Forest Sounds Classification

Project on Deep Learning Course

MSc in Data Science

Nikolaos Paraskakis / I.D.: 2321

Dimitrios Tselentis / I.D.: 2325

Target Dataset – FSC22

- Year: 2023
- Clips: 2025
- Clip Length: 5 seconds
- Duration: Not explicitly mentioned (≈ 2.81 hours)
- Classes: 27
- Balanced: 75 per class
- Task: Multi-class
- Source: Freesound
- Domain/Task: Forest environmental sounds

Universal Preprocessing

For each audio .wav file we apply the following preprocessing:

- Resample (if necessary) audio signal from *original_sample_rate* to *target_sample_rate*
- Mix down (if necessary) audio signal from stereo to mono
- Cut (if necessary) audio signal to have 5s (or 5xSAMPLE_RATE) length
- Right pad (if necessary) audio signal to have 5s (or 5xSAMPLE_RATE) length

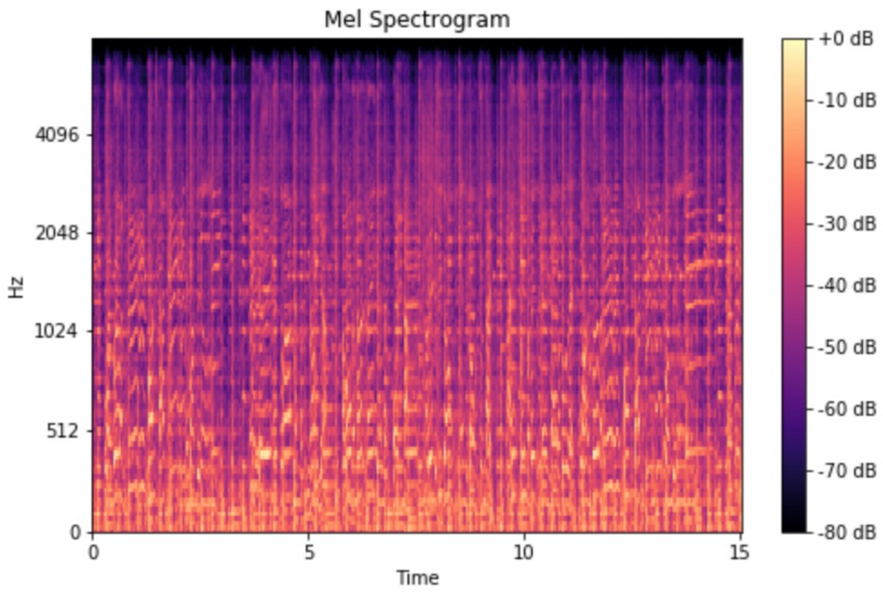
Mel-Spectrograms

Extracting a mel-spectrogram representation for each audio .wav file of the following format:

- Using *torchaudio.transforms.MelSpectrogram* with parameters like *sample_rate=22050, n_fft=2048, hop_length=512, n_mels=128*
- Using *librosa.power_to_db* to convert the power spectrogram to a decibel (dB) scale

Finally, we get mel-spectrograms of shape [128, T]

In this case, *T=216*.



Audiofeatures

Extracting a representation for each audio .wav file of the following format:

- MFCCs (Mel-Frequency Cepstral Coefficients) : [13, T]
- Chroma STFT (Short-Time Fourier Transform) : [12, T]
- Tonnetz (Tonnetz Representation) : [6, T]
- Spectral Contrast : [7, T]
- Spectral Centroids : [1, T]
- Spectral Bandwidth : [1, T]
- Spectral Flatness : [1, T]
- Spectral Rolloff : [1, T]
- Zero Crossing Rate : [1, T]

