NTU MIR 2025 - Homework 1

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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

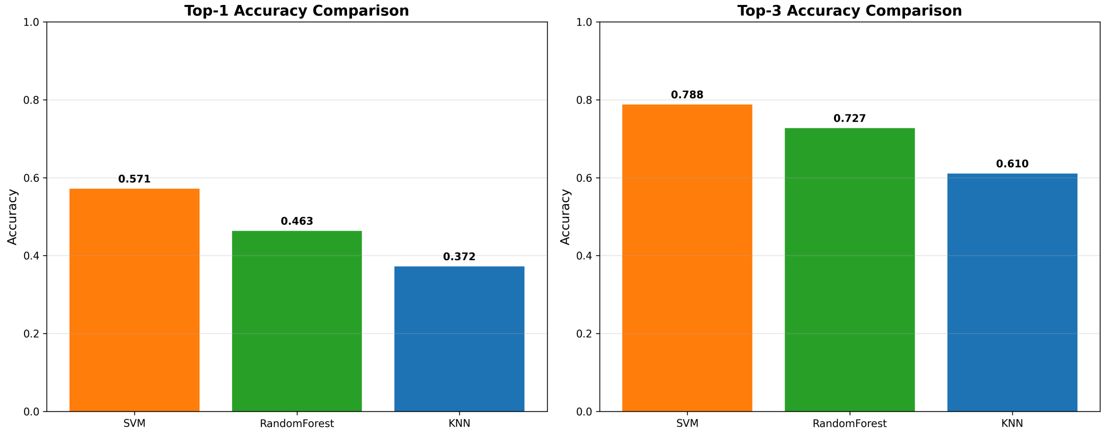
- **SVM:** Multiple kernels (RBF, Linear, Polynomial) with grid search (C, γ, degree hyperparameters)
- **Random Forest:** Grid search over 100-300 trees with hyperparameter tuning
- **k-NN:** Grid search over k=3-15 with distance weighting

