Duale Hochschule
Baden-Württemberg

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Robustness of a CNN for music genre classification

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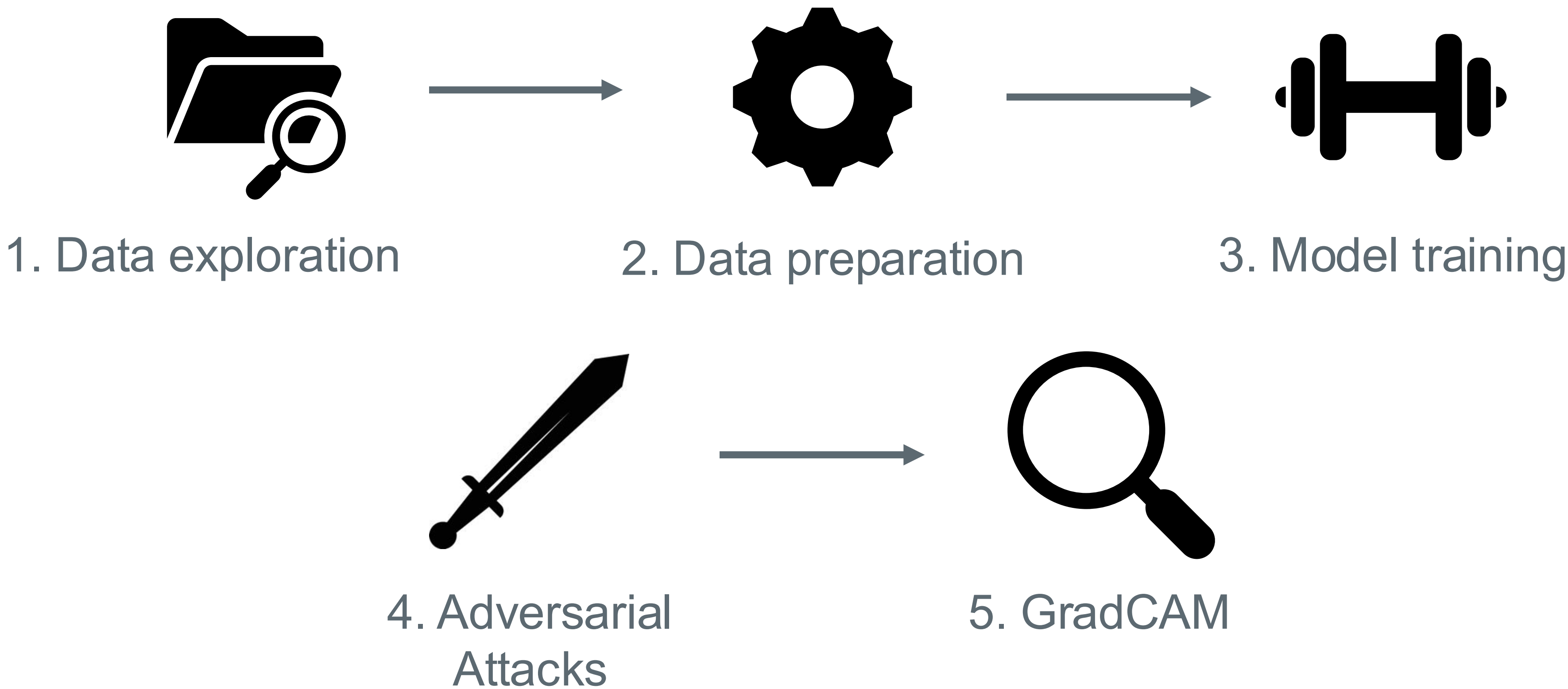
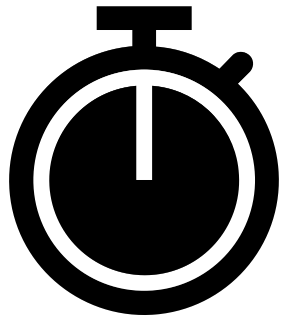
Methodology



GTZAN Dataset

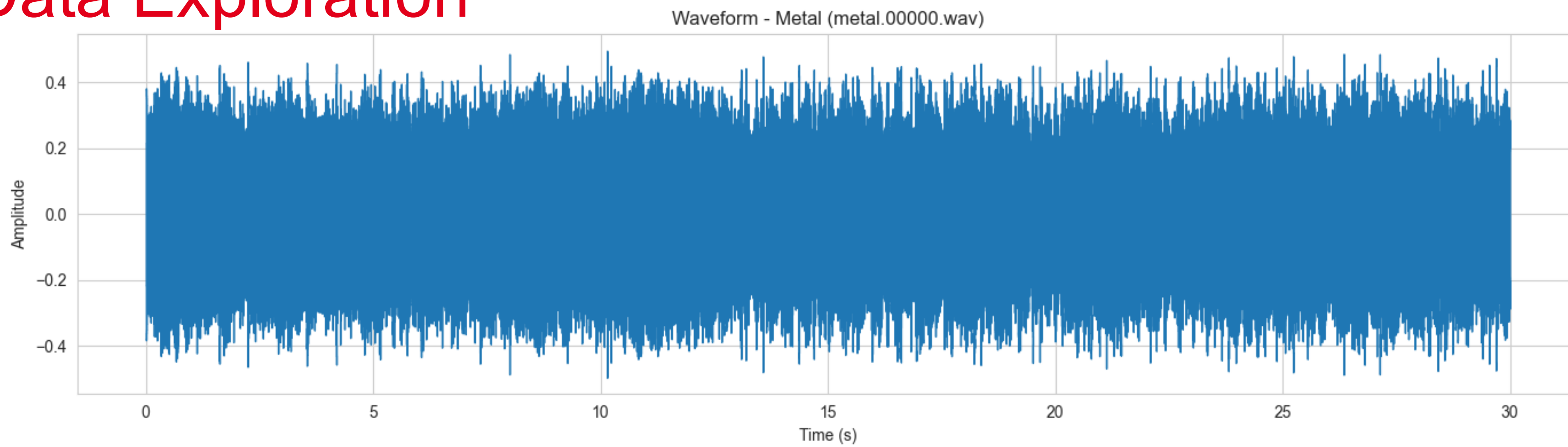
1000 songs
in 10 genres
(100 per genre)