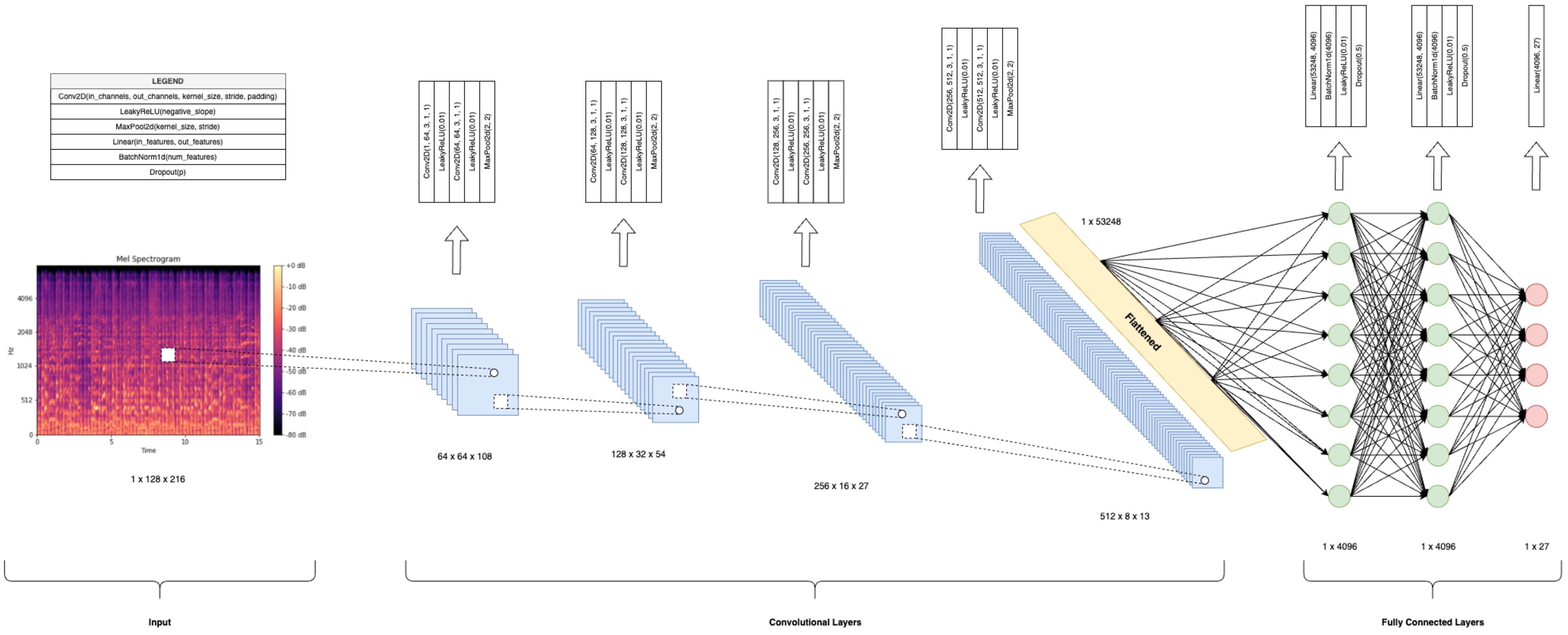
Dimension T depends on the length of the audio signal and the parameters *hop_length=512* and *n_fft=2048*.

Specifically, T represents the number of frames (or time steps) into which the audio signal is divided during feature extraction.

Finally, after concatenation we have a representation of shape [43, T].

Here, also, *T=216*.

Baseline Model



Training the Baseline Model on FSC22

- It is a multi-class classification problem
- Loss Function: *CrossEntropyLoss( )*
- During training we monitor average batch accuracy on the validation set
- Early Stopping Patience: 25 epochs
- Learning Rate Sceduler: ReduceLROnPlateau by monitoring average batch accuracy on the validation set
- Learning Rate Sceduler Patience: 10 epochs
- Starting with Learning Rate: 1e-5