Training Process

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

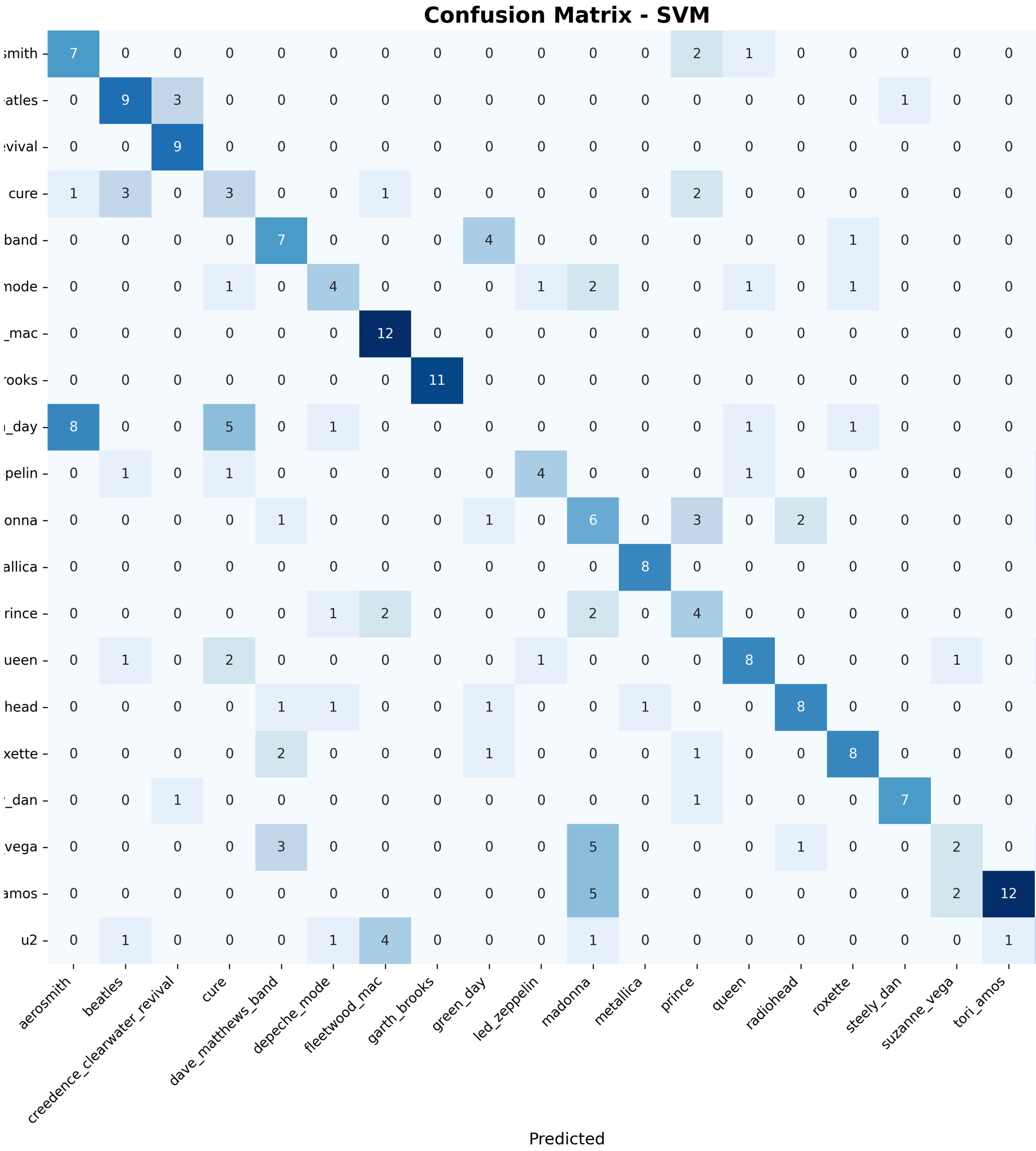
Model Comparison

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

Approach Overview

1. PANNs (Transfer Learning)

- Pretrained Audio Neural Networks
- 2048-dim embeddings
- Frozen feature extractor
- Fine-tuned classifier head

2. ResNet CNN (From Scratch)

- End-to-end learning
- Mel spectrogram input
- Residual blocks
- No pretrained weights