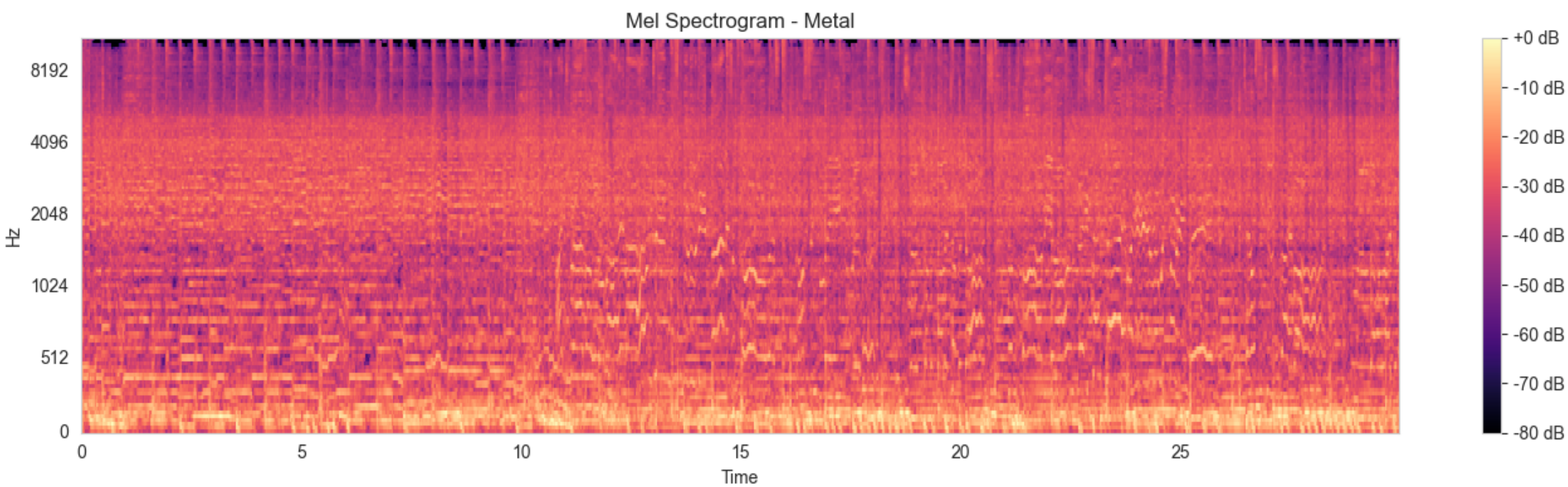


30 sec
as .wav

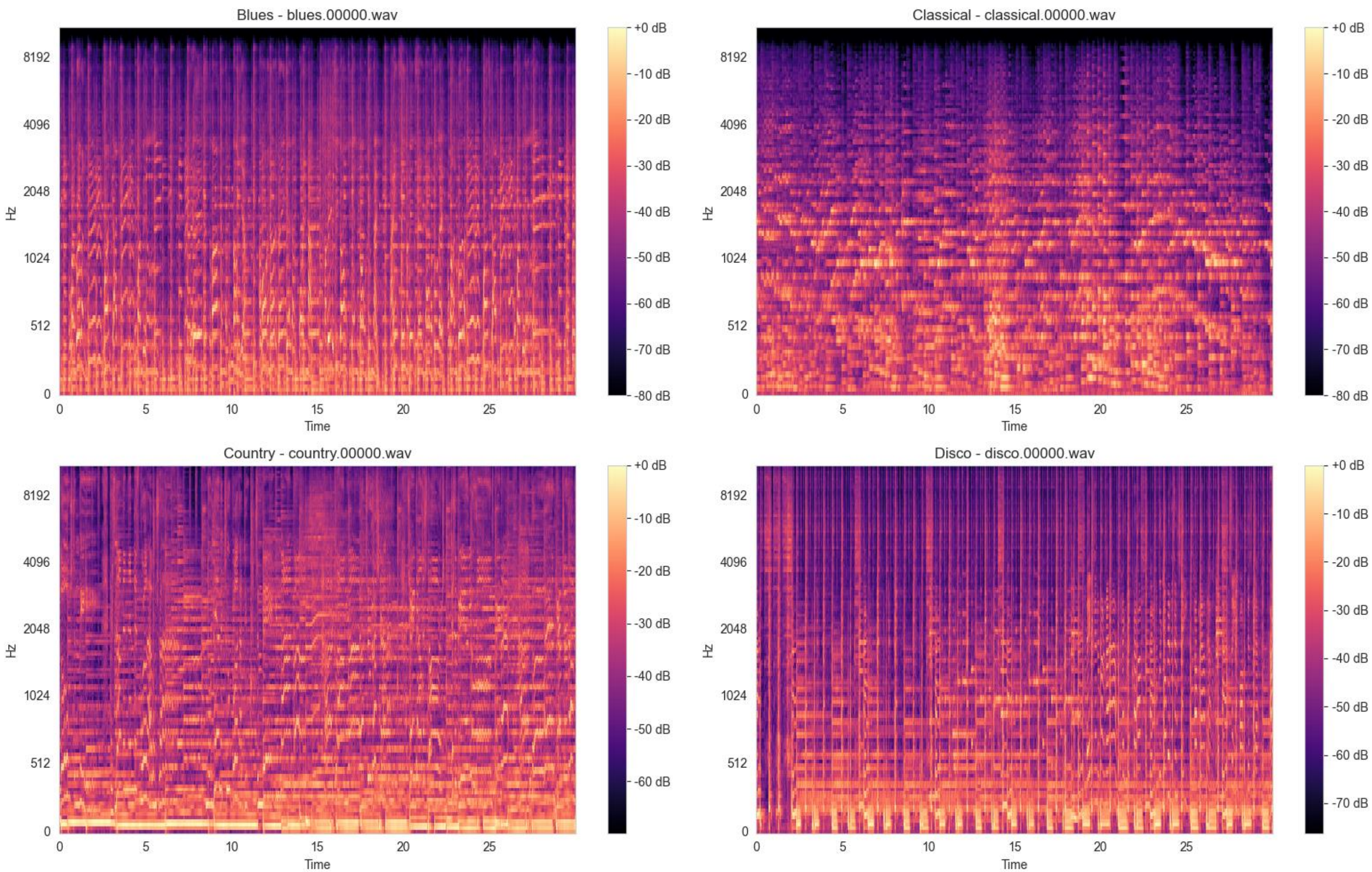
Mel spectograms,
feature tables

Data Exploration





Data Exploration



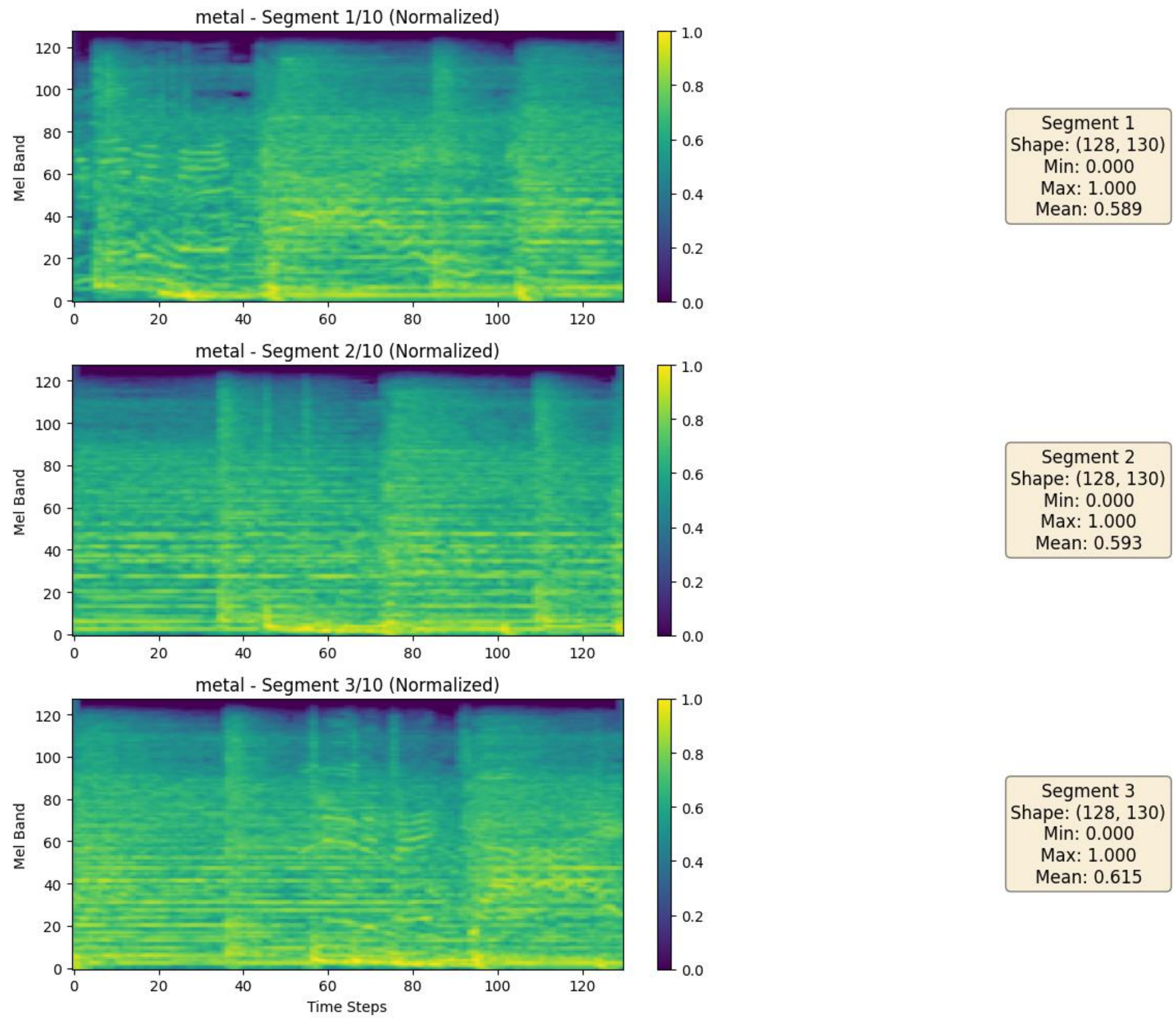
Preprocessing

- 70% Training (~700 Songs)
- 15% Validation (~150 Songs)
- 15% Test (~150 Songs)

Split into 10 segments á 3 sec

- 70% Training (~7000 segments)
- 15% Validation (~1500 segments)
- 15% Test (~1500 segments)

