

NTU MIR 2025 - Homework 1

Student: 邱冠銘

Student ID: R14921046

Task 1: Traditional Machine Learning for Artist Recognition

Audio Features Extracted

Core Features

- **MFCC Features:** 20 coefficients + Delta (velocity) + Delta-Delta (acceleration)
- **Mel Spectrogram:** 128 mel frequency bins with statistical aggregation
- **Spectral Features:** Centroid, Bandwidth (frequency-weighted), Rolloff (mel energy sum)

Additional Features

- **Energy Features:** RMS Energy with temporal statistics
- **Rhythm Features:** Zero Crossing Rate, Tempo (from onset strength detection)
- **Advanced Features:**
 - Chroma-like features (first 12 mel bins)
 - Spectral Contrast (6 frequency bands, peak-to-valley ratios)

Preprocessing Pipeline

Data Processing Steps

- **RobustScaler** for outlier resistance
- **Feature Selection** (SelectKBest, top 100 features)
- **Statistical Aggregation** (mean, std, max, min over time)

Feature Engineering

- **400+ dimensional features** → reduced to 100 via feature selection
- **GPU-accelerated extraction** with PyTorch for efficiency
- **Robust preprocessing** to handle NaN/inf values

Traditional ML Models

Models Implemented

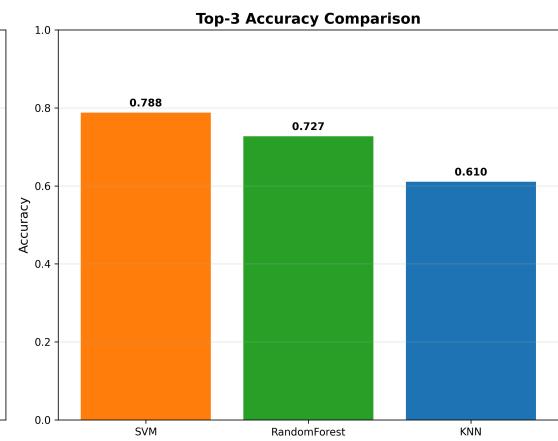
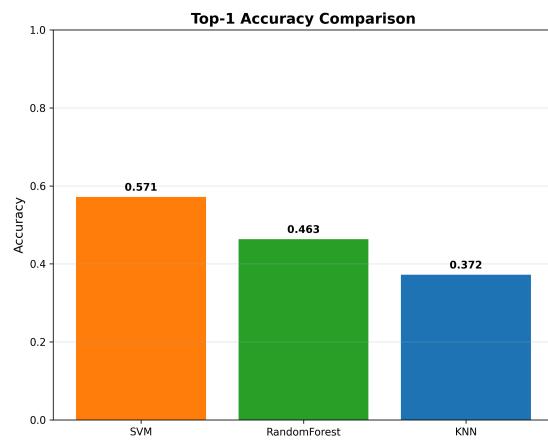
- **SVM:** Multiple kernels (RBF, Linear, Polynomial) with grid search (C , γ , degree hyperparameters)
- **Random Forest:** Grid search over 100-300 trees with hyperparameter tuning
- **k-NN:** Grid search over $k=3-15$ with distance weighting

Training Process

- **5-fold cross-validation** for hyperparameter tuning
- **Grid search** for optimal hyperparameters
- **Stratified validation** to ensure balanced evaluation

Model Comparison

Model	Top-1 Accuracy	Top-3 Accuracy
SVM	57.14%	78.79%
Random Forest	46.32%	72.73%
k-NN	37.23%	61.04%



Confusion Matrix - SVM

- Strong diagonal indicates good overall classification
 - Some artists more easily distinguishable than others (e.g Fleet Wood Mac, Green Day)
 - Confusion often occurs between similar music styles

Key Findings - Task 1

- **Best Model:** SVM with 57.14% top-1 and 78.79% top-3 accuracy
- **Feature diversity and proper preprocessing** are crucial
- **SVM with RBF kernel** works well for high-dimensional audio features

