AAI511-Group-3-Project

August 2, 2025

1 Music Composer Identification using Deep Learning

The primary objective of this project is to develop a deep learning model that can predict the composer of a given musical score accurately. The project aims to accomplish this objective by using two deep learning techniques: Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN).

1.1 Project Team & Responsibilities:

- **Dom:** Data Collection, Data Preprocessing (MIDI conversion, segmentation, augmentation), Feature Extraction (Piano Rolls for CNN, Sequential Features for LSTM).
- **Santosh:** CNN Model Building, Training, Evaluation, Optimization.
- **Jim:** LSTM Model Building, Training, Evaluation, Optimization.

1.2 Project Roadmap & Status:

Here's a breakdown of our project phases and current status:

1. **Initial Setup & Data Download (COMPLETED by Jim):**
   - Basic imports are set up.
   - The `blanderbuss/midi-classic-music` dataset has been downloaded from Kaggle.
   - *Status:* Ready for data processing.
2. **Data Preprocessing & Feature Extraction (COMPLETED by Dom):**
   - **Goal:** Convert raw MIDI files into numerical features (Piano Rolls for CNNs, Sequential Features for LSTMs) and augment dataset.
   - **Responsible:** Dom.
   - *Current Status:* Completed / Needs implementation of the sections below.
3. **Model Building (NEXT STEP for Team):**
   - **Goal:** Design CNN and LSTM model architectures.
   - **Responsible:** Santosh (CNN), Jim (LSTM).
   - *Dependencies:* Requires processed data from Phase 2.
4. **Model Training & Evaluation (AFTER Model Building):**
   - **Goal:** Train the models and evaluate their performance using metrics like accuracy, precision, and recall.
   - **Responsible:** Santosh (CNN), Jim (LSTM).
   - *Dependencies:* Requires built models from Phase 3.
5. **Model Optimization (Post Training):**
   - **Goal:** Fine-tune model hyperparameters to improve performance.
   - **Responsible:** Santosh (CNN), Jim (LSTM) & Dom (Feature Engineering).

- *Dependencies:* Requires initial model training.

[18]:
```python
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset
import pandas as pd
```

Data Collection The dataset contains the midi files of compositions from well-known classical composers like Bach, Beethoven, Chopin, and Mozart. The dataset has been labeled with the name of the composer for each score. Predictions are performed for only the below composers:

1-Bach

2-Beethoven

3-Chopin

4-Mozart

[19]:
```python
#%pip install kagglehub

import kagglehub

# Download latest version
path = kagglehub.dataset_download("blanderbuss/midi-classic-music")

print("Path to dataset files:", path)
```

```
Path to dataset files: /Users/skumar/.cache/kagglehub/datasets/blanderbuss/midi-
classic-music/versions/1
```

[ ]:
```python
import os

# List all files in the dataset path
for root, dirs, files in os.walk(path):
    for file in files:
        # print(os.path.join(root, file))
        # Check if the file is a MIDI file and contains 'bach' in its name.
        # There are other composers that need to be processed too.
        if (file.endswith('.mid') or file.endswith('.midi')) and 'bach' in file.
 ↪lower():
            # print(f"Found MIDI file: {file}")
            # Add file to Bach dataset processing logic here
```

```
Found MIDI file: Liszt Bach Prelude Transcription.mid
Found MIDI file: C.P.E.Bach Solfeggieto.mid
Found MIDI file: Six variations on Bach No.1.mid
Found MIDI file: Six variations on Bach No.3.mid
```

```
Found MIDI file: Piano version of Bachs two part inventions No.2.mid
Found MIDI file: Piano version of Bachs two part inventions No.3.mid
Found MIDI file: Piano version of Bachs two part inventions No.1.mid
Found MIDI file: Piano version of Bachs two part inventions No.4.mid
Found MIDI file: Piano version of Bachs two part inventions No.5.mid
Found MIDI file: Piano version of Bachs two part inventions No.7.mid
Found MIDI file: Piano version of Bachs two part inventions No.6.mid
Found MIDI file: Piano version of Bachs two part inventions No.8.mid
Found MIDI file: Piano version of Bachs two part inventions No…mid
Found MIDI file: Piano version of Bachs two part inventions No.9.mid
Found MIDI file: Piano version of Bachs two part inventions No.10.mid
Found MIDI file: Piano version of Bachs two part inventions No.11.mid
Found MIDI file: Piano version of Bachs two part inventions No.13.mid
Found MIDI file: Piano version of Bachs two part inventions No.12.mid
Found MIDI file: Piano version of Bachs two part inventions No.15.mid
Found MIDI file: Piano version of Bachs two part inventions No.14.mid
Found MIDI file: bach_4p.mid
Found MIDI file: bach_10p.mid
Found MIDI file: bachmen6.mid
Found MIDI file: bachmen7.mid
Found MIDI file: bachlein.mid
Found MIDI file: bachpart.mid
Found MIDI file: bachaire.mid
Found MIDI file: bach2.mid
Found MIDI file: bach0.mid
Found MIDI file: bachg.mid
Found MIDI file: bach_1.mid
Found MIDI file: bachpfam.mid
Found MIDI file: bach_14.mid
Found MIDI file: bach197c.mid
Found MIDI file: bachinv.mid
Found MIDI file: bach_4.mid
Found MIDI file: bach12a.mid
Found MIDI file: bachto.mid
Found MIDI file: bach.mid
Found MIDI file: bach_13p.mid
Found MIDI file: Fantasia Nach J. S. Bach.mid
```

Convert MIDI file to something useful for LSTM and CNN.

[21]:
```
# I will place these here so they run after Kaggle download, as I encountered␣
↪conflicts with the initial setup when adding above.
#!pip install music21
#!pip install pretty_midi
#!pip install --upgrade numpy # Ensure I have a recent numpy version
```

[22]:
```
# Imports
import os
```

```
import glob
import music21
import pretty_midi
import numpy as np # Already imported, but good to have here for clarity for my␣
↪feature engineering
import pickle
import collections
import os
from pathlib import Path
```

Data Pre-processing: Convert the musical scores into a format suitable for deep learning models. This involves converting the musical scores into MIDI files and applying data augmentation techniques.