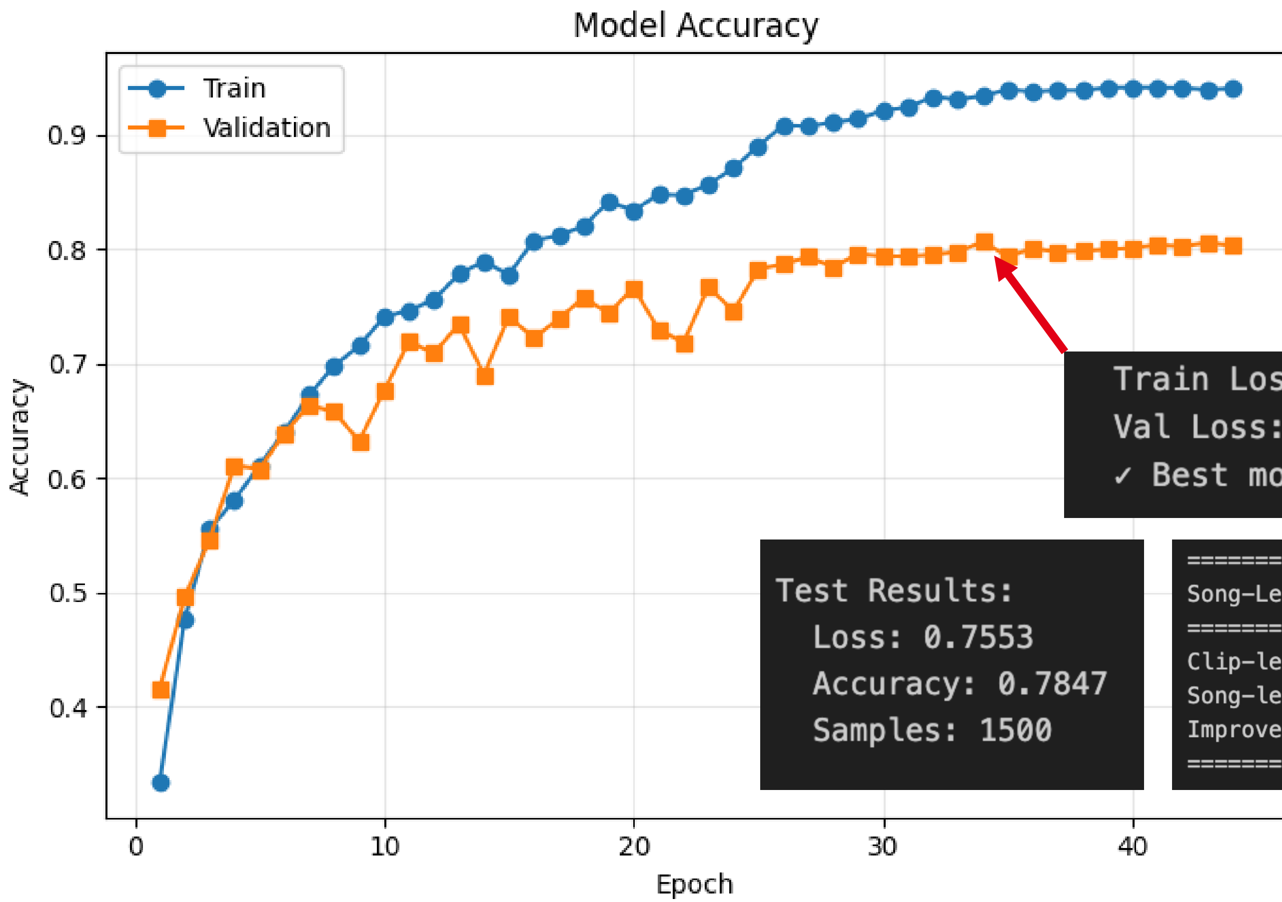
librosa


metal - Segment 1/10 (Normalized)
Mel Band
0
20
40
60
80
100
120
1.0
0.8
0.6
0.4
0.2
0.0
Segment 1
Shape: (128, 130)
Min: 0.000
Max: 1.000
Mean: 0.589
metal - Segment 2/10 (Normalized)
Mel Band
Segment 2
Shape: (128, 130)
Min: 0.000
Max: 1.000
Mean: 0.593
metal - Segment 3/10 (Normalized)
Mel Band
Time Steps
Segment 3
Shape: (128, 130)
Min: 0.000
Max: 1.000
Mean: 0.615

CNN Architecture

- Input: Mel Spectrogram 128 × 130 × 1
- Convolutional Blocks: 2x (Conv→ BatchNorm) → MaxPool → Dropout
- Progressive filters: 32 → 64 → 128 → 256
- Classification: Flatten → Dense(512) → Dense(10)
- 1,4M parameters

