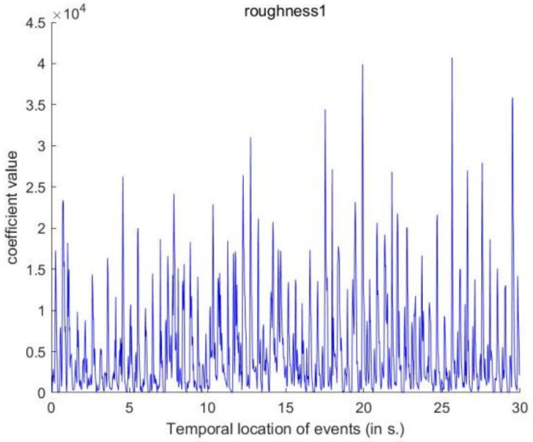


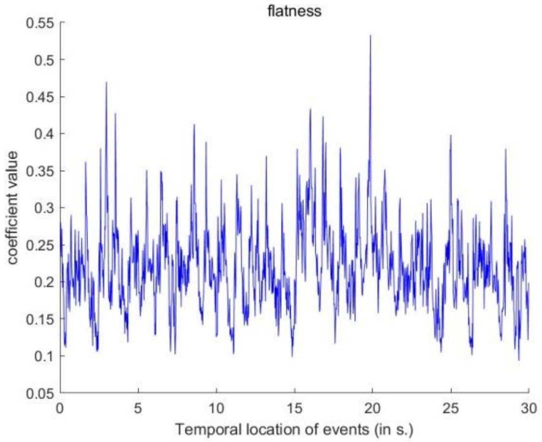
MIRToolbox

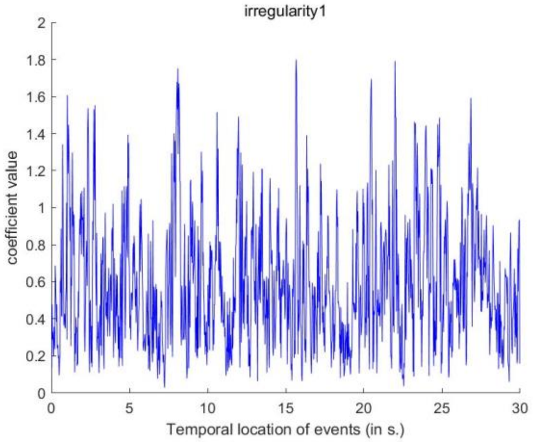
X_axis = Temporal location of events (in s.)