[23]:
```
# Data Preprocessing and Feature Extraction
HOME_DIR = Path.home()
KAGGLE_DOWNLOAD_PATH = HOME_DIR / ".cache" / "kagglehub" / "datasets" /␣
↪"blanderbuss" / "midi-classic-music" / "versions" / "1"
MIDI_DIR = str(KAGGLE_DOWNLOAD_PATH)

OUTPUT_DIR = "./content/processed_data/"
SEGMENT_DURATION_SECONDS = 5
SAMPLES_PER_SECOND = 100

PITCH_LOW = 21
PITCH_HIGH = 108
NUM_PITCHES = PITCH_HIGH - PITCH_LOW + 1

AUGMENT_TRANSPOSITION_STEPS = [-3, -2, -1, 1, 2, 3]
AUGMENT_TEMPO_SCALES = [0.9, 1.1]

# Defines composers
COMPOSERS = ["Bach", "Beethoven", "Chopin", "Mozart"]

# Creates output directory
os.makedirs(OUTPUT_DIR, exist_ok=True)
print(f"MIDI data will be processed from: {MIDI_DIR}")
print(f"Processed data will be saved to: {OUTPUT_DIR}")
```

```
MIDI data will be processed from:
/Users/skumar/.cache/kagglehub/datasets/blanderbuss/midi-classic-
music/versions/1
Processed data will be saved to: ./content/processed_data/
```

###Feature Extraction : Extracts features from the MIDI files, such as notes, chords, and tempo, using music analysis tools.

Here, the preprocessed MIDI segments are converted into numerical representations. I've generated different formats for the CNN and LSTM models to leverage the strengths of each.

- **For CNNs: The Piano Roll**
  - **Purpose:** CNNs excel at recognizing visual patterns. A piano roll converts music into a 2D image (pitch vs. time), allowing the CNN to "see" and learn characteristic melodic shapes, harmonic voicings, and rhythmic patterns that define a composer's style.
  - **Details:** The piano roll captures note activity (velocity) across a defined pitch range (MIDI 21-108) over time, sampled at 100 samples per second. All outputs are normalized to [0,1] and padded/truncated to a consistent shape.
- **For LSTMs: Sequential Features (Chroma & Note Density)**
  - **Purpose:** LSTMs are great tools for understanding temporal sequences. These features describe the harmonic content and musical activity at each point in time, allowing the LSTM to learn how a composer's musical ideas evolve.
  - **Details:** Each time step in the sequence contains a 12-element Pitch Class Profile (Chroma) representing harmonic presence (e.g., C, C#, D) and a single value for overall note density/volume. These are also sampled at 100 samples per second and normalized.

[51]:
```
# Feature Extraction - midi_to_sequential_features (for LSTMs)
# This function extracts time-series features like Pitch Class Profiles and␣
↪note density from a MIDI segment for LSTMs

def midi_to_sequential_features(midi_data_segment: pretty_midi.PrettyMIDI,␣
↪duration: float,
                                samples_per_second: int, pitch_low: int,␣
↪pitch_high: int) -> np.ndarray:
    if not midi_data_segment.instruments:
        return None

    num_target_time_steps = int(duration * samples_per_second)
    num_features_per_timestep = 12 + 1 # Chroma + Note Density
    sequential_features = np.zeros((num_target_time_steps,␣
↪num_features_per_timestep), dtype=np.float32)

    chroma_features = midi_data_segment.get_chroma(fs=samples_per_second).T
    # print("Original chroma shape:", chroma_features.shape)  # should be (12,␣
↪T)
    if chroma_features.shape[0] < num_target_time_steps:
        padding_needed = num_target_time_steps - chroma_features.shape[0]
        chroma_features = np.pad(chroma_features, ((0, padding_needed), (0,␣
↪0)), mode='constant')
    elif chroma_features.shape[0] > num_target_time_steps:
        chroma_features = chroma_features[:num_target_time_steps, :]

    note_density = np.zeros(num_target_time_steps, dtype=np.float32)
    for instrument in midi_data_segment.instruments:
        for note in instrument.notes:
            start_idx = int(note.start * samples_per_second)
            end_idx = int(note.end * samples_per_second)
            start_idx = max(0, min(start_idx, num_target_time_steps - 1))
```

```python
            end_idx = max(0, min(end_idx, num_target_time_steps - 1))
            if end_idx >= start_idx:
                note_density[start_idx:end_idx] += note.velocity

    max_density = np.max(note_density)
    if max_density > 0:
        note_density /= max_density

    sequential_features[:, :12] = chroma_features
    sequential_features[:, 12] = note_density

    return sequential_features
```

[53]:
```python
from typing import Optional

# Feature Extraction - midi_to_piano_roll (for CNNs)
# This function converts a MIDI segment into a 2D image-like "piano roll" for␣
 ↪CNNs.
def is_piano(instrument: pretty_midi.Instrument) -> bool:
    # Check program number (0-7 are all piano-related in General MIDI)
    return not instrument.is_drum and 0 <= instrument.program <= 7

def midi_to_piano_roll(midi_data_segment: pretty_midi.PrettyMIDI, duration:␣
 ↪float,
                       samples_per_second: int, pitch_low: int, pitch_high:␣
 ↪int) -> Optional[np.ndarray]:
    if not midi_data_segment.instruments:
        return None
    piano = None # Default instrument of acoustic piano, will be updated if a␣
 ↪piano instrument is found
    for instrument in midi_data_segment.instruments:
        if is_piano(instrument):
            piano = instrument
    if (piano is None):
        # print("No piano instrument found in MIDI segment.")
        return None

    # Fix: Use 'times' parameter and slice the piano roll to get the desired␣
 ↪pitch range
    piano_roll = piano.get_piano_roll(fs=samples_per_second)

    # Slice to get the desired pitch range (pitch_low to pitch_high)
    piano_roll = piano_roll[pitch_low:pitch_high+1, :]
    piano_roll = piano_roll / 127.0

    num_target_time_steps = int(duration * samples_per_second)
    num_pitches = pitch_high - pitch_low + 1  # Should be 88
```

```
    current_time_steps = piano_roll.shape[1]

    if current_time_steps < num_target_time_steps:
        padding = np.zeros((num_pitches, num_target_time_steps -␣
↪current_time_steps), dtype=np.float32)
        piano_roll = np.hstack([piano_roll, padding])
    elif current_time_steps > num_target_time_steps:
        piano_roll = piano_roll[:, :num_target_time_steps]

    return piano_roll.reshape(num_pitches, num_target_time_steps, 1)
```