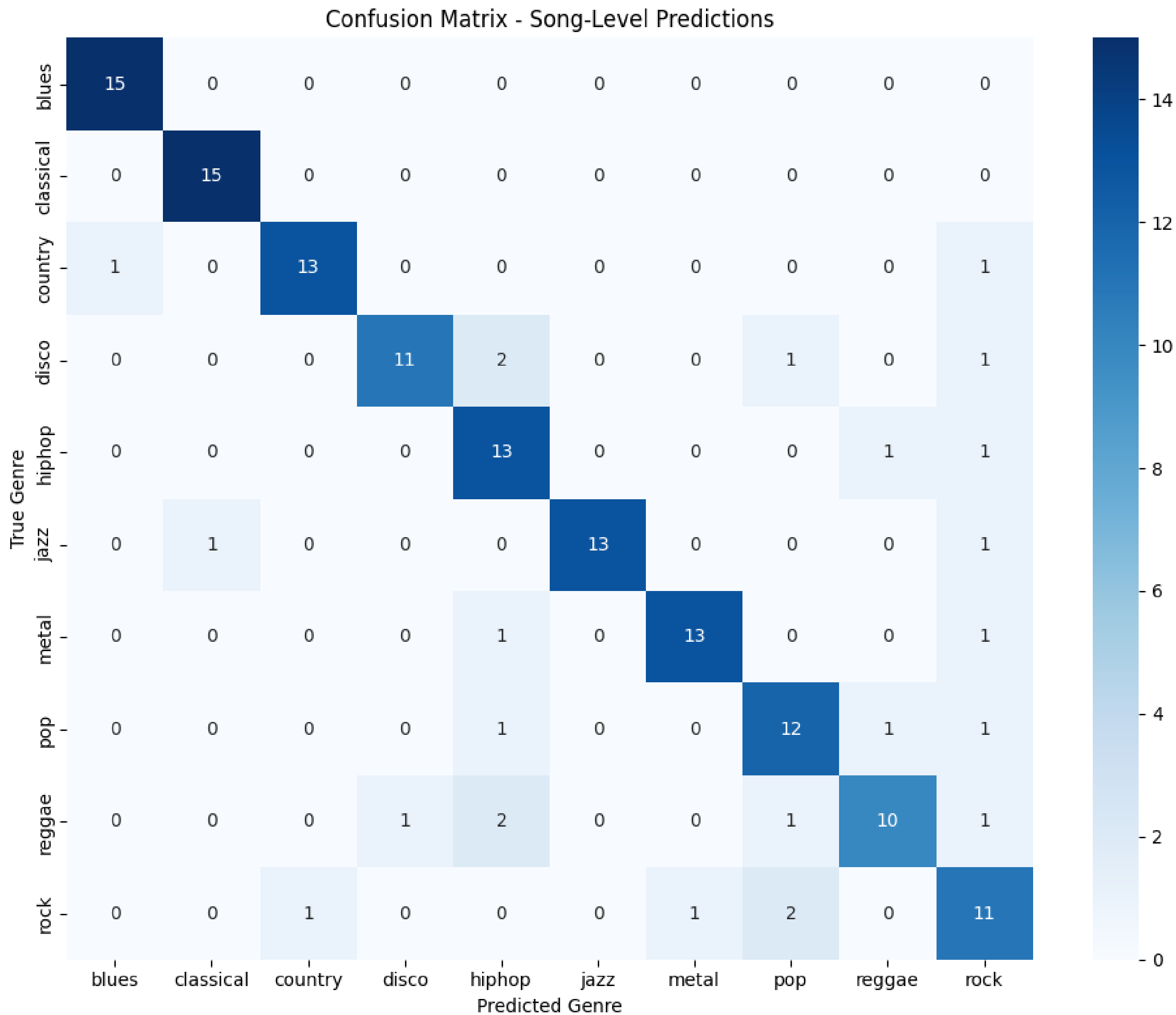
Training Results




```
Train Loss: 0.1983, Train Acc: 0.9341
Val Loss: 0.8362, Val Acc: 0.8064
✓ Best model saved (val_acc: 0.8064)
```

```
Test Results:
  Loss: 0.7553
  Accuracy: 0.7847
  Samples: 1500
```

```
============================================================
Song-Level Evaluation (Soft Voting)
============================================================
Clip-level accuracy: 0.7847 (1500 clips)
Song-level accuracy: 0.8400 (150 songs)
Improvement: +5.53%
============================================================
```


Confusion Matrix - Song-Level Predictions
True Genre
Predicted Genre
blues
classical
country
disco
hiphop
jazz
metal
pop
reggae
rock
blues: 15 0 0 0 0 0 0 0 0 0
classical: 0 15 0 0 0 0 0 0 0 0
country: 1 0 13 0 0 0 0 0 0 1
disco: 0 0 0 11 2 0 0 1 0 1
hiphop: 0 0 0 0 13 0 0 0 1 1
jazz: 0 1 0 0 0 13 0 0 0 1
metal: 0 0 0 0 1 0 13 0 0 1
pop: 0 0 0 0 1 0 0 12 1 1
reggae: 0 0 0 1 2 0 0 1 10 1
rock: 0 0 1 0 0 0 1 2 0 11
14
12
10
8
6
4
2
0

Adversarial Attacks

FGSM (Fast Gradient Sign Method)