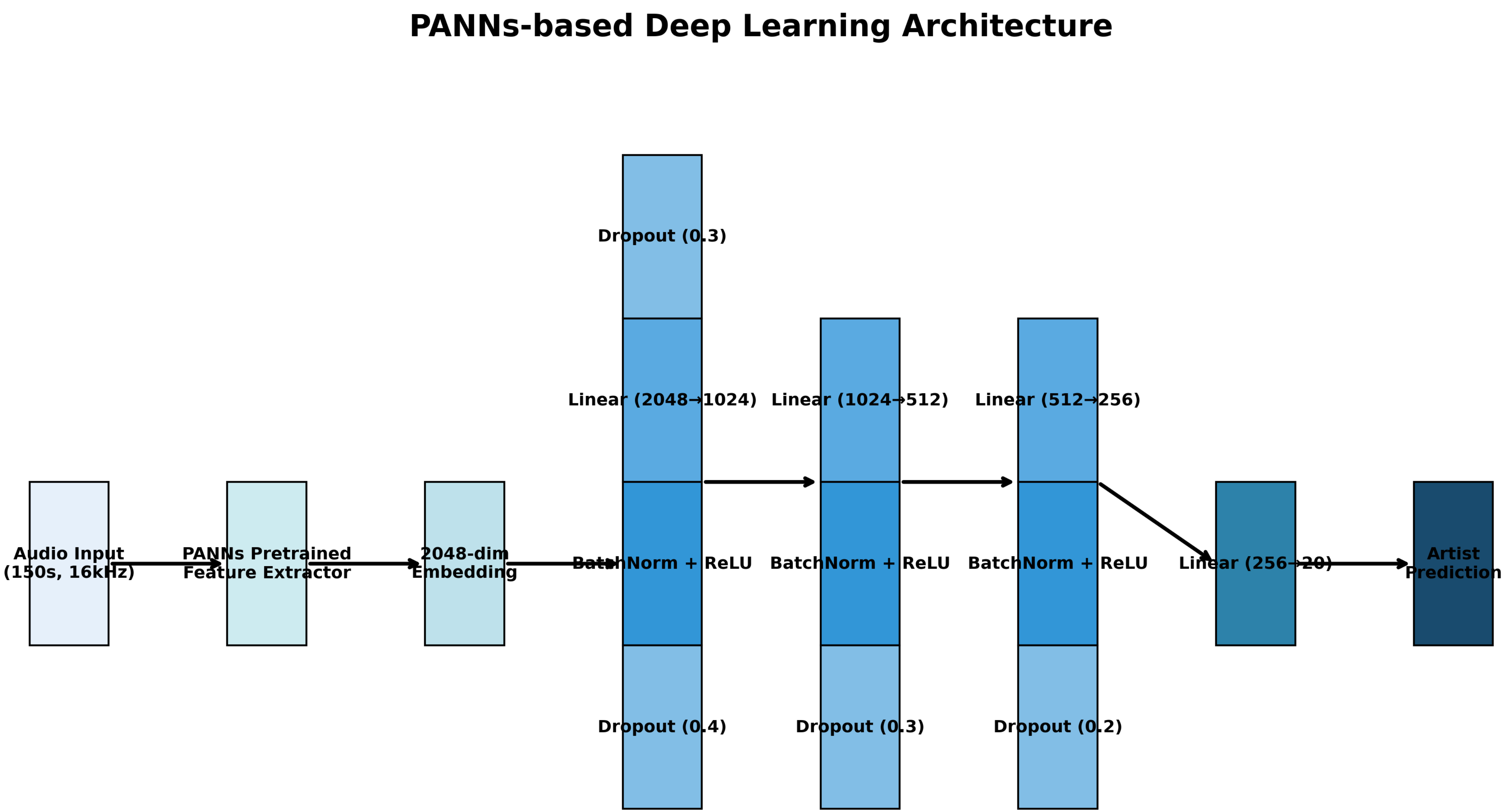
Model 1 - PANNs

Architecture

- **Feature Extractor:** Pretrained PANNs (frozen)
- **Embedding:** 2048-dim
- **Classifier:** 4-layer MLP
    - 2048 → 1024 → 512 → 256 → 20

Training

- **Input:** 150s @ 16kHz
- **Batch:** 8, **Epochs:** 100
- **Augmentation:** Crop, noise, stretch
- **Optimizer:** Adam (lr=0.005)
- **Scheduler:** ReduceLROnPlateau


PANNs-based Deep Learning Architecture
Audio Input (150s, 16kHz)
PANNs Pretrained Feature Extractor
2048-dim Embedding
Dropout (0.3)
Linear (2048→1024)
BatchNorm + ReLU
Dropout (0.4)
Linear (1024→512)
BatchNorm + ReLU
Dropout (0.3)
Linear (512→256)
BatchNorm + ReLU
Dropout (0.2)
Linear (256→20)
Artist Prediction