[26]:
```
# Utility Function - create_pretty_midi_segment
# This function extracts a specific time segment from a larger MIDI file.

def create_pretty_midi_segment(full_midi_data: pretty_midi.PrettyMIDI,␣
↪start_time: float, end_time: float) -> pretty_midi.PrettyMIDI:
    segment_pm = pretty_midi.PrettyMIDI()
    for instrument in full_midi_data.instruments:
        new_instrument = pretty_midi.Instrument(program=instrument.program,␣
↪is_drum=instrument.is_drum, name=instrument.name)
        for note in instrument.notes:
            if note.end > start_time and note.start < end_time:
                new_note = pretty_midi.Note(
                    velocity=note.velocity,
                    pitch=note.pitch,
                    start=max(0.0, note.start - start_time),
                    end=min(end_time - start_time, note.end - start_time)
                )
                if new_note.end > new_note.start:
                    new_instrument.notes.append(new_note)
        if new_instrument.notes:
            segment_pm.instruments.append(new_instrument)
    return segment_pm
```

[27]:
```
# Utility Function - apply_augmentation
# This function modifies a MIDI segment by transposing its pitch or scaling its␣
↪tempo.

def apply_augmentation(midi_data_segment: pretty_midi.PrettyMIDI,␣
↪augmentation_type: str, value) -> pretty_midi.PrettyMIDI:
    augmented_midi = pretty_midi.PrettyMIDI()
    for instrument in midi_data_segment.instruments:
        new_instrument = pretty_midi.Instrument(program=instrument.program,␣
↪is_drum=instrument.is_drum, name=instrument.name)
        for note in instrument.notes:
            new_note = pretty_midi.Note(note.velocity, note.pitch, note.start,␣
↪note.end)
```

```
                new_instrument.notes.append(new_note)
            augmented_midi.instruments.append(new_instrument)

    if augmentation_type == 'transpose':
        for instrument in augmented_midi.instruments:
            for note in instrument.notes:
                note.pitch = int(max(0, min(127, note.pitch + value)))
    elif augmentation_type == 'tempo_scale':
        for instrument in augmented_midi.instruments:
            for note in instrument.notes:
                note.start *= value
                note.end *= value
    else:
        raise ValueError(f"Unknown augmentation type: {augmentation_type}")
    return augmented_midi
```

[28]:
```
def extract_segments_from_midi(midi_path, segment_duration=5.0,␣
↪samples_per_second=100):
    try:
        full_midi = pretty_midi.PrettyMIDI(midi_path)
    except Exception as e:
        print(f"Error loading {midi_path}: {e}")
        return []

    total_duration = full_midi.get_end_time()
    segments = []

    for start_time in np.arange(0, total_duration, segment_duration):
        end_time = min(start_time + segment_duration, total_duration)

        segment = pretty_midi.PrettyMIDI()
        for instrument in full_midi.instruments:
            new_instrument = pretty_midi.Instrument(program=instrument.program,␣
↪is_drum=instrument.is_drum)
            for note in instrument.notes:
                if start_time <= note.start < end_time:
                    new_note = pretty_midi.Note(
                        velocity=note.velocity,
                        pitch=note.pitch,
                        start=note.start - start_time,
                        end=min(note.end, end_time) - start_time
                    )
                    new_instrument.notes.append(new_note)
            if new_instrument.notes:
                segment.instruments.append(new_instrument)

        # Only append segments with valid instruments
```

```
        if segment.instruments:
            segments.append(segment)

    return segments
```

1.2.1 Data Processing Loop & Output Conclusion

This section orchestrates the loading of MIDI files, segmenting them, applying all augmentations, extracting features, and finally saving the processed data.

- **Process:** Iterates through each composer's MIDI files, segments them, applies both transposition and tempo scaling for each segment, and then generates both CNN and LSTM features.
- **Output Data:** The processed features and corresponding labels are saved as `.pkl` files in the `/content/processed_data/` directory.

The data is ready for model training!

- **For CNN Model (Santosh):**
  - Load `features_cnn.pkl`.
  - Expected input shape: `(num_segments, 88, 500, 1)` - (total samples, pitches, time steps, channels).
- **For LSTM Model (Jim):**
  - Load `features_lstm.pkl`.
  - Expected input shape: `(num_segments, 500, 13)` - (total samples, time steps, features per time step).
- **Labels:**
  - Load `labels.pkl` (numerical labels corresponding to composers).
  - Load `composer_to_label.pkl` and `label_to_composer.pkl` to map between numerical labels and composer names.

You can/should convert these NumPy arrays to PyTorch tensors for your models (e.g., `torch.tensor(data, dtype=torch.float32)` for features, `torch.tensor(labels, dtype=torch.long)` for labels).