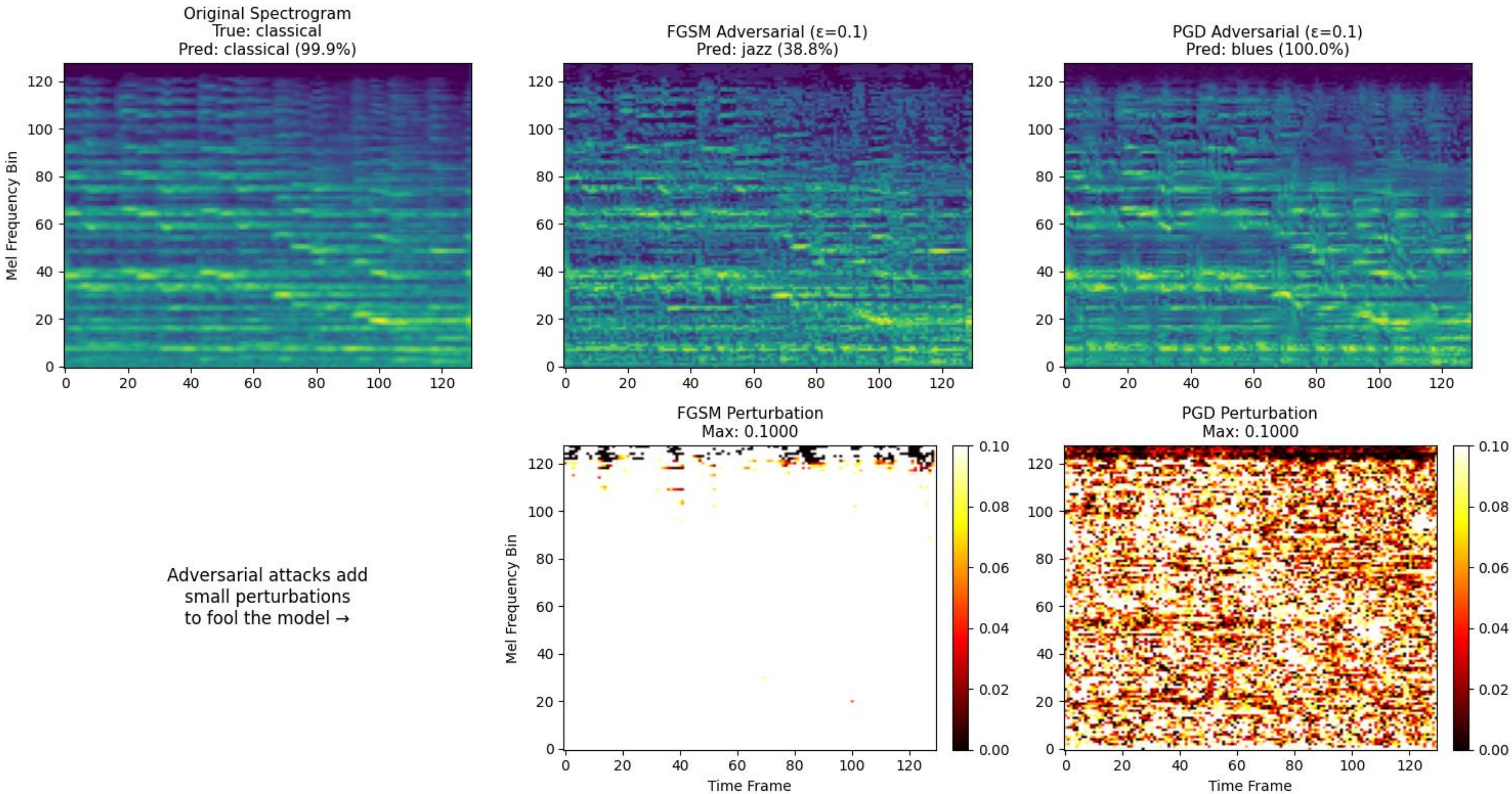
- Single Step Attack
- Moves input in direction of gradient

PGD (Projected Gradient Descent)

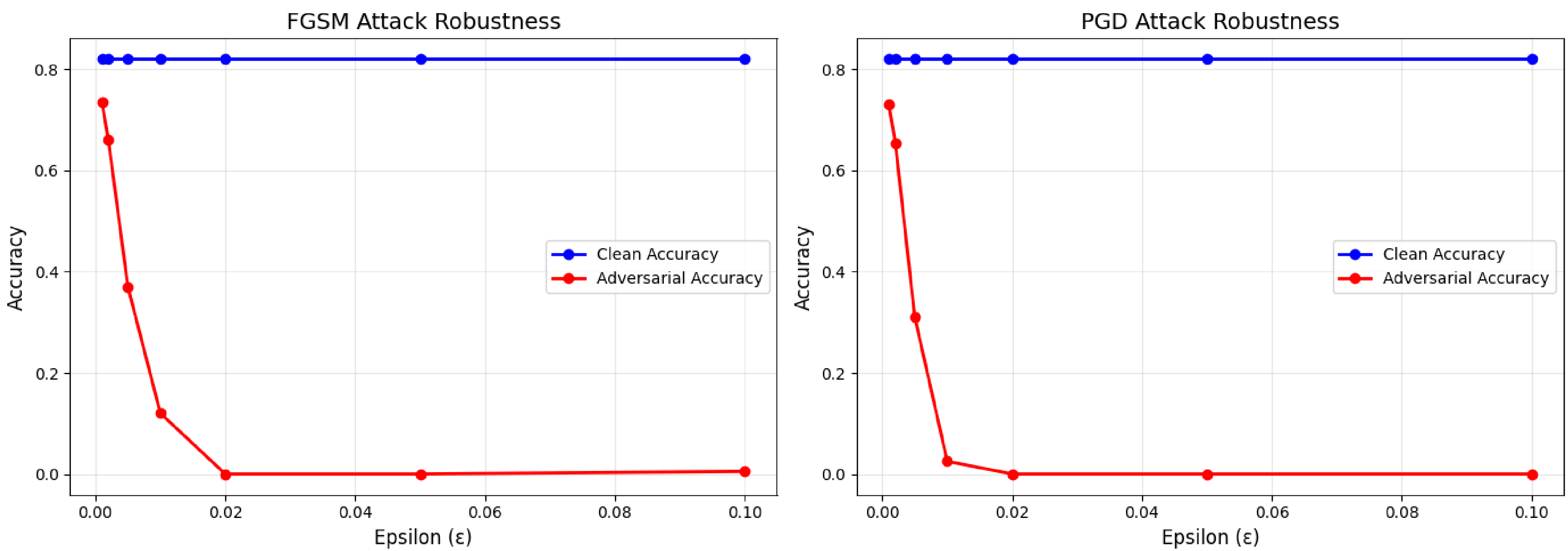
- Multi-step iterative attack
- Takes small steps and projects back into allowed perturbation range

Adversarial Robustness Toolbox

Adversarial Attacks



Adversarial Attacks



GradCAM

1. Baseline Analysis (Correct Predictions)

- 20 correctly classified samples (2 per genre)
- **Goal:** Understand what features the model uses normally