Spectral

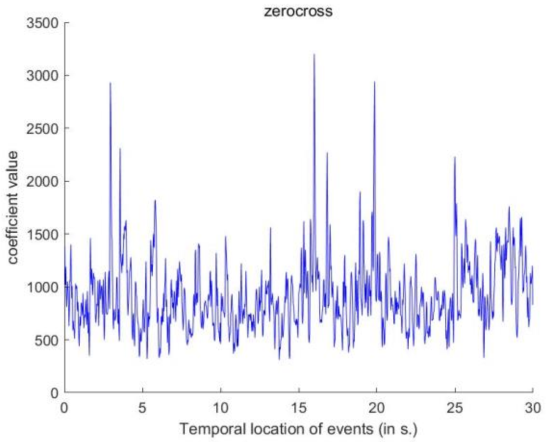


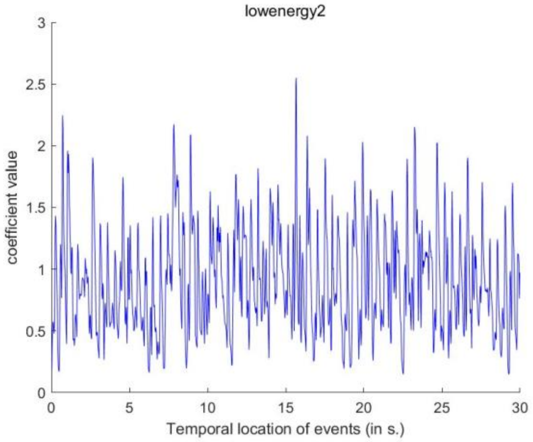


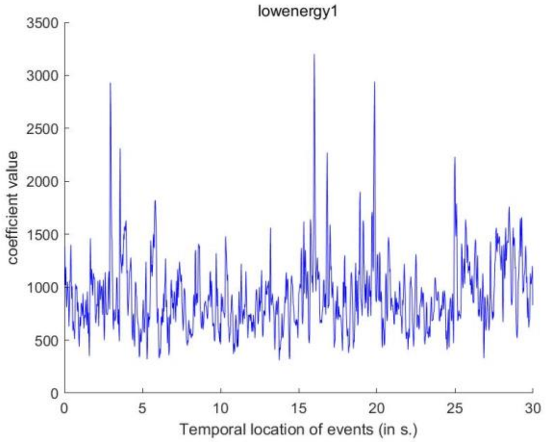


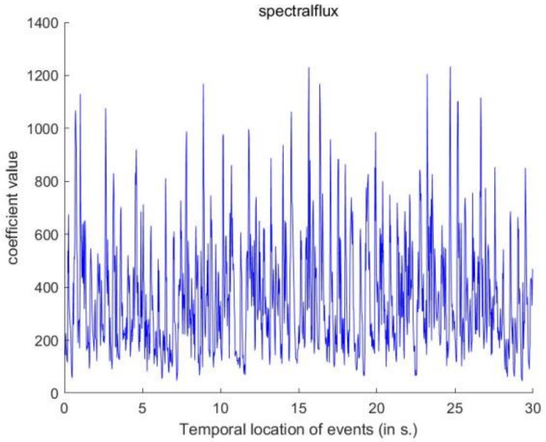


Timbre





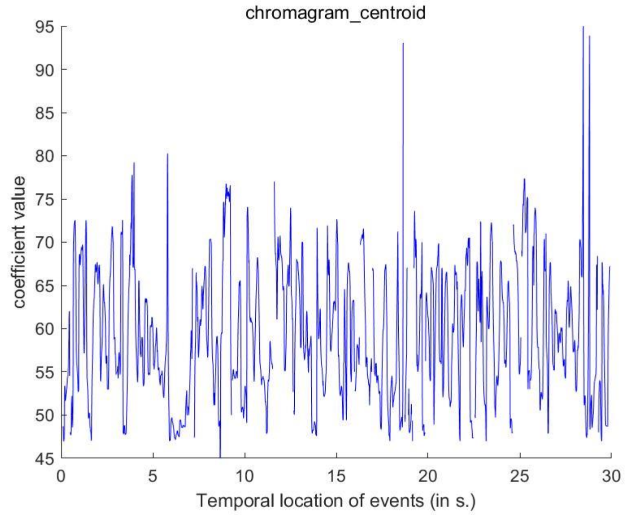


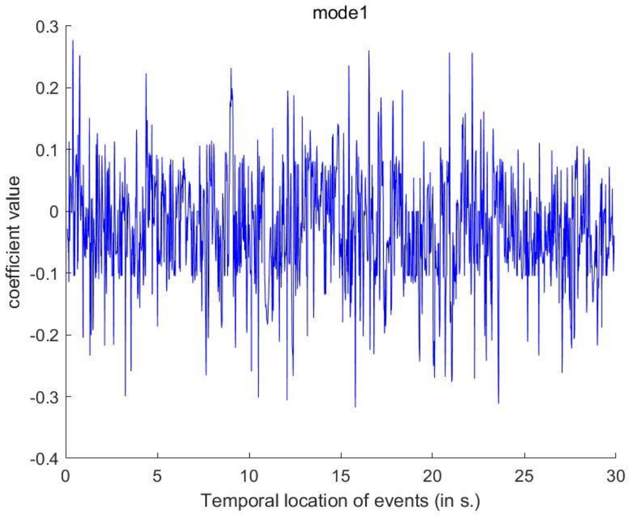


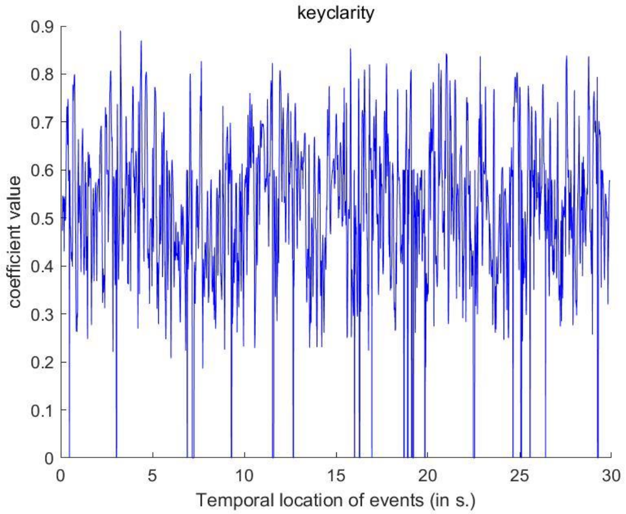
MIRToolbox

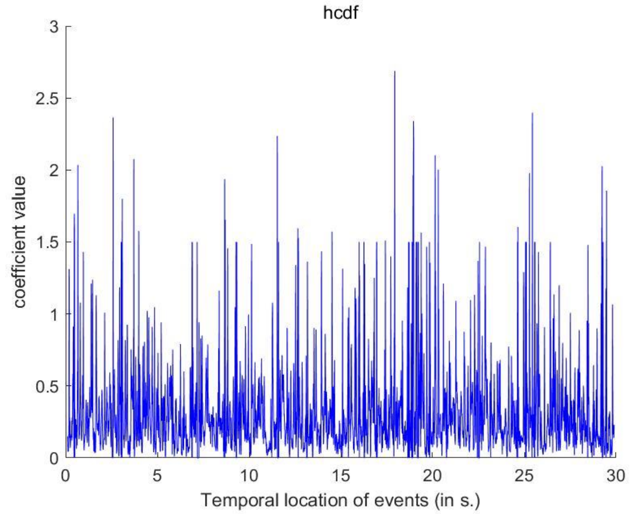
X_axis = Temporal location of events (in s.)