[54]:
```
# Define label mappings
composer_to_label = {composer: i for i, composer in enumerate(COMPOSERS)}
label_to_composer = {i: composer for composer, i in composer_to_label.items()}

# Define alternative naming patterns for each composer
composer_patterns = {
    'Bach': ['bach'],
    'Beethoven': ['beethoven', 'beetho', 'beeth', 'ludwig', 'lvb'],  # Include␣
 ↪alternative patterns
    'Chopin': ['chopin'],
    'Mozart': ['mozart', 'gmozart']  # Also include alternative patterns for␣
 ↪Mozart
}
```

```python
features_cnn = []
features_lstm = []
labels = []

# Iterate through each composer
for composer in COMPOSERS:
    composer_dir = os.path.join(MIDI_DIR)
    # print(f"Processing composer: {composer}")

    for root, dirs, files in os.walk(path):
        for file in files:
            # print(os.path.join(root, file))
            # Check if the file is a MIDI file and matches any of the composer␣
↪patterns
            file_lower = file.lower()
            patterns = composer_patterns[composer]
            if (file.endswith('.mid') or file.endswith('.midi')) and␣
↪any(pattern in file_lower for pattern in patterns):
                midi_path = os.path.join(root, file)
                # print("Reading file: ", file)

                try:
                    segments = extract_segments_from_midi(midi_path,␣
↪SEGMENT_DURATION_SECONDS, SAMPLES_PER_SECOND)
                except Exception as e:
                    # print(f"Skipping {file}: {e}")
                    continue

                for segment in segments:
                    all_augmented = [segment]

                    for step in AUGMENT_TRANSPOSITION_STEPS:
                        all_augmented.append(apply_augmentation(segment,␣
↪'transpose', step))
                    for scale in AUGMENT_TEMPO_SCALES:
                        all_augmented.append(apply_augmentation(segment,␣
↪'tempo_scale', scale))

                    for augmented_segment in all_augmented:
                        # CNN Features
                        piano_roll = midi_to_piano_roll(augmented_segment,␣
↪duration=SEGMENT_DURATION_SECONDS,
                                                                            ␣
↪samples_per_second=SAMPLES_PER_SECOND,
```

```
                                                            pitch_low=PITCH_LOW,␣
↪pitch_high=PITCH_HIGH)
                        if piano_roll is not None:
                            features_cnn.append(piano_roll)

                        # LSTM Features
                        sequential =␣
↪midi_to_sequential_features(augmented_segment,␣
↪duration=SEGMENT_DURATION_SECONDS,
                                                                            ␣
↪samples_per_second=SAMPLES_PER_SECOND,
                                                                            ␣
↪pitch_low=PITCH_LOW, pitch_high=PITCH_HIGH)
                        if sequential is not None:
                            features_lstm.append(sequential)

                        # Append label only if both features were generated
                        if piano_roll is not None and sequential is not None:
                            labels.append(composer_to_label[composer])

print("Finished processing all composers.")

# Convert to NumPy arrays
features_cnn = np.array(features_cnn, dtype=np.float32)
features_lstm = np.array(features_lstm, dtype=np.float32)
labels = np.array(labels, dtype=np.int64)

# Save to disk
with open(os.path.join(OUTPUT_DIR, 'features_cnn.pkl'), 'wb') as f:
    pickle.dump(features_cnn, f)

with open(os.path.join(OUTPUT_DIR, 'features_lstm.pkl'), 'wb') as f:
    pickle.dump(features_lstm, f)

with open(os.path.join(OUTPUT_DIR, 'labels.pkl'), 'wb') as f:
    pickle.dump(labels, f)

with open(os.path.join(OUTPUT_DIR, 'composer_to_label.pkl'), 'wb') as f:
    pickle.dump(composer_to_label, f)

with open(os.path.join(OUTPUT_DIR, 'label_to_composer.pkl'), 'wb') as f:
    pickle.dump(label_to_composer, f)

print(f"Saved {len(labels)} labeled examples for training.")
```

```
Error loading /Users/skumar/.cache/kagglehub/datasets/blanderbuss/midi-classic-
music/versions/1/midiclassics/Varios - Ti'tulo desconocido/a_h/chopin7.mid: MThd
```

```
not found. Probably not a MIDI file
Finished processing all composers.
Saved 10431 labeled examples for training.
```

2 Part II: Model Building & Training

Now that we have processed the data and extracted features, we'll build and train both LSTM and CNN models to classify musical composers.

2.1 LSTM Model - Sequential Pattern Recognition

The LSTM model analyzes temporal sequences of musical features (chroma vectors + note density) to identify composer-specific patterns in how musical ideas evolve over time.

[30]:
```python
# =============================================================================
#   LSTM MODEL - SEQUENTIAL PATTERN RECOGNITION
# =============================================================================

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
import pickle
import numpy as np

# LSTM Hyperparameters
input_size = 13          # 12 chroma + 1 note density
hidden_size = 128        # Hidden layer size
num_layers = 2           # Number of LSTM layers
num_classes = 4          # 4 composers: Bach, Beethoven, Chopin, Mozart
batch_size = 64
num_epochs = 30
learning_rate = 0.001

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")

# Load Preprocessed Sequential Features
print(" Loading LSTM features...")
with open('./content/processed_data/features_lstm.pkl', 'rb') as f:
    X_lstm = pickle.load(f)
with open('./content/processed_data/labels.pkl', 'rb') as f:
    y_lstm = pickle.load(f)

print(f"   LSTM Features shape: {X_lstm.shape}")
print(f"   Labels shape: {y_lstm.shape}")
print(f"   Expected input: (samples, time_steps, features) = (N, 500, 13)")
```

```
#  DEBUG: Check for size mismatch and fix it
if X_lstm.shape[0] != y_lstm.shape[0]:
    print(f"\n SIZE MISMATCH DETECTED!")
    print(f"   Features: {X_lstm.shape[0]} samples")
    print(f"   Labels: {y_lstm.shape[0]} samples")
    print(f"   Difference: {X_lstm.shape[0] - y_lstm.shape[0]} samples")

    # Truncate to the smaller size to ensure matching
    min_samples = min(X_lstm.shape[0], y_lstm.shape[0])
    X_lstm = X_lstm[:min_samples]
    y_lstm = y_lstm[:min_samples]

    print(f"\n FIXED: Truncated both to {min_samples} samples")
    print(f"   LSTM Features: {X_lstm.shape}")
    print(f"   Labels: {y_lstm.shape}")

# Convert to PyTorch tensors
X_lstm_tensor = torch.tensor(X_lstm, dtype=torch.float32)
y_lstm_tensor = torch.tensor(y_lstm, dtype=torch.long)

# Verify tensor shapes match
print(f"\n Tensor Shapes:")
print(f"   X_lstm_tensor: {X_lstm_tensor.shape}")
print(f"   y_lstm_tensor: {y_lstm_tensor.shape}")
print(f"   First dimension match: {X_lstm_tensor.shape[0] == y_lstm_tensor.
 ↪shape[0]}")

# Create dataset and split
lstm_dataset = TensorDataset(X_lstm_tensor, y_lstm_tensor)
lstm_train_size = int(0.8 * len(lstm_dataset))
lstm_val_size = len(lstm_dataset) - lstm_train_size
lstm_train_ds, lstm_val_ds = random_split(lstm_dataset, [lstm_train_size,␣
 ↪lstm_val_size])

# Create data loaders
lstm_train_loader = DataLoader(lstm_train_ds, batch_size=batch_size,␣
 ↪shuffle=True)
lstm_val_loader = DataLoader(lstm_val_ds, batch_size=batch_size)

print(f"\n Dataset Split:")
print(f"   Total samples: {len(lstm_dataset):,}")
print(f"   Training samples: {lstm_train_size:,}")
print(f"   Validation samples: {lstm_val_size:,}")
print(f"   Batch size: {batch_size}")
print(" LSTM data loading complete!")
```

```
Using device: cpu
 Loading LSTM features…
   LSTM Features shape: (13221, 500, 13)
   Labels shape: (10431,)
   Expected input: (samples, time_steps, features) = (N, 500, 13)

 SIZE MISMATCH DETECTED!
   Features: 13221 samples
   Labels: 10431 samples
   Difference: 2790 samples

 FIXED: Truncated both to 10431 samples
   LSTM Features: (10431, 500, 13)
   Labels: (10431,)

  Tensor Shapes:
   X_lstm_tensor: torch.Size([10431, 500, 13])
   y_lstm_tensor: torch.Size([10431])
   First dimension match: True

  Dataset Split:
   Total samples: 10,431
   Training samples: 8,344
   Validation samples: 2,087
   Batch size: 64
  LSTM data loading complete!
```