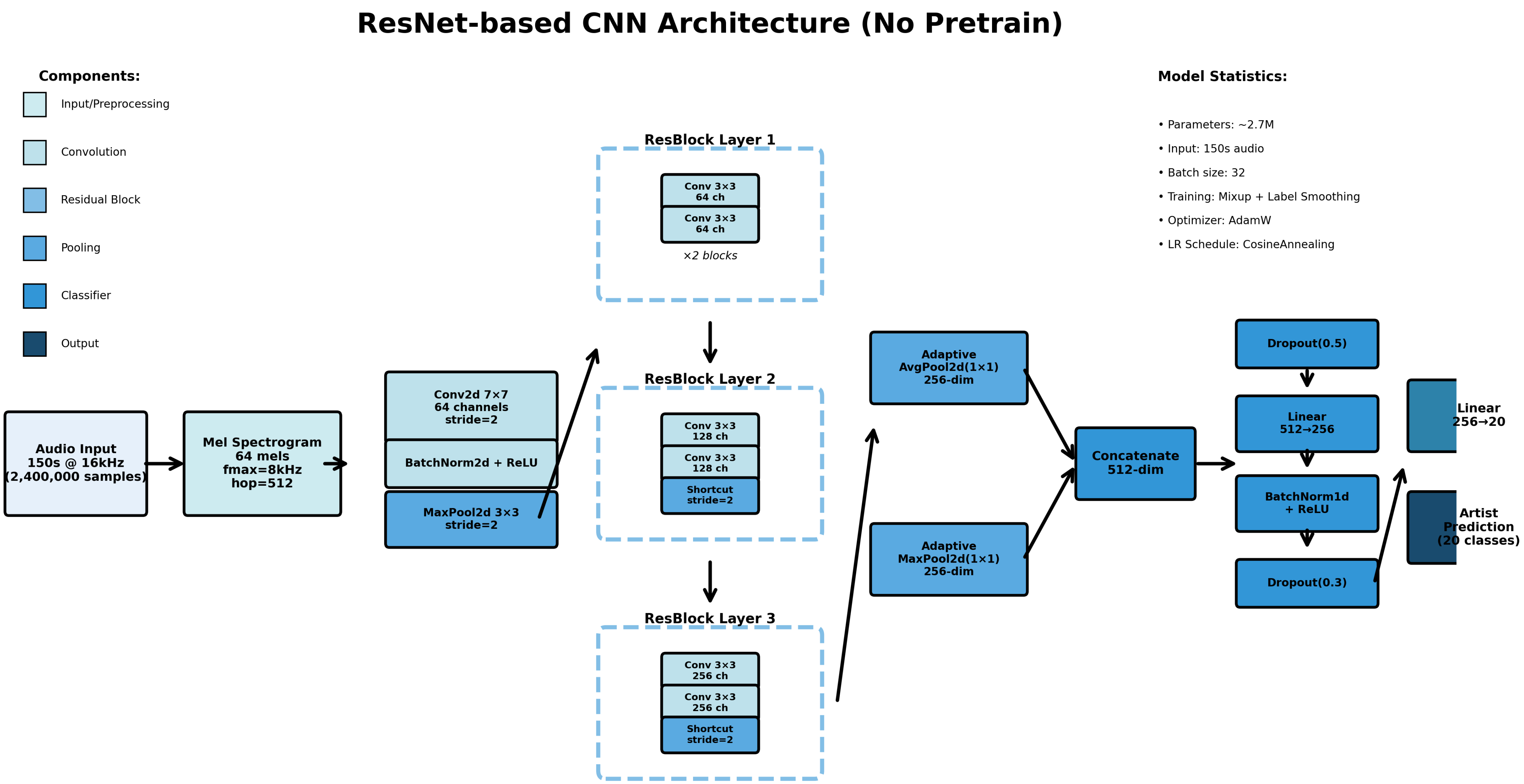
Model 2 - ResNet

Architecture

- **Input:** Mel spectrogram (64 mels)
- **Layers:** 7×7 conv → ResBlocks (64, 128, 256)
- **Pooling:** Dual (Avg+Max) → 512-dim
- **Classifier:** 512→256→20
- **Params:** ~2.7M