Tonal





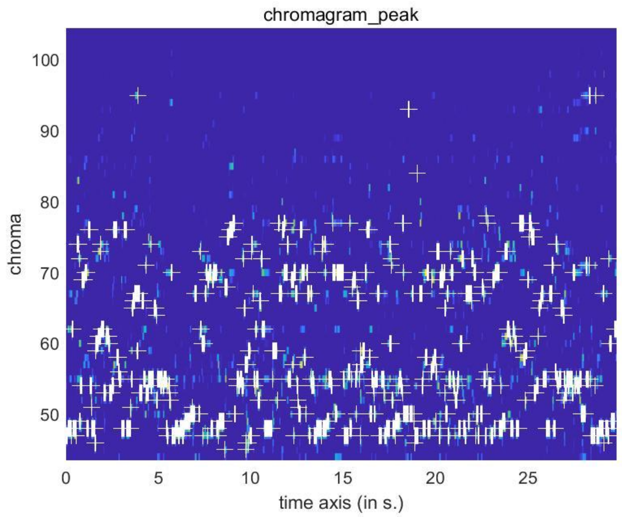


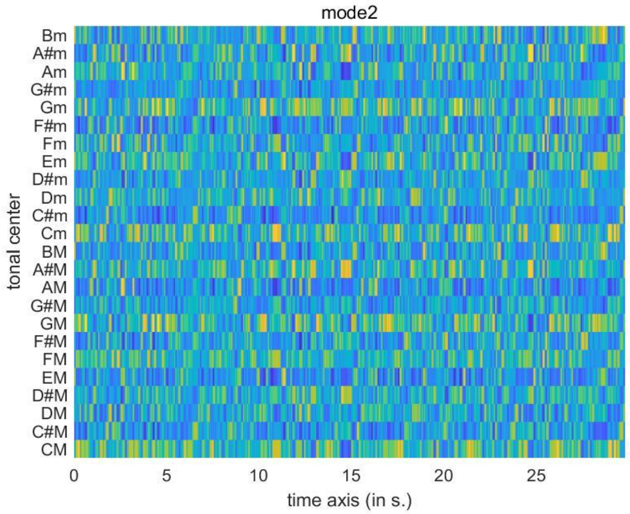


MIRToolbox

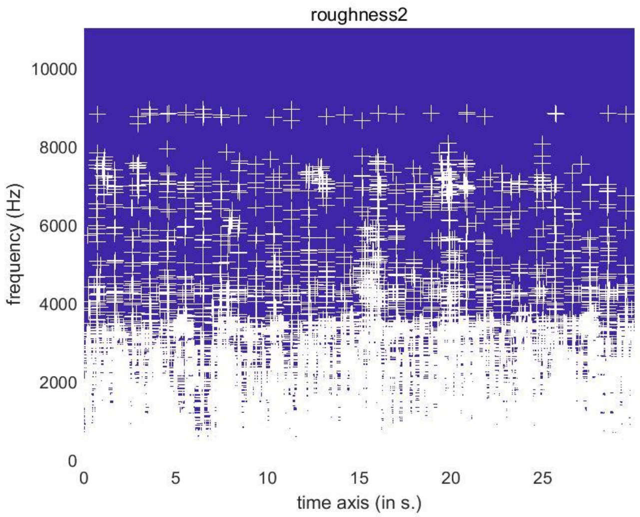
X_axis = time axis (in s.)