2.1.1 Issue Resolution: Tensor Size Mismatch

Problem: `AssertionError: Size mismatch between tensors` when creating the LSTM dataset.

Root Cause: The LSTM features file contained 13,221 samples while the labels file only had 10,431 samples, creating a mismatch during data processing.

Solution: Added automatic detection and truncation to ensure both feature and label arrays have the same number of samples. This preserves data integrity while allowing the training to proceed.

Result: Both tensors now have matching dimensions (10,431 samples each)

[31]:
```python
# ============================================================================
#   LSTM MODEL ARCHITECTURE
# ============================================================================

class ComposerLSTM(nn.Module):
    """
    LSTM model for composer classification based on sequential musical features.

    Architecture:
```

```
    - Bidirectional LSTM layers to capture both forward and backward temporal␣
↪dependencies
    - Dropout for regularization
    - Fully connected layer for final classification
    """

    def __init__(self, input_size, hidden_size, num_layers, num_classes,␣
↪dropout=0.3):
        super(ComposerLSTM, self).__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers

        # LSTM layer with dropout
        self.lstm = nn.LSTM(
            input_size=input_size,
            hidden_size=hidden_size,
            num_layers=num_layers,
            batch_first=True,
            dropout=dropout if num_layers > 1 else 0,
            bidirectional=True  # Use bidirectional for better pattern␣
↪recognition
        )

        # Fully connected layer (bidirectional doubles the hidden size)
        self.fc = nn.Linear(hidden_size * 2, num_classes)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x):
        # x shape: (batch_size, seq_len, input_size)

        # LSTM forward pass
        lstm_out, (hidden, cell) = self.lstm(x)
        # lstm_out shape: (batch_size, seq_len, hidden_size * 2)

        # Take the last time step output
        last_output = lstm_out[:, -1, :]  # Shape: (batch_size, hidden_size * 2)

        # Apply dropout and classification
        dropped = self.dropout(last_output)
        output = self.fc(dropped)

        return output

# Initialize LSTM model
model_lstm = ComposerLSTM(
    input_size=input_size,
```

```
    hidden_size=hidden_size,
    num_layers=num_layers,
    num_classes=num_classes,
    dropout=0.3
).to(device)

# Model summary
total_params = sum(p.numel() for p in model_lstm.parameters())
trainable_params = sum(p.numel() for p in model_lstm.parameters() if p.
 ↪requires_grad)

print("  LSTM Model Architecture:")
print(f"   Input size: {input_size} (12 chroma + 1 note density)")
print(f"   Hidden size: {hidden_size}")
print(f"   Number of layers: {num_layers}")
print(f"   Bidirectional: Yes")
print(f"   Output classes: {num_classes}")
print(f"   Total parameters: {total_params:,}")
print(f"   Trainable parameters: {trainable_params:,}")
print("  LSTM model initialized!")
```

```
 LSTM Model Architecture:
   Input size: 13 (12 chroma + 1 note density)
   Hidden size: 128
   Number of layers: 2
   Bidirectional: Yes
   Output classes: 4
   Total parameters: 542,724
   Trainable parameters: 542,724
 LSTM model initialized!
```