Task 2: Deep Learning for Artist Recognition

Deep Learning Architecture

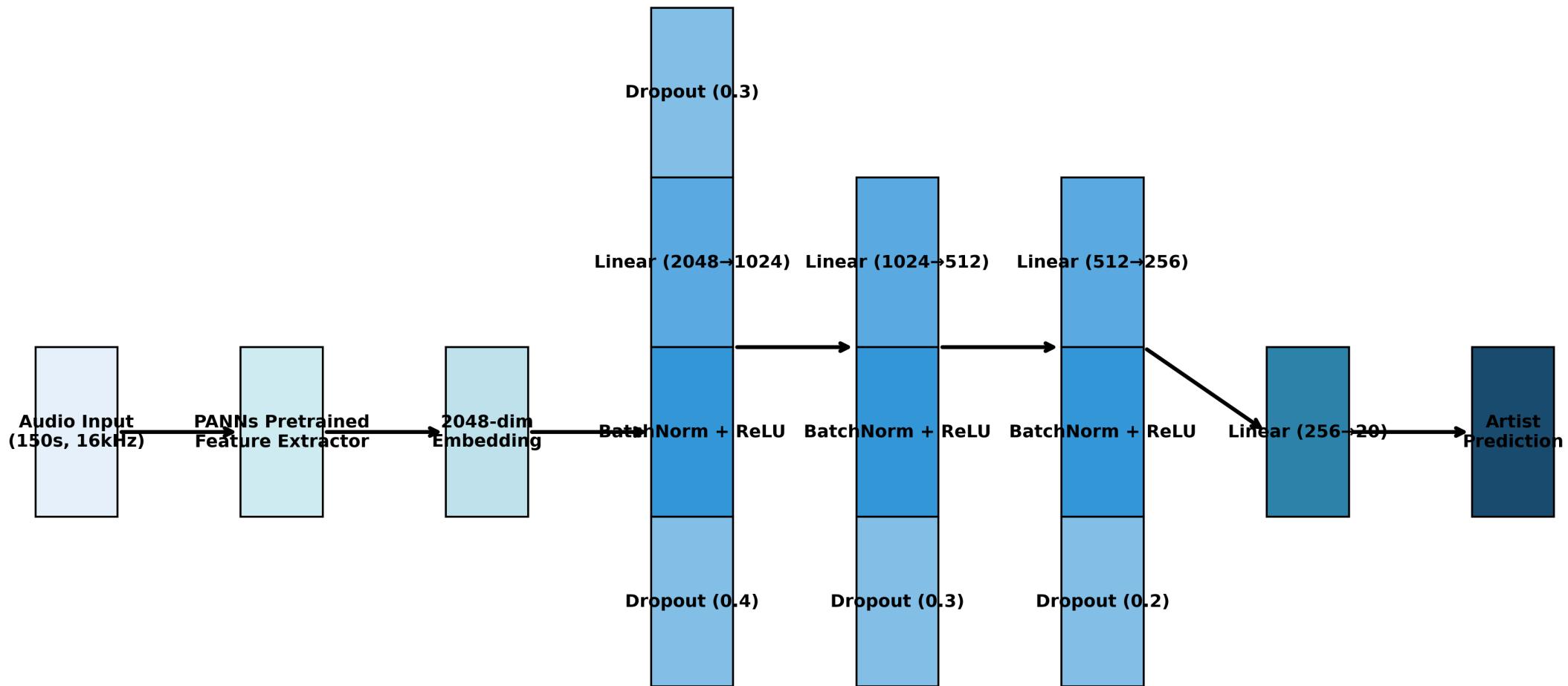
PANNs-based Model

- **Pretrained Features:** PANNs (Pretrained Audio Neural Networks) for feature extraction
- **Feature Dimension:** 2048-dimensional embeddings from pretrained model
- **Architecture:** Multi-layer classifier with batch normalization and dropout