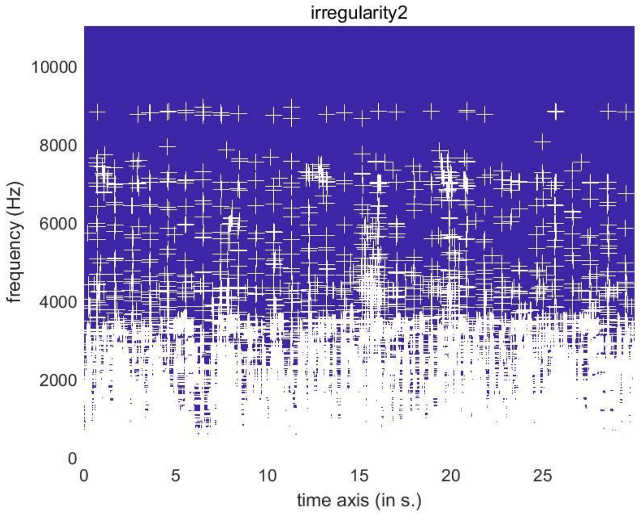
Tonal





Spectral

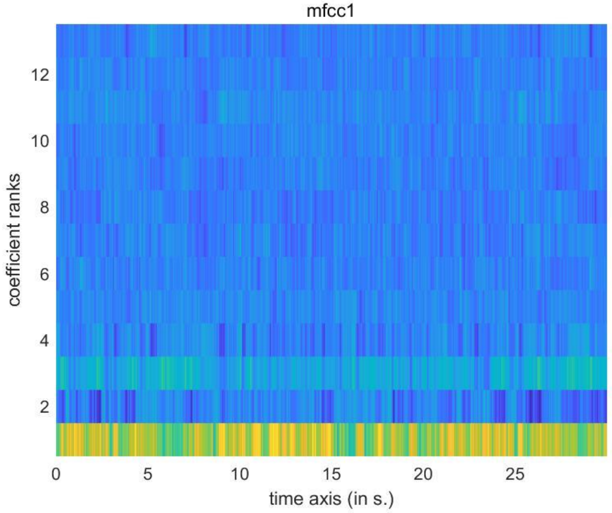


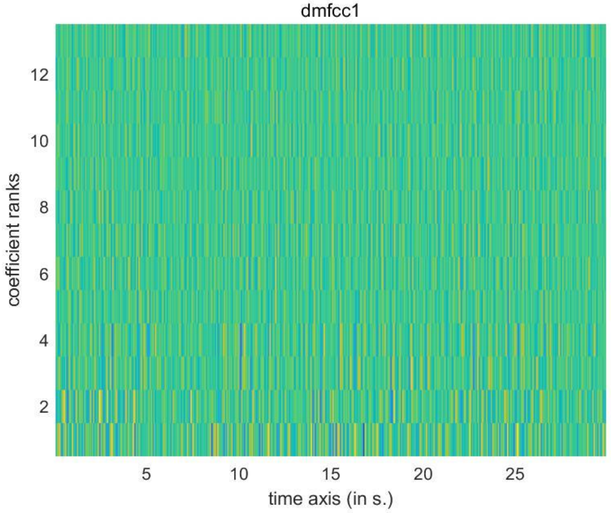


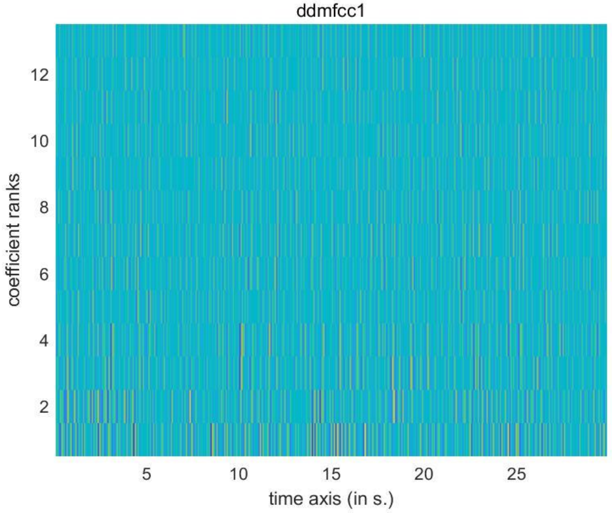
MIRToolbox

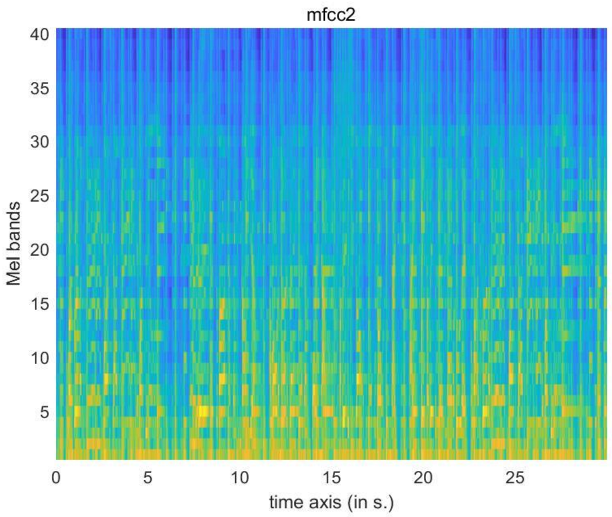
X_axis = time axis (in s.)