Performance of the Baseline Model

EPOCHS : 80

MELSPECTROGRAMS

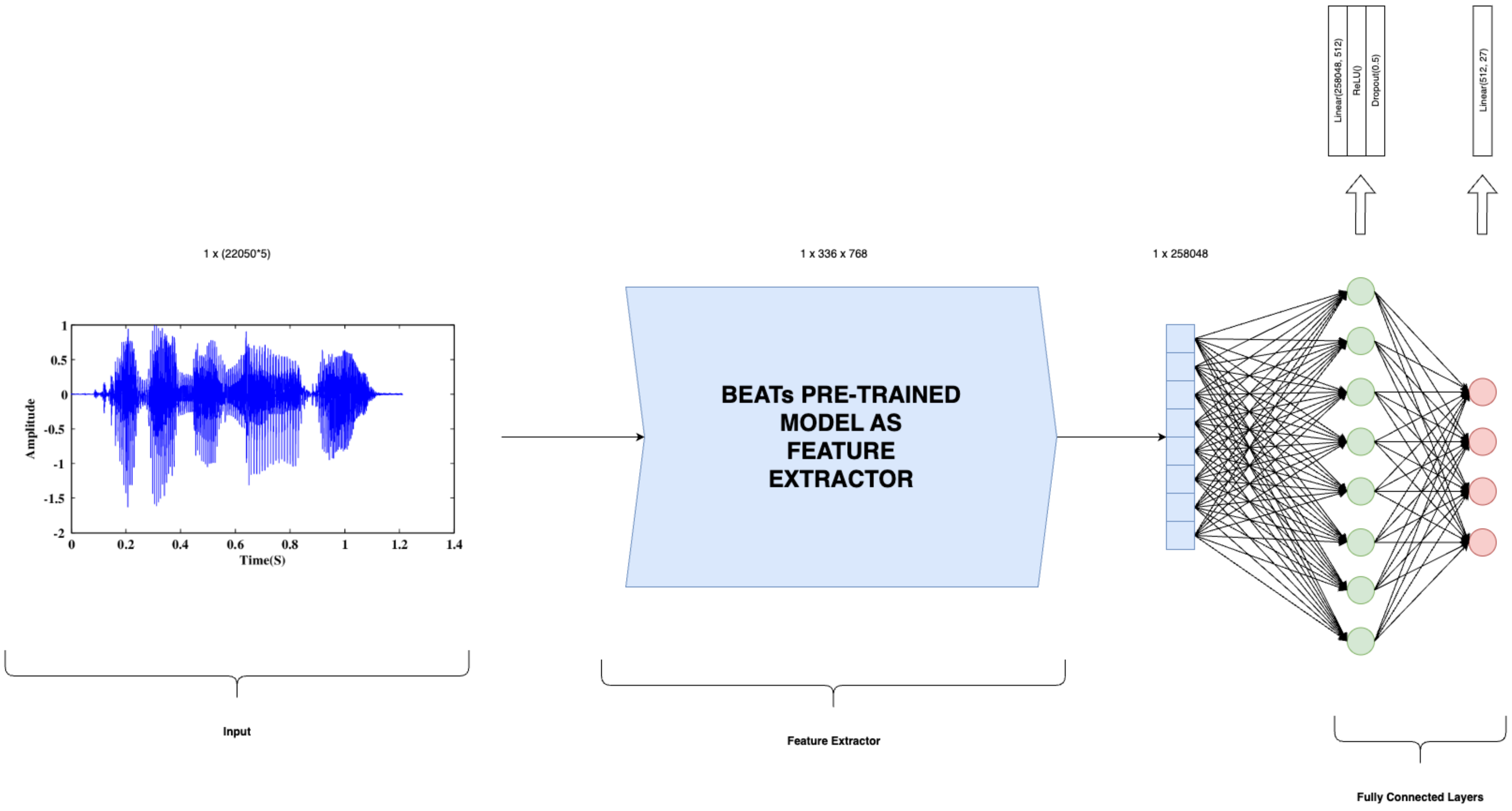
Metric	Training Set	Validation Set	Test Set
Accuracy	100%	66%	70%
Precision	100%	67%	71%
Recall	100%	66%	70%
F1 Score	100%	65%	69%
Loss Function	0.011	1.216	1.133

EPOCHS : 148

AUDIOFEATURES

Metric	Training Set	Validation Set	Test Set
Accuracy	99%	57%	56%
Precision	99%	57%	58%
Recall	99%	57%	55%
F1 Score	99%	56%	55%
Loss Function	0.105	1.525	1.434

State-of-the-art Model



Performance of the State-of-the-art Model

EPOCHS : 60

Metric	Training Set	Validation Set	Test Set
Accuracy	100%	87%	89%
Precision	100%	87%	90%
Recall	100%	87%	89%
F1 Score	100%	86%	89%
Loss Function	0.004	0.452	0.368

BEATsFEATURES

Augmentation of FSC22

We will do augmentation of the training data to boost the performance of the baseline model.

We choose a percentage of the training data to augment, while retaining proportions between classes.

Augmentation Types:

- Type A:

  Using *audiomentations.Shift* we shift the audio .wav files by a random value between -0.5 and 0.5 seconds.

- Type B:

  Using *audiomentations.Gain we randomly adjust the audio gain between -12 and 12 dB.*

  Using *audiomentations.TimeStretch* we stretch/compress the audio duration by a factor between 0.9 and 1.2 (no change of pitch).