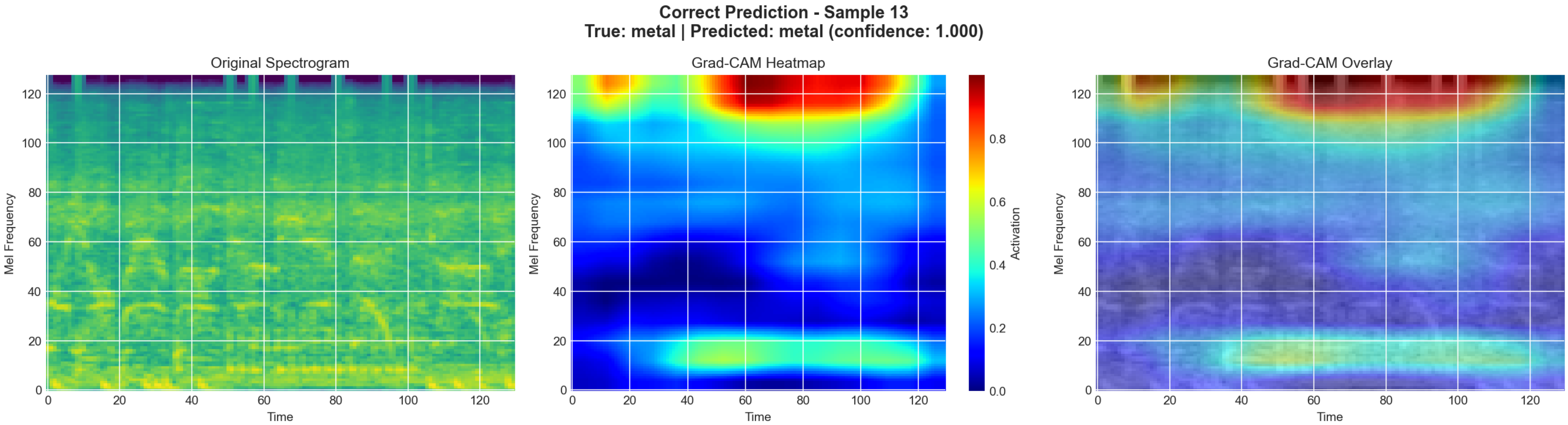
2. Natural Failures (Error Analysis)

- 5 misclassified samples without attacks
- **Goal:** Identify confusion sources

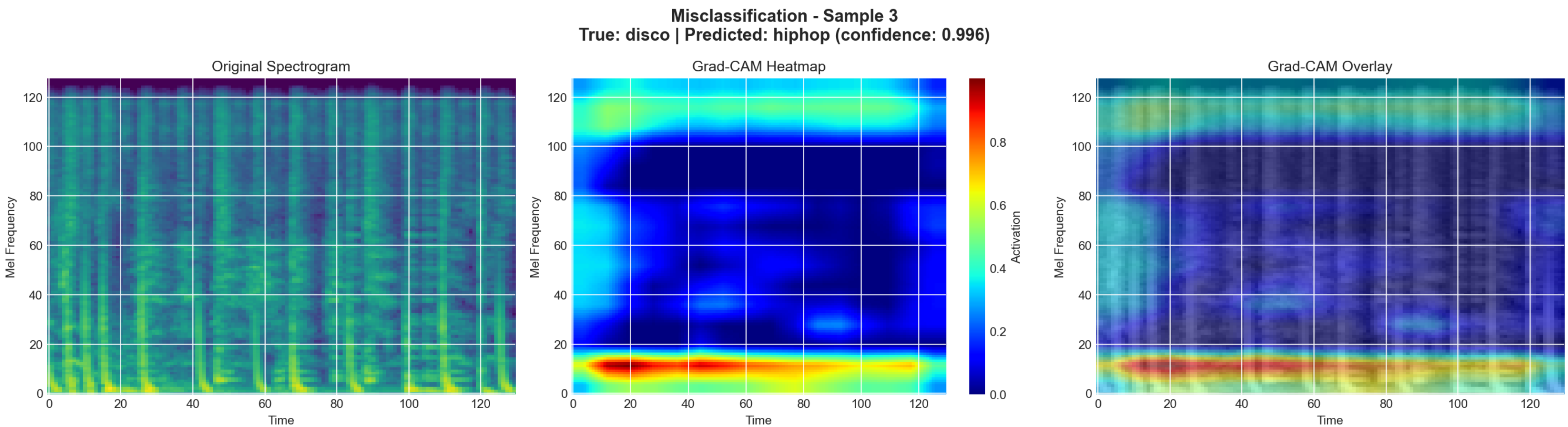
3. Adversarial Analysis (FGSM & PGD, ε=0.1)

- 20 samples under FGSM + 20 under PGD attacks
- Side-by-side comparisons: Clean vs. Adversarial
- **Goal:** How do attacks alter model perception?