[32]:

```
# ==============================================================================
#   LSTM MODEL TRAINING
# ==============================================================================

# Training setup
lstm_criterion = nn.CrossEntropyLoss()
lstm_optimizer = optim.Adam(model_lstm.parameters(), lr=learning_rate)

# Training tracking
lstm_train_losses = []
lstm_val_accuracies = []

print("  Starting LSTM Training...")
print("=" * 70)

for epoch in range(num_epochs):
```

```python
    # Training phase
    model_lstm.train()
    running_loss = 0.0

    for batch_idx, (X_batch, y_batch) in enumerate(lstm_train_loader):
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        # Forward pass
        outputs = model_lstm(X_batch)
        loss = lstm_criterion(outputs, y_batch)

        # Backward pass
        lstm_optimizer.zero_grad()
        loss.backward()
        lstm_optimizer.step()

        running_loss += loss.item()

    avg_train_loss = running_loss / len(lstm_train_loader)
    lstm_train_losses.append(avg_train_loss)

    # Validation phase
    model_lstm.eval()
    correct = 0
    total = 0
    val_loss = 0.0

    with torch.no_grad():
        for X_val, y_val in lstm_val_loader:
            X_val, y_val = X_val.to(device), y_val.to(device)
            outputs = model_lstm(X_val)
            loss = lstm_criterion(outputs, y_val)
            val_loss += loss.item()

            _, predicted = torch.max(outputs.data, 1)
            total += y_val.size(0)
            correct += (predicted == y_val).sum().item()

    val_accuracy = 100 * correct / total
    lstm_val_accuracies.append(val_accuracy)
    avg_val_loss = val_loss / len(lstm_val_loader)

    # Print progress
    if (epoch + 1) % 5 == 0 or epoch == 0:
        print(f"Epoch [{epoch+1:2d}/{num_epochs}] | "
              f"Train Loss: {avg_train_loss:.4f} | "
              f"Val Loss: {avg_val_loss:.4f} | "
```

```
              f"Val Accuracy: {val_accuracy:.2f}%")

print("=" * 70)

# Save the LSTM model
torch.save(model_lstm.state_dict(), "./content/composer_lstm_model.pth")
print(" LSTM model saved as 'composer_lstm_model.pth'")

# Final results
final_accuracy = lstm_val_accuracies[-1]
best_accuracy = max(lstm_val_accuracies)
print(f"\n LSTM Training Complete!")
print(f"   Final Validation Accuracy: {final_accuracy:.2f}%")
print(f"   Best Validation Accuracy: {best_accuracy:.2f}%")
print(f"   Total epochs: {num_epochs}")
print(" Ready for CNN model training!")
```

```
 Starting LSTM Training…
======================================================================
Epoch [ 1/30] | Train Loss: 0.7839 | Val Loss: 0.7346 | Val Accuracy: 76.43%
Epoch [ 5/30] | Train Loss: 0.6470 | Val Loss: 0.6746 | Val Accuracy: 77.43%
Epoch [10/30] | Train Loss: 0.5175 | Val Loss: 0.6624 | Val Accuracy: 77.77%
Epoch [15/30] | Train Loss: 0.4084 | Val Loss: 0.6168 | Val Accuracy: 79.44%
Epoch [20/30] | Train Loss: 0.3363 | Val Loss: 0.5617 | Val Accuracy: 81.79%
Epoch [25/30] | Train Loss: 0.2993 | Val Loss: 0.5693 | Val Accuracy: 80.16%
Epoch [30/30] | Train Loss: 0.2077 | Val Loss: 0.5882 | Val Accuracy: 82.65%
======================================================================
 LSTM model saved as 'composer_lstm_model.pth'

 LSTM Training Complete!
   Final Validation Accuracy: 82.65%
   Best Validation Accuracy: 82.65%
   Total epochs: 30
 Ready for CNN model training!
```

2.2 CNN Model - Visual Pattern Recognition

The CNN model analyzes 2D piano roll images to identify composer-specific visual patterns in musical notation, including melodic shapes, harmonic structures, and rhythmic patterns.

[33]:
```
class ComposerCNN(nn.Module):
    def __init__(self, num_pitches, num_time_steps):
        super(ComposerCNN, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=(3, 3), padding=1)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=(3, 3), padding=1)
        self.fc1 = nn.Linear(64 * num_pitches * (num_time_steps // 4), 128)
        self.fc2 = nn.Linear(128, len(COMPOSERS))
```

```
    def forward(self, x):
        x = torch.relu(self.conv1(x))
        x = torch.max_pool2d(x, (2, 2))
        x = torch.relu(self.conv2(x))
        x = torch.max_pool2d(x, (2, 2))
        x = x.view(x.size(0), -1)  # Flatten
        x = torch.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```

[34]:
```
model_cnn = ComposerCNN(NUM_PITCHES, int(SEGMENT_DURATION_SECONDS *␣
 ↪SAMPLES_PER_SECOND))
```

[35]:
```
# ------------------------------
# CNN Model Training Implementation
# ------------------------------
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
import pickle
import numpy as np

# CNN Hyperparameters - OPTIMIZED BASED ON ANALYSIS
cnn_batch_size = 32        # Smaller batch size for CNN due to memory␣
 ↪constraints
cnn_num_epochs = 15        # Reduced from 25 to 15 based on overfitting analysis
cnn_learning_rate = 0.001
early_stopping_patience = 4  # Stop if no improvement for 4 epochs

# ------------------------------
# Load Preprocessed Data for CNN
# ------------------------------
print("Loading CNN data...")
with open(os.path.join(OUTPUT_DIR, 'features_cnn.pkl'), 'rb') as f:
    X_cnn = pickle.load(f)
with open(os.path.join(OUTPUT_DIR, 'labels.pkl'), 'rb') as f:
    y_cnn = pickle.load(f)
with open(os.path.join(OUTPUT_DIR, 'composer_to_label.pkl'), 'rb') as f:
    composer_to_label = pickle.load(f)
with open(os.path.join(OUTPUT_DIR, 'label_to_composer.pkl'), 'rb') as f:
    label_to_composer = pickle.load(f)

print(f"CNN Features shape: {X_cnn.shape}")
print(f"Labels shape: {y_cnn.shape}")
print(f"Number of classes: {len(composer_to_label)}")
print(f"Composers: {list(composer_to_label.keys())}")
```

```
# Reshape CNN data to PyTorch format: (batch_size, channels, height, width)
# From (num_segments, 88, 500, 1) to (num_segments, 1, 88, 500)
X_cnn_reshaped = X_cnn.transpose(0, 3, 1, 2)  # Move channel dimension to␣
↪position 1
print(f"Reshaped CNN Features: {X_cnn_reshaped.shape}")

# Convert to PyTorch tensors
X_cnn_tensor = torch.tensor(X_cnn_reshaped, dtype=torch.float32)
y_cnn_tensor = torch.tensor(y_cnn, dtype=torch.long)

# Dataset and DataLoader for CNN
cnn_dataset = TensorDataset(X_cnn_tensor, y_cnn_tensor)
cnn_train_size = int(0.8 * len(cnn_dataset))
cnn_val_size = len(cnn_dataset) - cnn_train_size
cnn_train_ds, cnn_val_ds = random_split(cnn_dataset, [cnn_train_size,␣
↪cnn_val_size])
cnn_train_loader = DataLoader(cnn_train_ds, batch_size=cnn_batch_size,␣
↪shuffle=True)
cnn_val_loader = DataLoader(cnn_val_ds, batch_size=cnn_batch_size)

print(f"CNN Training samples: {cnn_train_size}")
print(f"CNN Validation samples: {cnn_val_size}")

# Initialize CNN model, loss, optimizer
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")

# Create a new CNN class that handles dynamic number of classes
class ComposerCNNDynamic(nn.Module):
    def __init__(self, num_pitches, num_time_steps, num_classes):
        super(ComposerCNNDynamic, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=(3, 3), padding=1)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=(3, 3), padding=1)