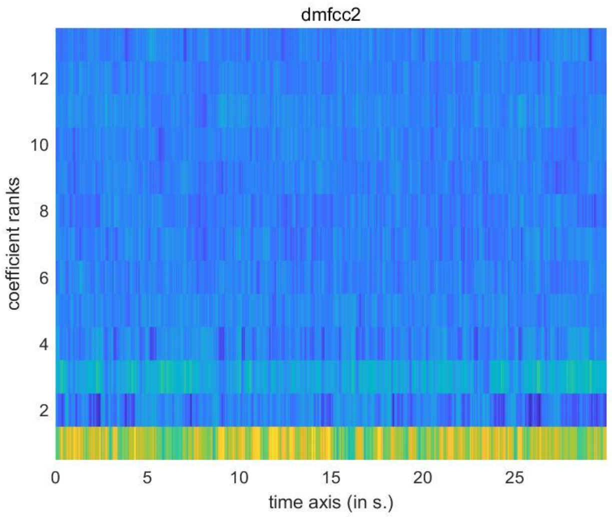
Spectral

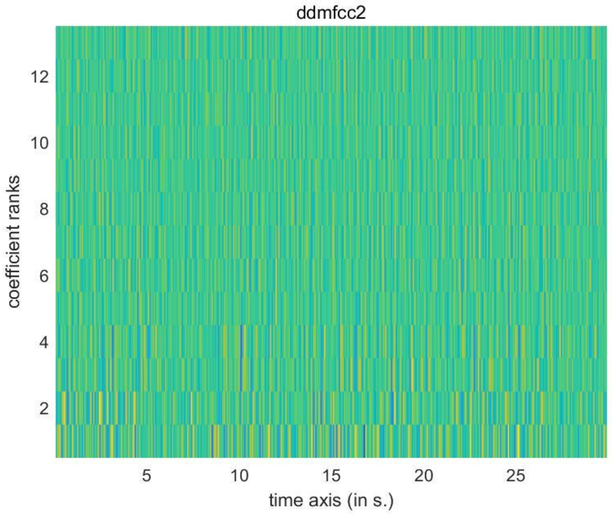




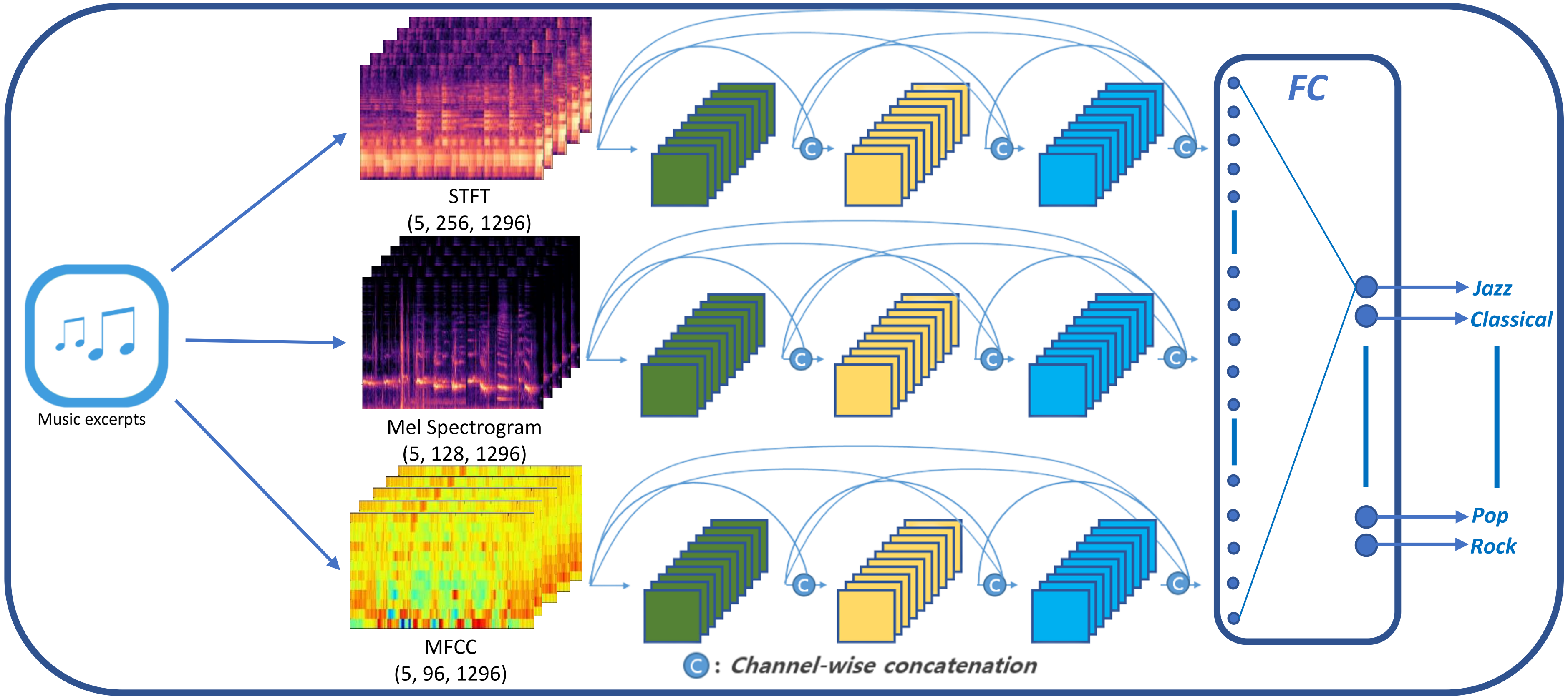








Code Analysis(proposed)