Training

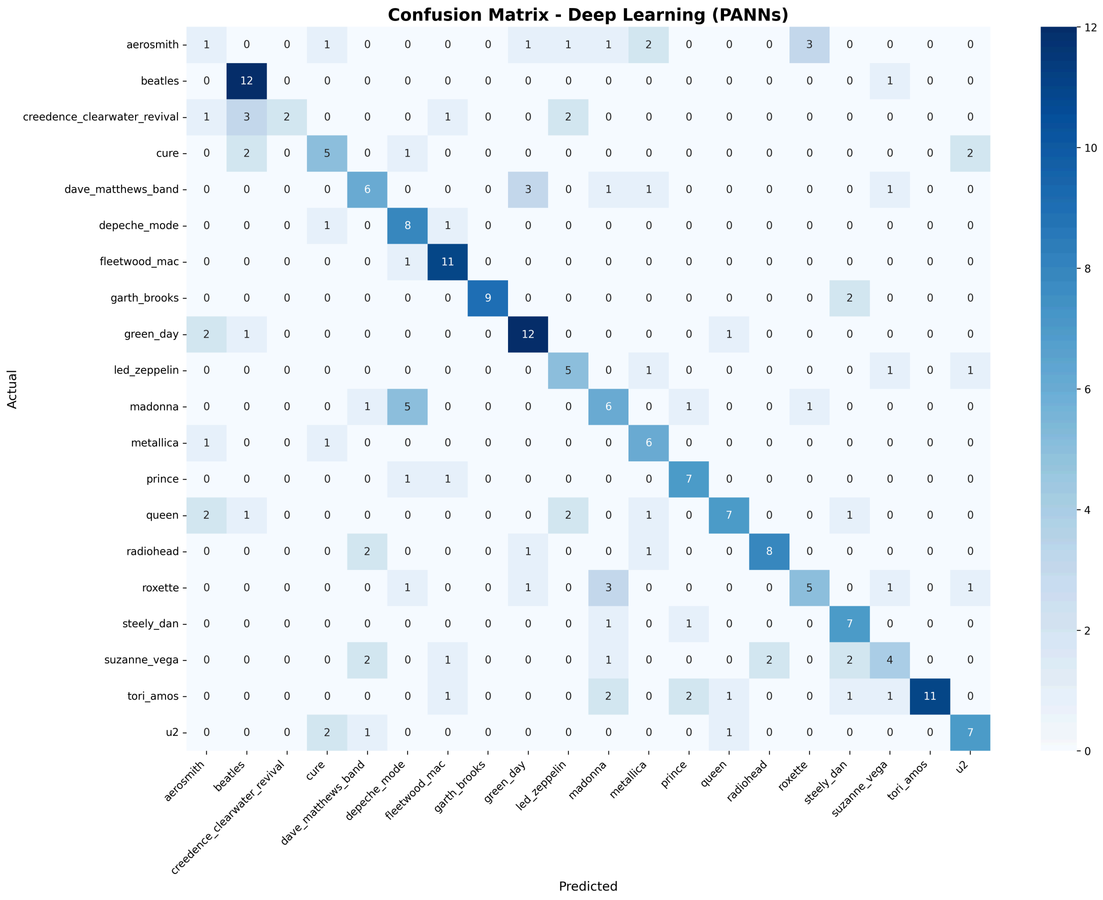
- **Input:** 150s @ 16kHz
- **Batch:** 32, **Epochs:** 100
- **Augmentation:** Crop, noise, **mixup**
- **Optimizer:** AdamW (lr=0.01)
- **Scheduler:** CosineAnnealing
- **Label Smoothing:** 0.1