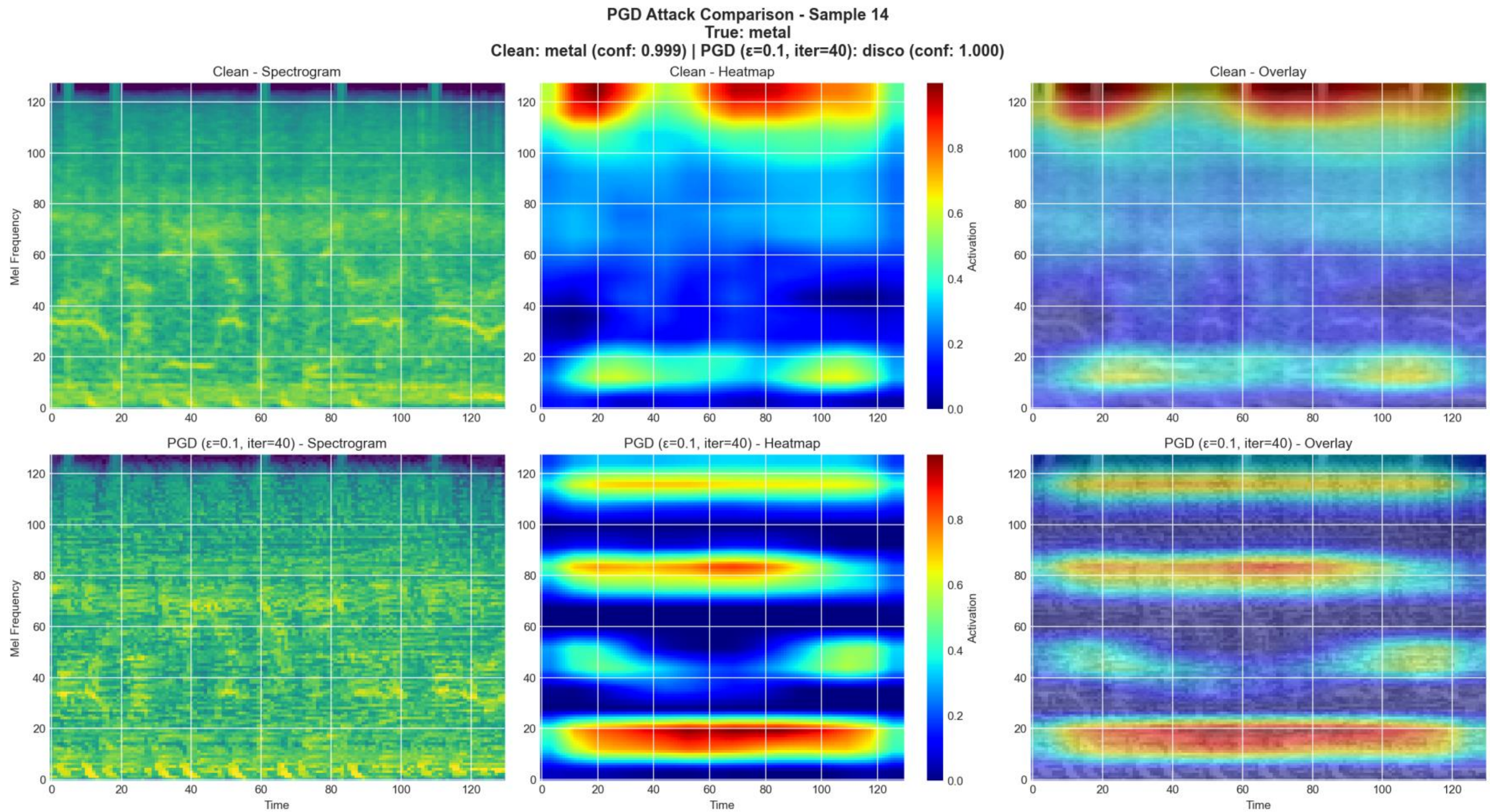
GradCAM – Baseline Analysis



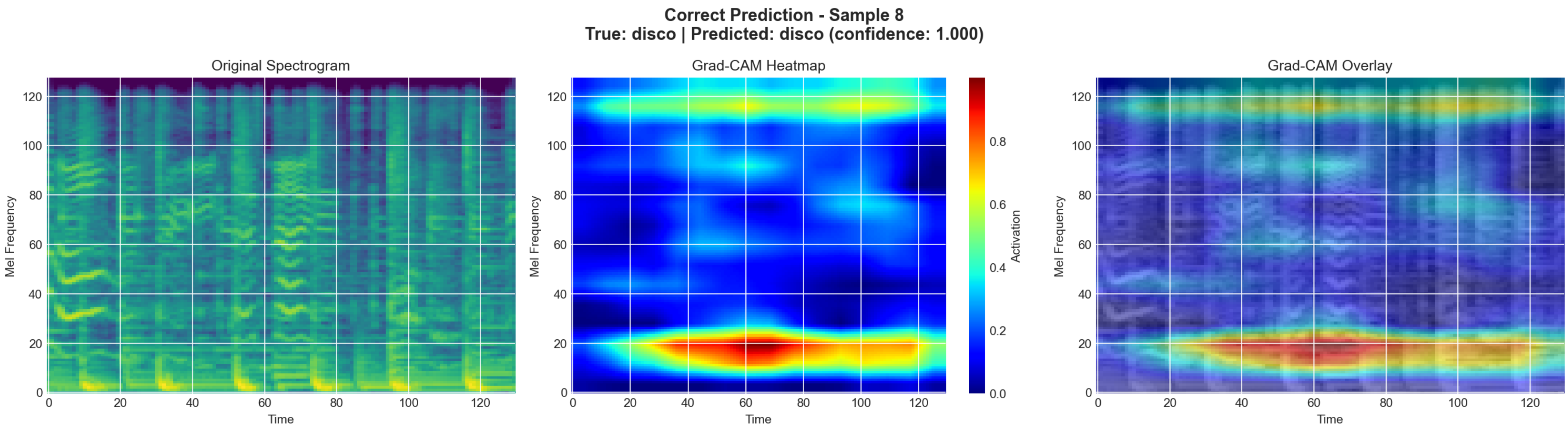
GradCAM – Natural Failures



GradCAM – Adversarial Attacks



GradCAM – Adversarial Attacks



Conclusion

Key Findings	Insight
Model accuracy: 84% song-level	Good baseline performance
Adversarial vulnerability: ~100% at $\varepsilon=0.02$	Highly vulnerable without defense mechanisms
Grad-CAM on clean data: Meaningful attention	Model learns musically relevant features
Grad-CAM under attacks: Artificial patterns	Attacks exploit attention mechanisms