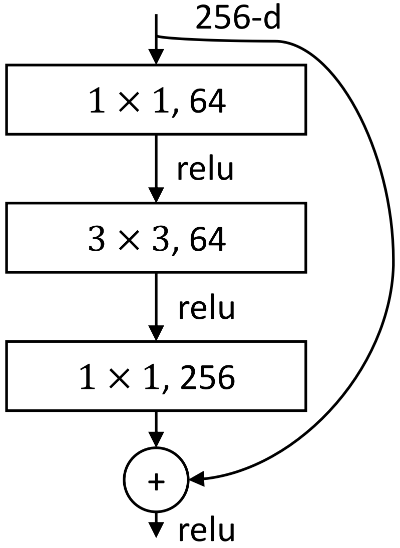


Optimizer : Adam optimization algorithm
Batch size : 32
Learning rate = 0.001
Training set : Test set = 8:2

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.

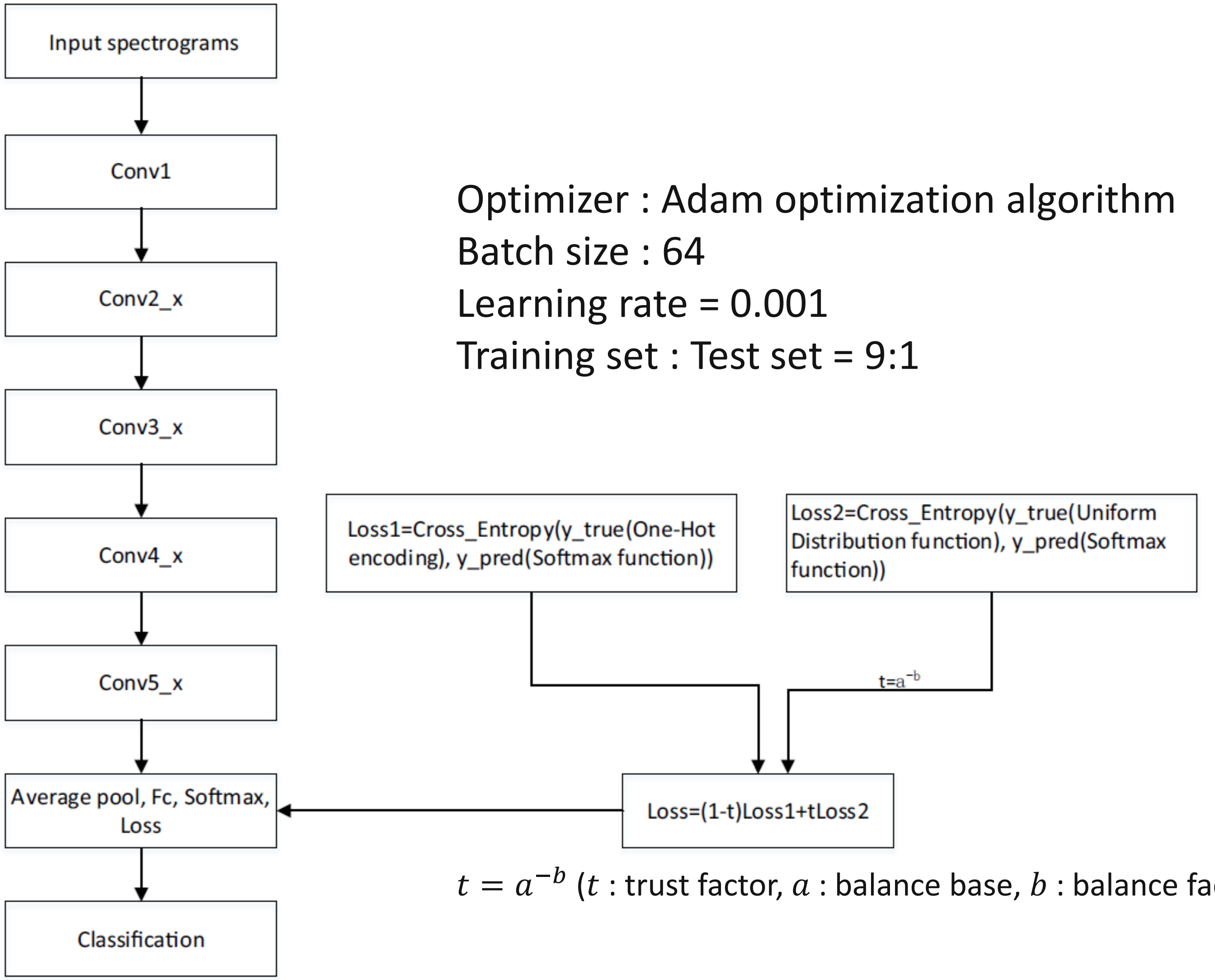
layer name	ouput size	50-layer
conv1	112×112	7×7, 64, stride 2
conv2 _x	56×56	3×3 max pool, stride 2 $\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$
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)