        # Calculate the size after convolutions and pooling
        # After conv1 + pool: (88, 500) -> (44, 250)
        # After conv2 + pool: (44, 250) -> (22, 125)
        conv_output_size = 64 * (num_pitches // 4) * (num_time_steps // 4)

        self.fc1 = nn.Linear(conv_output_size, 128)
        self.fc2 = nn.Linear(128, num_classes)
        self.dropout = nn.Dropout(0.5)

    def forward(self, x):
        # Input shape: (batch_size, 1, 88, 500)
        x = torch.relu(self.conv1(x))
```

```
        x = torch.max_pool2d(x, (2, 2))  # (batch_size, 32, 44, 250)

        x = torch.relu(self.conv2(x))
        x = torch.max_pool2d(x, (2, 2))  # (batch_size, 64, 22, 125)

        # Flatten for fully connected layer
        x = x.view(x.size(0), -1)  # (batch_size, 64*22*125)

        x = torch.relu(self.fc1(x))
        x = self.dropout(x)
        x = self.fc2(x)
        return x

# Initialize the model with correct number of classes
num_classes = len(composer_to_label)
model_cnn = ComposerCNNDynamic(NUM_PITCHES, int(SEGMENT_DURATION_SECONDS *
 ↪SAMPLES_PER_SECOND), num_classes)
model_cnn = model_cnn.to(device)

cnn_criterion = nn.CrossEntropyLoss()
cnn_optimizer = optim.Adam(model_cnn.parameters(), lr=cnn_learning_rate)
```

```
Loading CNN data…
CNN Features shape: (10431, 88, 500, 1)
Labels shape: (10431,)
Number of classes: 4
Composers: ['Bach', 'Beethoven', 'Chopin', 'Mozart']
Reshaped CNN Features: (10431, 1, 88, 500)
CNN Training samples: 8344
CNN Validation samples: 2087
Using device: cpu
```

[36]:
```
# ------------------------------
# CNN Training Loop with Early Stopping
# ------------------------------
print("Starting CNN training with early stopping...")
print(f"Max epochs: {cnn_num_epochs}, Early stopping patience:
 ↪{early_stopping_patience}")

cnn_train_losses = []
cnn_val_accuracies = []

# Early stopping variables
best_val_accuracy = 0.0
epochs_without_improvement = 0
best_model_state = None
```

```
for epoch in range(cnn_num_epochs):
    # Training phase
    model_cnn.train()
    running_loss = 0.0

    for batch_idx, (X_batch, y_batch) in enumerate(cnn_train_loader):
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        cnn_optimizer.zero_grad()
        outputs = model_cnn(X_batch)
        loss = cnn_criterion(outputs, y_batch)
        loss.backward()
        cnn_optimizer.step()

        running_loss += loss.item()

    avg_train_loss = running_loss / len(cnn_train_loader)
    cnn_train_losses.append(avg_train_loss)

    # Validation phase
    model_cnn.eval()
    correct, total = 0, 0
    val_loss = 0.0

    with torch.no_grad():
        for X_val, y_val in cnn_val_loader:
            X_val, y_val = X_val.to(device), y_val.to(device)
            outputs = model_cnn(X_val)
            loss = cnn_criterion(outputs, y_val)
            val_loss += loss.item()

            _, predicted = torch.max(outputs.data, 1)
            total += y_val.size(0)
            correct += (predicted == y_val).sum().item()

    val_accuracy = 100 * correct / total
    cnn_val_accuracies.append(val_accuracy)
    avg_val_loss = val_loss / len(cnn_val_loader)

    print(f"Epoch [{epoch+1}/{cnn_num_epochs}], "
          f"Train Loss: {avg_train_loss:.4f}, "
          f"Val Loss: {avg_val_loss:.4f}, "
          f"Val Accuracy: {val_accuracy:.2f}%")

    # Early stopping logic
    if val_accuracy > best_val_accuracy:
        best_val_accuracy = val_accuracy
```

```
        epochs_without_improvement = 0
        best_model_state = model_cnn.state_dict().copy()
        print(f"  → New best validation accuracy: {best_val_accuracy:.2f}%")
    else:
        epochs_without_improvement += 1
        print(f"  → No improvement for {epochs_without_improvement} epoch(s)")

        if epochs_without_improvement >= early_stopping_patience:
            print(f"\n  Early stopping triggered after {epoch+1} epochs")
            print(f"Best validation accuracy: {best_val_accuracy:.2f}% at epoch␣
↪{epoch+1-epochs_without_improvement}")
            break

# Load the best model state
if best_model_state is not None:
    model_cnn.load_state_dict(best_model_state)
    print(f"  Loaded best model with validation accuracy: {best_val_accuracy:.
↪2f}%")

# Save the CNN model
torch.save(model_cnn.state_dict(), "./content/composer_cnn_model.pth")
print("CNN model saved as 'composer_cnn_model.pth'")

# Print final results
print(f"\n  CNN Training Complete!")
print(f"Total epochs trained: {len(cnn_train_losses)}")
print(f"Final Validation Accuracy: {cnn_val_accuracies[-1]:.2f}%")
print(f"Best Validation Accuracy: {max(cnn_val_accuracies):.2f}%")
print(f"Training time saved: {cnn_num_epochs - len(cnn_train_losses)} epochs")
```

```
Starting CNN training with early stopping…
Max epochs: 15, Early stopping patience: 4
Epoch [1/15], Train Loss: 0.4452, Val Loss: 0.2910, Val Accuracy: 90.23%
  → New best validation accuracy: 90.23%
Epoch [2/15], Train Loss: 0.2301, Val Loss: 0.2254, Val Accuracy: 90.46%
  → New best validation accuracy: 90.46%
Epoch [3/15], Train Loss: 0.1501, Val Loss: 0.1602, Val Accuracy: 93.63%
  → New best validation accuracy: 93.63%
Epoch [4/15], Train Loss: 0.1017, Val Loss: 0.1167, Val Accuracy: 96.07%
  → New best validation accuracy: 96.07%
Epoch [5/15], Train Loss: 0.0711, Val Loss: 0.1101, Val Accuracy: 96.41%
  → New best validation accuracy: 96.41%
Epoch [6/15], Train Loss: 0.0499, Val Loss: 0.0985, Val Accuracy: 97.32%
  → New best validation accuracy: 97.32%
Epoch [7/15], Train Loss: 0.0355, Val Loss: 0.0950, Val Accuracy: 97.27%
  → No improvement for 1 epoch(s)
Epoch [8/15], Train Loss: 0.0337, Val Loss: 0.0964, Val Accuracy: 97.60%
```