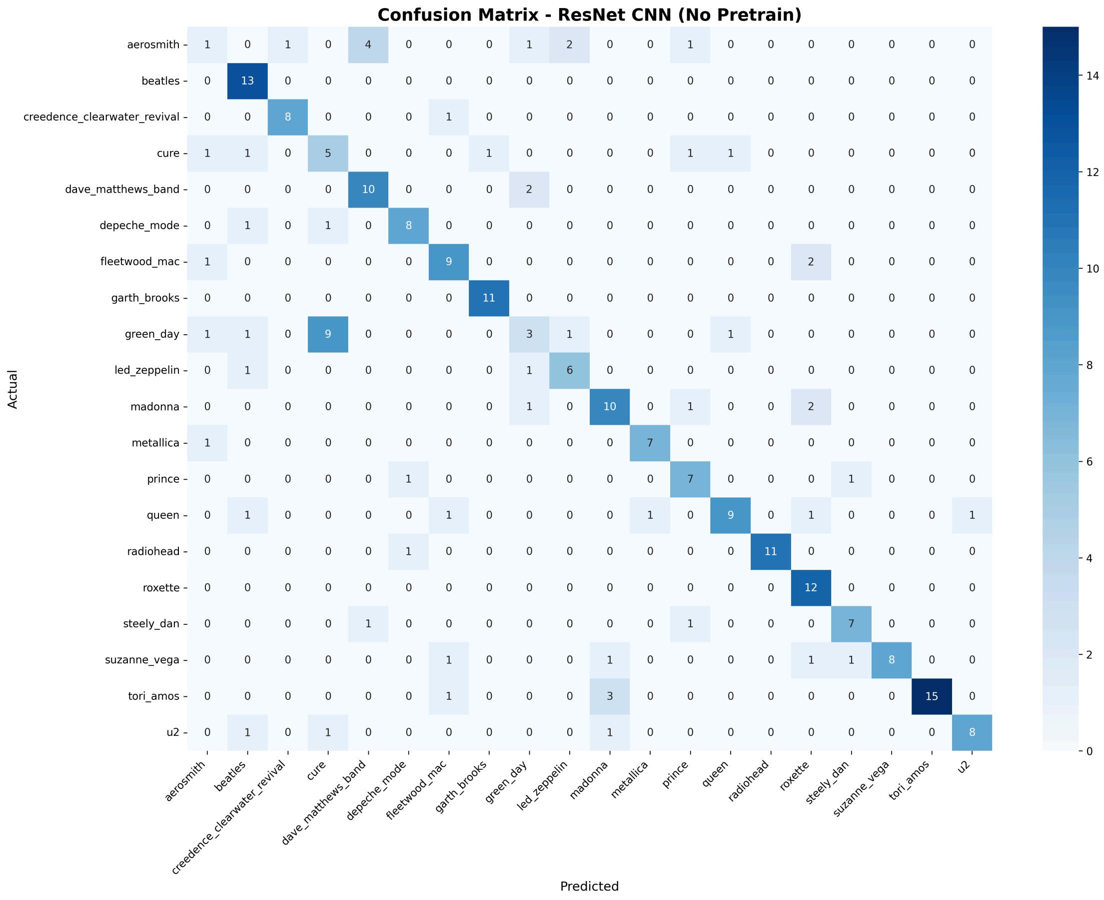

ResNet-based CNN Architecture (No Pretrain)
Components:
Input/Preprocessing
Convolution
Residual Block
Pooling
Classifier
Output
Model Statistics:
• Parameters: ~2.7M
• Input: 150s audio
• Batch size: 32
• Training: Mixup + Label Smoothing
• Optimizer: AdamW
• LR Schedule: CosineAnnealing
Audio Input 150s @ 16kHz (2,400,000 samples)
Mel Spectrogram 64 mels fmax=8kHz hop=512
Conv2d 7×7 64 channels stride=2
BatchNorm2d + ReLU
MaxPool2d 3×3 stride=2
ResBlock Layer 1
Conv 3×3 64 ch
Conv 3×3 64 ch
×2 blocks
ResBlock Layer 2
Conv 3×3 128 ch
Conv 3×3 128 ch
Shortcut stride=2
ResBlock Layer 3
Conv 3×3 256 ch
Conv 3×3 256 ch
Shortcut stride=2
Adaptive AvgPool2d(1×1) 256-dim
Adaptive MaxPool2d(1×1) 256-dim
Concatenate 512-dim
Dropout(0.5)
Linear 512→256
BatchNorm1d + ReLU
Dropout(0.3)
Linear 256→20
Artist Prediction (20 classes)