Model Components

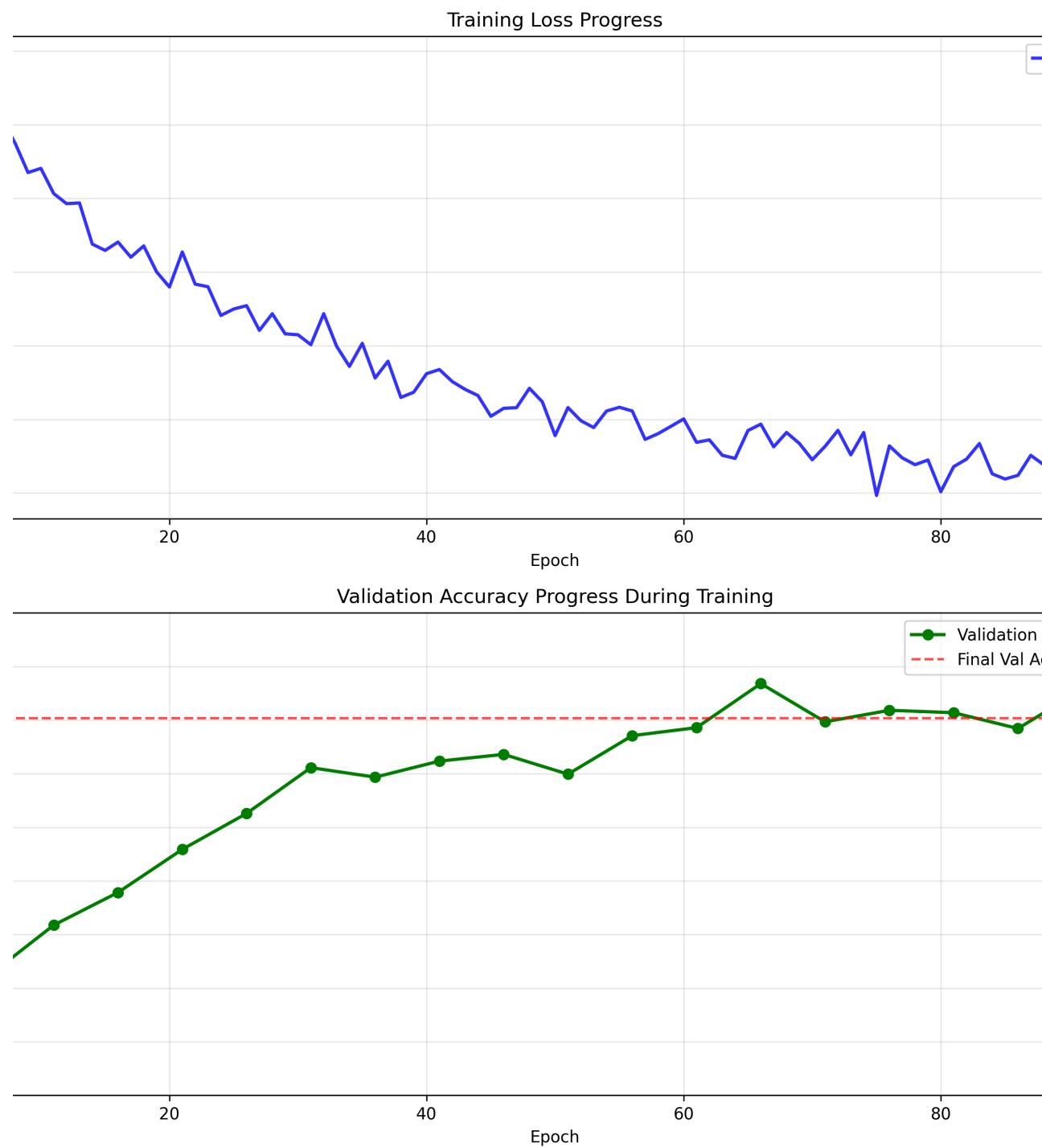
- **Feature Extractor:** PANNs pretrained model (frozen)
- **Classifier Head:** 4-layer neural network ($2048 \rightarrow 1024 \rightarrow 512 \rightarrow 256 \rightarrow 20$)
- **Regularization:** Dropout layers (0.3, 0.4, 0.3, 0.2) and BatchNorm1d

PANNS-based Deep Learning Architecture



Training Progress

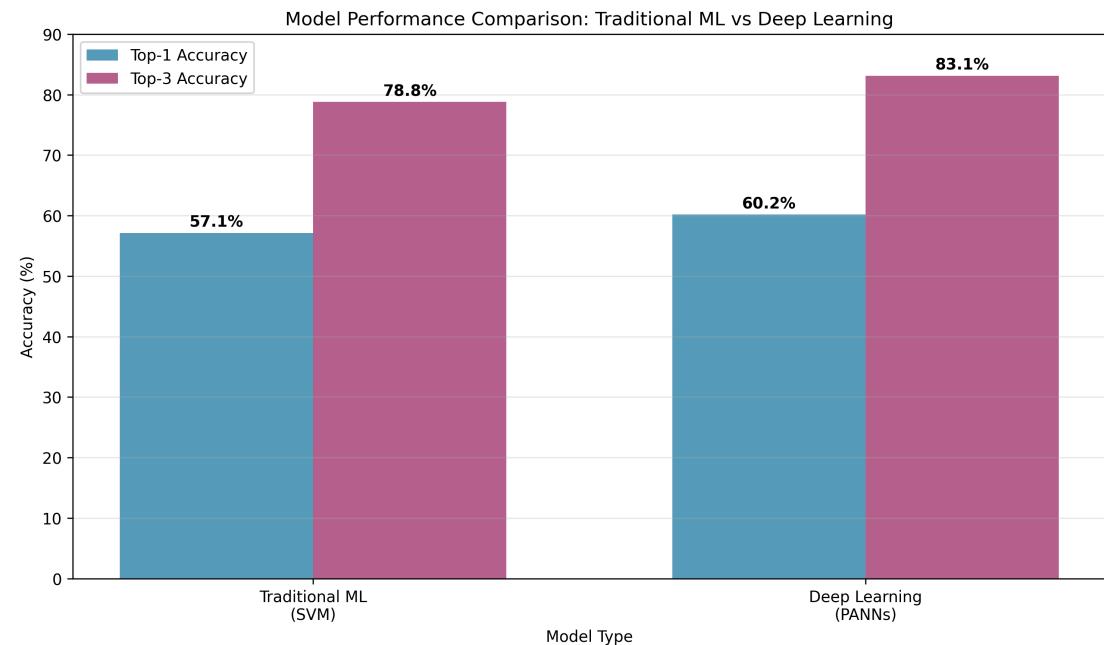
- **Training Loss:** Steady decrease over 100 epochs
- **Validation Accuracy:** Converged to 60.17%
- **Learning Curve:** Shows proper convergence without overfitting