Optimizer : Adam optimization algorithm
Batch size : 64
Learning rate = 0.001
Training set : Test set = 9:1



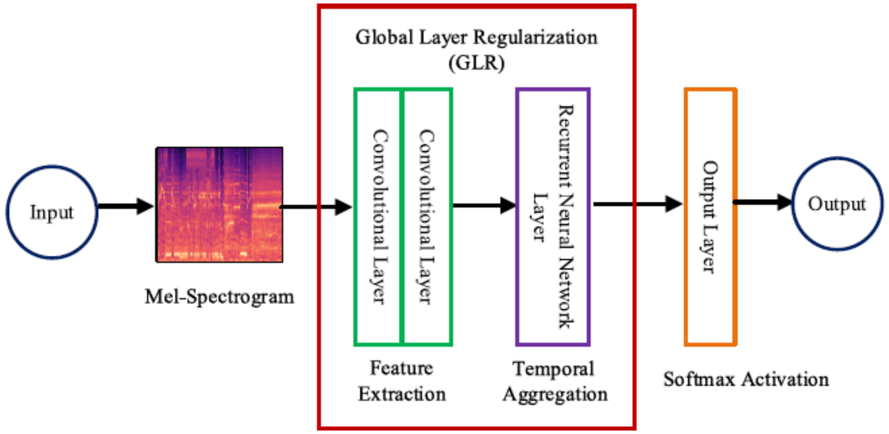
$t = a^{-b}$ (t : trust factor, a : balance base, b : balance factor)

Code Analysis(ResNet50_trust)

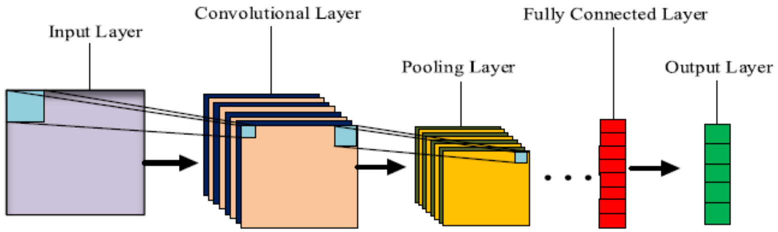
Dataset	Types(the number of music audios)	Duration of each audio	Types(the number of music spectrograms)	Total number of music spectrograms
FMA	Classical(300) Electronic(300) Jazz(306) Rock(300)	30s	Classical(1800) Electronic(1800) Jazz(1836) Rock(1800)	7236
GTZAN_4	Classical(100) Disco(100) Jazz(100) 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(Ashraf et al.)

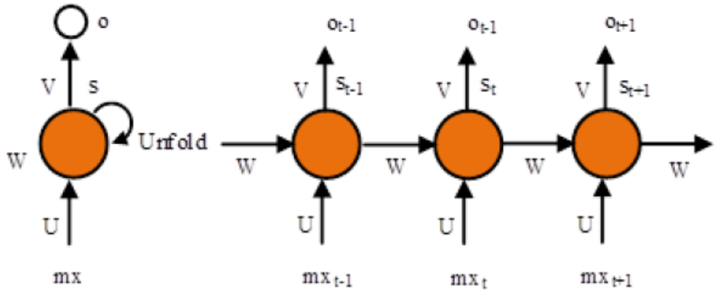
[15] Ashraf, M., Geng, G., Wang, X., Ahmad, F., & Abid, F. (2020). A Globally Regularized Joint Neural Architecture for Music Classification. IEEE Access, 8, 220980-220989.