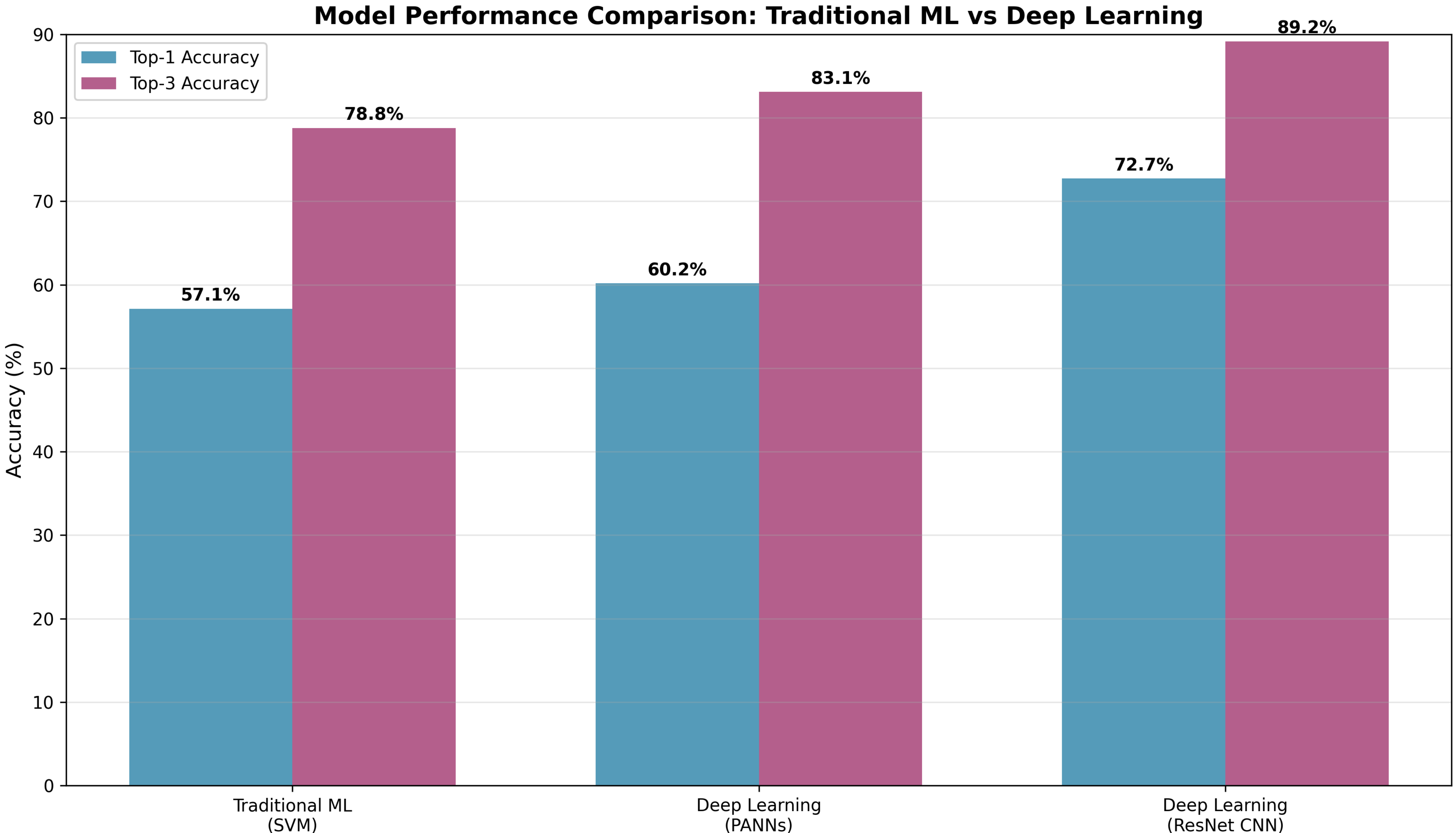
Model Comparison Table

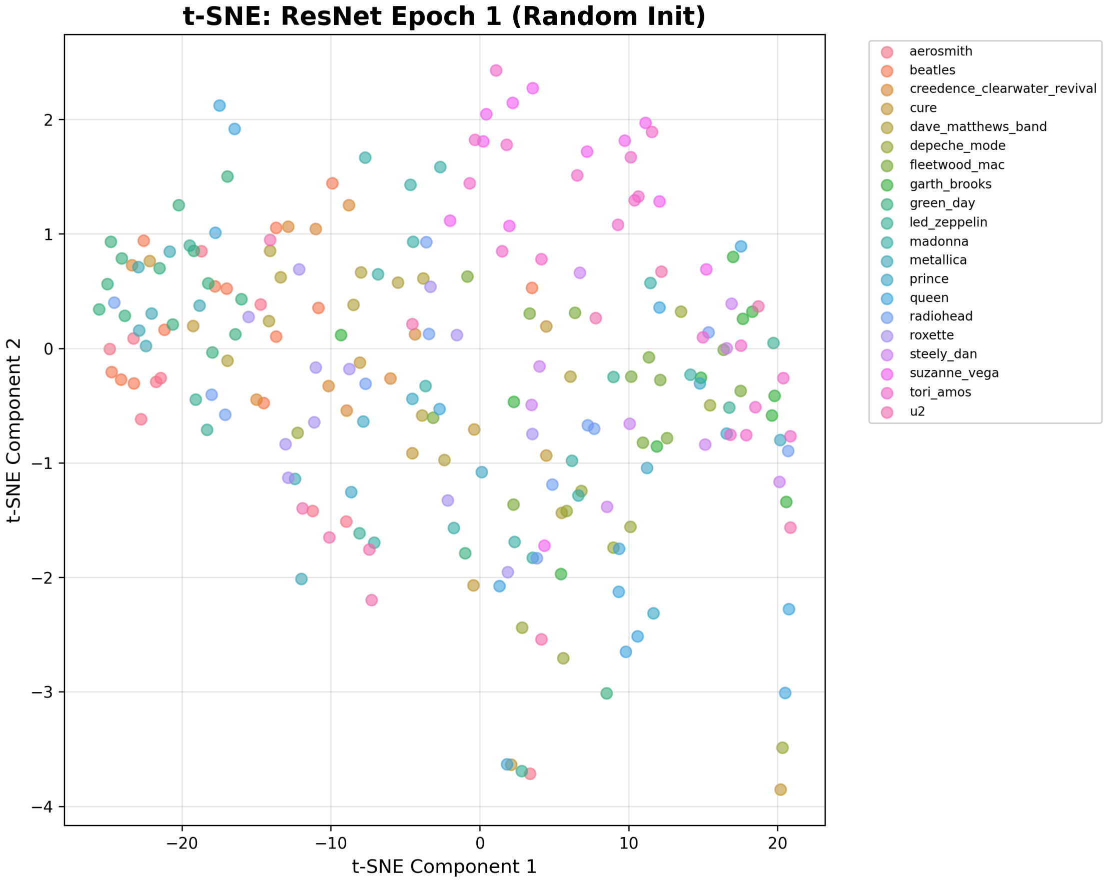
Model	Type	Top-1	Top-3	Advantage
SVM	Traditional ML	57.14%	78.79%	Fast, interpretable
PANNs	Transfer Learning	60.17%	83.12%	Pretrained
ResNet	**End-to-end DL**	**72.73%**	**89.18%**	**Best**