  Using *audiomentations.Shift* we shift the audio .wav files by a random value between -0.5 and 0.5 seconds.

- Type AB:

  We do both: Type A, and Type B.

Percentage Types:

- 50%
- 100%

Training of the Baseline Model on Augmented Data

- Loss Function: *CrossEntropyLoss( )*
- During training we monitor average batch accuracy on the validation set
- Early Stopping Patience: 25 epochs
- Learning Rate Sceduler: ReduceLROnPlateau by monitoring average batch accuracy on the validation set
- Learning Rate Sceduler Patience: 10 epochs
- Starting with Learning Rate: 1e-5

Performance of the Baseline Model on Augmented Data

EPOCHS : 79

Metric	Training Set	Validation Set	Test Set
Accuracy	100%	67%	75%
Precision	100%	69%	77%
Recall	100%	67%	75%
F1 Score	100%	67%	75%
Loss Function	0.006	1.242	0.975

MELSPECTROGRAMS
TYPE_B_50

Transfer Dataset – FSD50K

- Year: 2020
- Clips: 51,197
- Clip Length: 0.3-30 seconds
- Duration: 108 hours
- Classes: 200
- Task: Multi-label
- Source: Freesound
- Unbalanced: 97 - 14K

Training the Baseline Model on FSD50K

From the architecture shown before regarding the Baseline Model, we made the following modifications:

- Last dense layer has size of 200 (number of classes)
- Now we have a multi-label classification problem
- Loss Function: *BCEWithLogitsLoss( )*
- During training we monitor global F1 score with macro averaging on the validation set
- Early Stopping Patience: 25 epochs
- Learning Rate Sceduler: ReduceLROnPlateau by monitoring average batch accuracy on the validation set
- Learning Rate Sceduler Patience: 10 epochs
- Starting with Learning Rate: 1e-5

Performance of the Baseline Model on FSD50K

EPOCHS : 50

Metric	Training Set	Validation Set	Test Set
Accuracy	100%	99%	98%
Precision	100%	53%	63%
Recall	100%	20%	17%
F1 Score	100%	27%	23%
Loss Function	0.0007	0.049	0.069

MELSPECTROGRAMS

Transfer learning to FSC22

We have trained the Baseline Model on FSD50K.

We will do transfer learning of that model on the target dataset FSC22:

- Freeze all layers except the last fully connected layers (dense layers)
- Loss Function: *CrossEntropyLoss( )*
- During training we monitor average batch accuracy on the validation set
- Early Stopping Patience: 25 epochs
- Learning Rate Sceduler: ReduceLROnPlateau by monitoring average batch accuracy on the validation set
- Learning Rate Sceduler Patience: 10 epochs
- Starting with Learning Rate: 1e-5

Performance of the Baseline Model on FSC22 after Transfer Learning

EPOCHS : 97

Metric	Training Set	Validation Set	Test Set
Accuracy	100%	72%	77%
Precision	100%	73%	78%
Recall	100%	72%	77%
F1 Score	100%	72%	77%
Loss Function	0.0015	0.995	0.81

MELSPECTROGRAMS

Transfer Learning of pretrained VGG16 from ImageNet to FSC22

We loaded VGG16 with pretrained weights (trained on ImageNet).

We did the following modifications on VGG16:

- Changed the first convolutional layers to get input images of one channel
- Resized our mel-spectrograms to 224 x 224
- Changed the last dense layer to have size 27 (number of classes)

We experimented with the following freezing scenarios (freeze all except):

- classifier[-1]
- classifier[3:]
- features[24:], avgpool, classifier
- features[17:], avgpool, classifier
- features[10:], avgpool, classifier [best one]

Performance of VGG16 on FSC22 after Transfer Learning

EPOCHS : 37

Metric	Training Set	Validation Set	Test Set
Accuracy	100%	71%	74%
Precision	100%	72%	75%
Recall	100%	71%	74%
F1 Score	100%	71%	73%
Loss Function	0.031	1.319	1.143

MELSPECTROGRAMS

Performance of all models on Test set of FSC22

Model	F1 Score	Epochs
Baseline Audio Features	55%	148
Baseline Spectrograms	69%	80
Transfer Learning VGG16 (Trained on ImageNet)	73%	37
Baseline Spectrograms Augmented	75%	79
Transfer Learning (Trained on FSD50K)	77%	97
State of the Art (BEATs)	89%	60