Proposed globally regularized CNN-RNN architecture



Block diagram of typical convolutional neural network



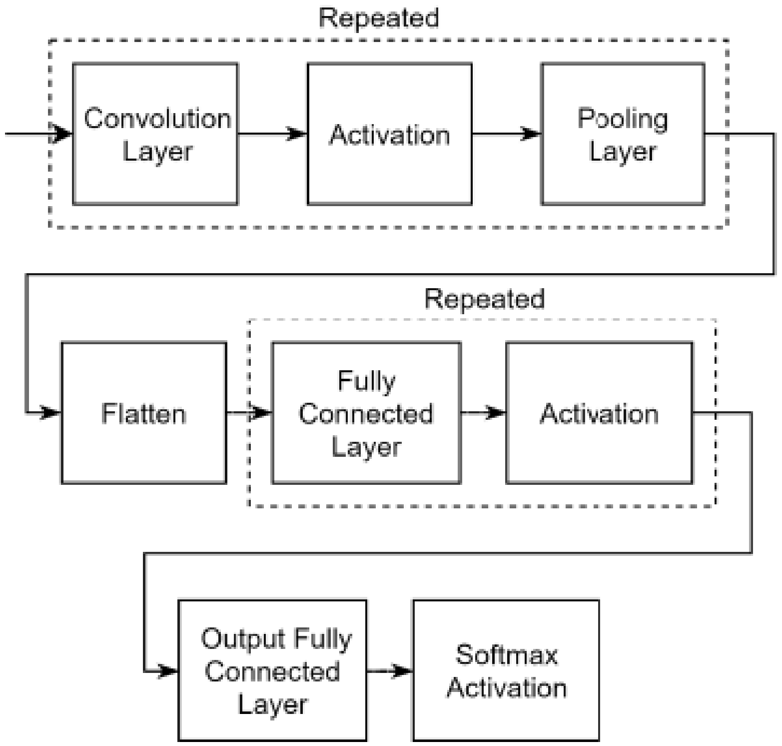
Unfolding structure of recurrent neural network

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l$$
$$\sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H} (a_i^l - \mu^l)^2}$$

Global Layer Regularization calculation

Code Analysis(Elbir et al.)

[16] Elbir, A., Çam, H. B., Iyican, M. E., Öztürk, B., & Aydin, N. (2018, October). Music genre classification and recommendation by using machine learning techniques. In 2018 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1-5). IEEE.



Convolutional Neural Network Configuration

1 - 2D Convolution Layer, 5x5 sized 32 filters, LeakyReLU activation function

2 - Max Pooling Layer

3 - 2D Convolution Layer, 5x5 sized 32 filters, LeakyReLU activation function

4 - Max Pooling Layer

5 - 2D Convolution Layer, 5x5 sized 32 filters, LeakyReLU activation function

6 - Max Pooling Layer

7 - 2D Convolution Layer, 5x5 sized 32 filters, LeakyReLU activation function

8 - Average Pooling Layer

9 - Flatten Layer

10 - Dense Layer, 256 nodes, LeakyReLU activation function

11 - Dense Layer, 128 nodes, LeakyReLU activation function

12 - Dense Layer, 64 nodes, LeakyReLU activation function

13 - Dense Layer, 10 nodes, Softmax activation function, as output layer

Convolutional Neural Network Summarization

Dataset statistics

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

Comparison Results

Dataset (Genre)	Proposed	ResNet50_trust(t =2)	Ashraf et al.	Elbir et al.	-	GA	Mel & MFCC
Ballroom	58.79 ± 3.96	44.29	-	39.29 ± 3.82	-	$\mathbf{83.67 \pm 4.64}$	70.0 ± 3.70
Ballroom-Extended	$\mathbf{85.32 \pm 0.61}$	70.81	-	-	-	64.49 ± 1.41	81.7 ± 1.55
FMA-MEDIUM	-	-	-	-	-	51.98 ± 0.88	-
FMA-SMALL	51.69	-	-	-	-	20.14 ± 1.56	56.3 ± 0.99
GTZAN	$\mathbf{87.7 \pm 3.01}$	71.00	-	58.85 ± 3.79	-	75.70 ± 3.03	86.4 ± 2.14
HOMBURG	$\mathbf{54.13 \pm 1.91}$	50.26	-	47.14 ± 1.89	-	31.17 ± 2.88	-
ISMIR04	80.07 ± 1.64	69.41	-	62.28 ± 2.42	-	$\mathbf{89.89 \pm 1.97}$	-
MICM	$\mathbf{49.39 \pm 1.79}$	37.72	-	-	-	7.80 ± 3.20	40.0 ± 2.85
Seyerlehner-Unique	$\mathbf{71.03 \pm 1.49}$	62.18	-	-	-	65.59 ± 1.92	-
Avg . Rank	-	-	-	-	-	-	-

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., Singhania, 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.
[6] Bisharad, D., & Laskar, R. H. (2019, October). Music Genre Recognition Using Residual Neural Networks. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON) (pp. 2063-2068). IEEE.
[7] Zhang, S., Gu, H., & Li, R. (2019). MUSIC GENRE CLASSIFICATION: NEAR-REALTIME VS SEQUENTIAL APPROACH.
[8] Chillara, S., Kavitha, A. S., Neginhal, S. A., Haldia, S., & Vidyullatha, K. S. (2019). Music genre classification using machine learning algorithms: a comparison. Int Res J Eng Technol, 6(5), 851-858.
[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
[15] Ashraf, M., Geng, G., Wang, X., Ahmad, F., & Abid, F. (2020). A Globally Regularized Joint Neural Architecture for Music Classification. IEEE Access, 8, 220980-220989.
[16] Elbir, A., Çam, H. B., Iyican, M. E., Öztürk, B., & Aydin, N. (2018, October). Music genre classification and recommendation by using machine learning techniques. In 2018 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1-5). IEEE.