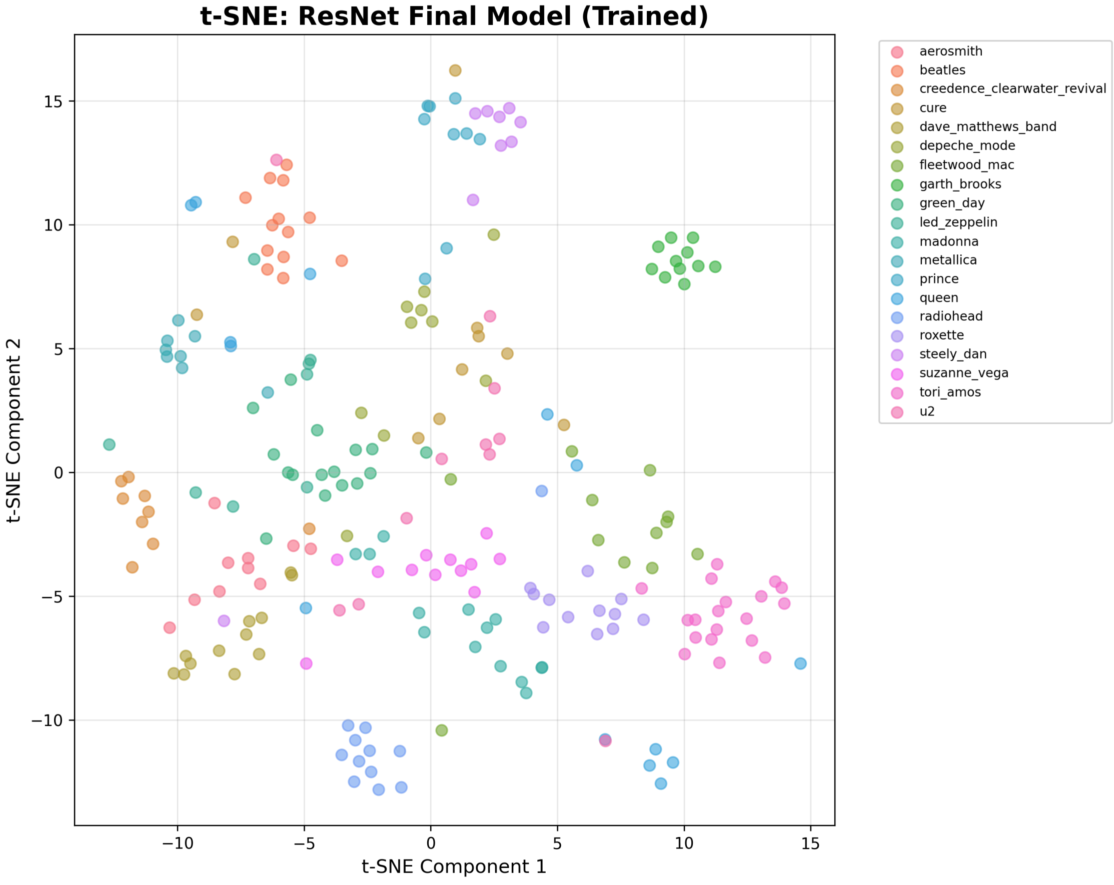
Confusion Matrices






Model Performance Comparison: Traditional ML vs Deep Learning
Top-1 Accuracy
Top-3 Accuracy
Accuracy (%)
0
10
20
30
40
50
60
70
80
90
57.1%
78.8%
60.2%
83.1%
72.7%
89.2%
Traditional ML
(SVM)
Deep Learning
(PANNs)
Deep Learning
(ResNet CNN)


t-SNE: ResNet Epoch 1 (Random Init)
t-SNE Component 1
t-SNE Component 2
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
u2


t-SNE: ResNet Final Model (Trained)
t-SNE Component 1
t-SNE Component 2
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
u2

Improvements Summary

vs SVM (Baseline)

- PANNs: +3.03% / +4.33%
- **ResNet: +15.59% / +10.39%**

ResNet vs PANNs

- Top-1: **+12.56%**
- Top-3: **+6.06%**
- Params: 2.7M vs 81M+

Key Insights

Deep Learning vs Traditional ML - The Performance Gap:

- **Feature learning advantage**: Deep learning automatically discovers hierarchical audio patterns (spectral, temporal, timbral) while SVM relies on hand-crafted MFCC features
- **Representation power**: ResNet's 2.7M parameters capture complex artist signatures vs. SVM's linear decision boundaries with limited expressiveness
- **Data utilization**: Neural networks excel at extracting patterns from raw audio across 150s duration, while traditional ML struggles with high-dimensional feature spaces
- **Why ResNet > PANNs**: Task-specific end-to-end training learns artist-discriminative features directly, while transfer learning from AudioSet general audio events doesn't align well with music artist classification domain

Quick Start

Inference Steps

- 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: PANNs Model

- `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

Task 2: ResNet CNN 🏆

- `task2_train_wo_pretrain.py` -> ResNet CNN from scratch
- `task2_inference_wo_pretrain.py` -> Generate predictions
- `task2_gen_report_wo_pretrain.py` -> Generates visualizations

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*.
- **ResNet**: He, K., et al. (2016). Deep Residual Learning for Image Recognition. *CVPR*.
- **Mixup**: Zhang, H., et al. (2018). mixup: Beyond Empirical Risk Minimization. *ICLR*.
- **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

Thank you for your time