Results

Metric	Performance
Val Top-1 Accuracy	60.17%
Val Top-3 Accuracy	83.12%

- **Top-1:** +3.03% over SVM
- **Top-3:** +4.33% over SVM



Confusion Matrix - Deep Learning

Observations

- Similar performance to SVM in top-1 accuracy
- **Superior top-3 accuracy**
(83.12% vs 78.79%)
- Strong performance on popular artists (Beatles, Fleetwood Mac)
- Better generalization with pretrained features

Confusion Matrix - Deep Learning (PANNs)

	aerosmith	beatles	creedence_clearwater_revival	cure	dave_matthews_band	depeche_mode	fleetwood_mac	garth_brooks	green_day	led_zeppelin	madonna	metallica	prince	queen	radiohead	roxette	steely_dan	suzanne_vega	tori_amos	Predicted
aerosmith	1	0	0	1	0	0	0	0	1	1	1	2	0	0	0	3	0	0	0	
atles	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0		
vival	1	3	2	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	
cure	0	2	0	5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
band	0	0	0	0	6	0	0	0	3	0	1	1	0	0	0	0	0	1	0	
node	0	0	0	1	0	8	1	0	0	0	0	0	0	0	0	0	0	0	0	
_mac	0	0	0	0	0	1	11	0	0	0	0	0	0	0	0	0	0	0	0	
ooks	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	2	0	0	
l_day	2	1	0	0	0	0	0	0	0	12	0	0	0	0	1	0	0	0	0	
elin	0	0	0	0	0	0	0	0	0	5	0	1	0	0	0	0	0	1	0	
onna	0	0	0	0	1	5	0	0	0	0	6	0	1	0	0	1	0	0	0	
allica	1	0	0	1	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	
rince	0	0	0	0	0	1	1	0	0	0	0	7	0	0	0	0	0	0	0	
ueen	2	1	0	0	0	0	0	0	0	2	0	1	0	7	0	0	1	0	0	
head	0	0	0	0	2	0	0	0	1	0	0	1	0	0	8	0	0	0	0	
xette	0	0	0	0	0	1	0	0	1	0	3	0	0	0	0	5	0	1	0	
_dan	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	7	0	0	
vega	0	0	0	0	2	0	1	0	0	0	1	0	0	0	2	0	2	4	0	
amos	0	0	0	0	0	0	1	0	0	0	2	0	2	1	0	0	1	1	11	
u2	0	0	0	0	2	1	0	0	0	0	0	0	0	1	0	0	0	0	0	

Predicted

Key Findings - Task 2

- **PANNS pretrained features** provide rich 2048-dimensional embeddings
- **Performance Improvements** over traditional ML:
 - Top-1 accuracy: +3.03% (57.14% → 60.17%)
 - Top-3 accuracy: +4.33% (78.79% → 83.12%)
- **Longer audio duration (150s)** captures more musical context
- **Deep learning** excels at learning complex audio-artist mappings

Tutorial

Quick Start

- Link: https://drive.google.com/file/d/1zpGiya4O_AF6SqTxcd-alf4x9OWGaY9R/view
- Steps:
 - `pip install -r requirements.txt` -> Install dependencies
 - `bash get_dataset.sh` -> Download dataset
 - `python task2_inference.py` -> Inference

Implementation & Reproducibility

Task 1: Traditional ML

- `task1_preprocessing.py` -> Extract features and preprocess data
- `task1_train.py` -> Train models and save results
- `task1_gen_report.py` -> Generate confusion matrix and comparison charts

Task 2: Deep Learning

- `task2_train.py` -> PANNs-based classifier with 150s audio
- `task2_inference.py` -> Generate predictions for test set
- `task2_gen_report.py` -> Generates confusion matrix and needed charts

References

- **PANNS:** Kong, Q., et al. (2020). PANNS: Large-Scale Pretrained Audio Neural Networks for Audio Pattern Recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*.
- **Librosa:** McFee, B., et al. (2015). librosa: Audio and Music Signal Analysis in Python. *Proceedings of the 14th Python in Science Conference*.
- **MFCCs:** Logan, B. (2000). Mel Frequency Cepstral Coefficients for Music Modeling. *International Symposium on Music Information Retrieval*.
- **Spectral Features:** Peeters, G. (2004). A Large Set of Audio Features for Sound Description. *CUIDADO Project*.

Thank you for your time