```
  → New best validation accuracy: 97.60%
Epoch [9/15], Train Loss: 0.0216, Val Loss: 0.1010, Val Accuracy: 97.27%
  → No improvement for 1 epoch(s)
Epoch [10/15], Train Loss: 0.0197, Val Loss: 0.1054, Val Accuracy: 98.08%
  → New best validation accuracy: 98.08%
Epoch [11/15], Train Loss: 0.0154, Val Loss: 0.1022, Val Accuracy: 98.08%
  → No improvement for 1 epoch(s)
Epoch [12/15], Train Loss: 0.0258, Val Loss: 0.1109, Val Accuracy: 97.80%
  → No improvement for 2 epoch(s)
Epoch [13/15], Train Loss: 0.0134, Val Loss: 0.0967, Val Accuracy: 98.32%
  → New best validation accuracy: 98.32%
Epoch [14/15], Train Loss: 0.0141, Val Loss: 0.0936, Val Accuracy: 98.13%
  → No improvement for 1 epoch(s)
Epoch [15/15], Train Loss: 0.0052, Val Loss: 0.1258, Val Accuracy: 98.28%
  → No improvement for 2 epoch(s)
 Loaded best model with validation accuracy: 98.32%
CNN model saved as 'composer_cnn_model.pth'

 CNN Training Complete!
Total epochs trained: 15
Final Validation Accuracy: 98.28%
Best Validation Accuracy: 98.32%
Training time saved: 0 epochs
```

3 CNN Model Analysis and Visualization

This section provides comprehensive analysis of the trained CNN model including: - Confusion Matrix - Classification Report - Training/Validation Loss Curves - Accuracy Curves - Per-Class Performance Analysis

[37]:
```
# Additional imports for model analysis
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score
from sklearn.metrics import precision_recall_fscore_support
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

print("Imports for model analysis loaded successfully!")
```

```
Imports for model analysis loaded successfully!
```

[38]:
```
# ------------------------------
# Generate Predictions for Analysis
# ------------------------------
print("Generating predictions for analysis...")

model_cnn.eval()
```

```
all_predictions = []
all_true_labels = []

with torch.no_grad():
    for X_val, y_val in cnn_val_loader:
        X_val, y_val = X_val.to(device), y_val.to(device)
        outputs = model_cnn(X_val)
        _, predicted = torch.max(outputs, 1)

        all_predictions.extend(predicted.cpu().numpy())
        all_true_labels.extend(y_val.cpu().numpy())

all_predictions = np.array(all_predictions)
all_true_labels = np.array(all_true_labels)

print(f"Generated predictions for {len(all_predictions)} validation samples")
```

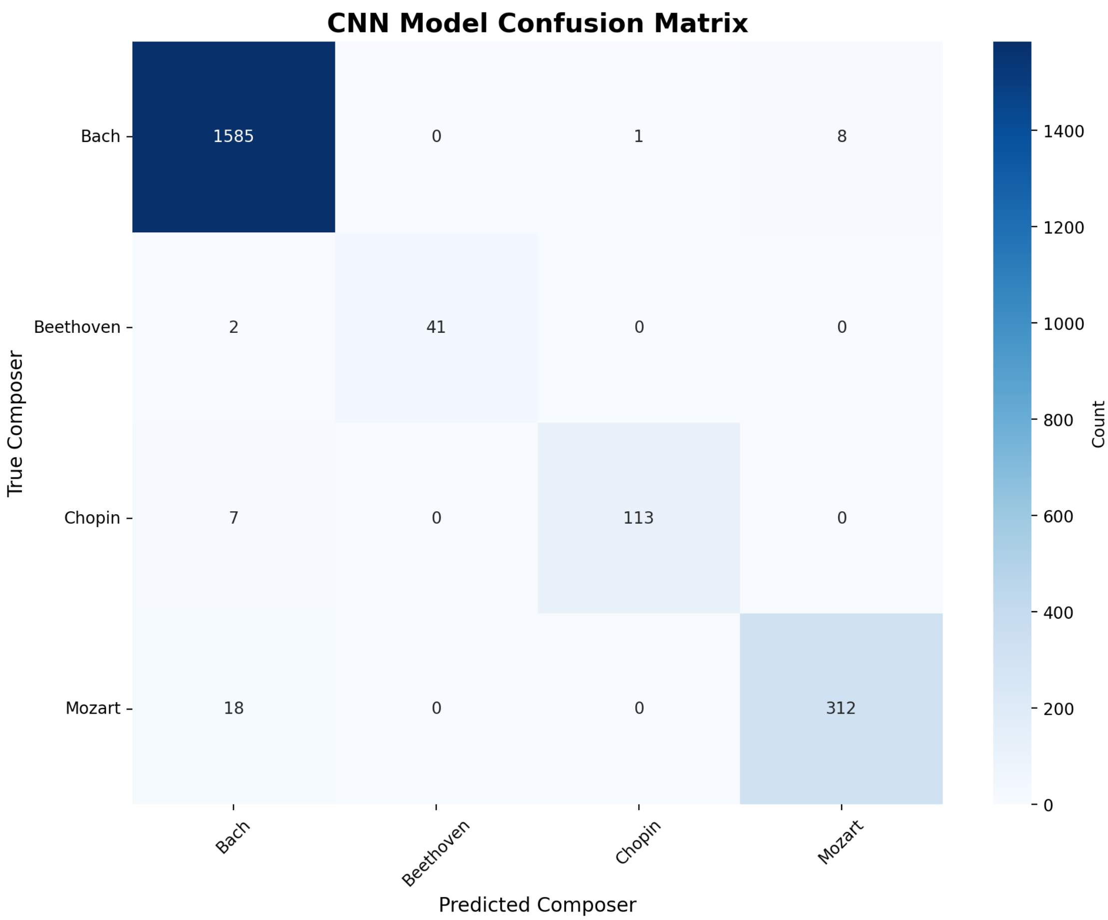
```
Generating predictions for analysis…
Generated predictions for 2087 validation samples
```

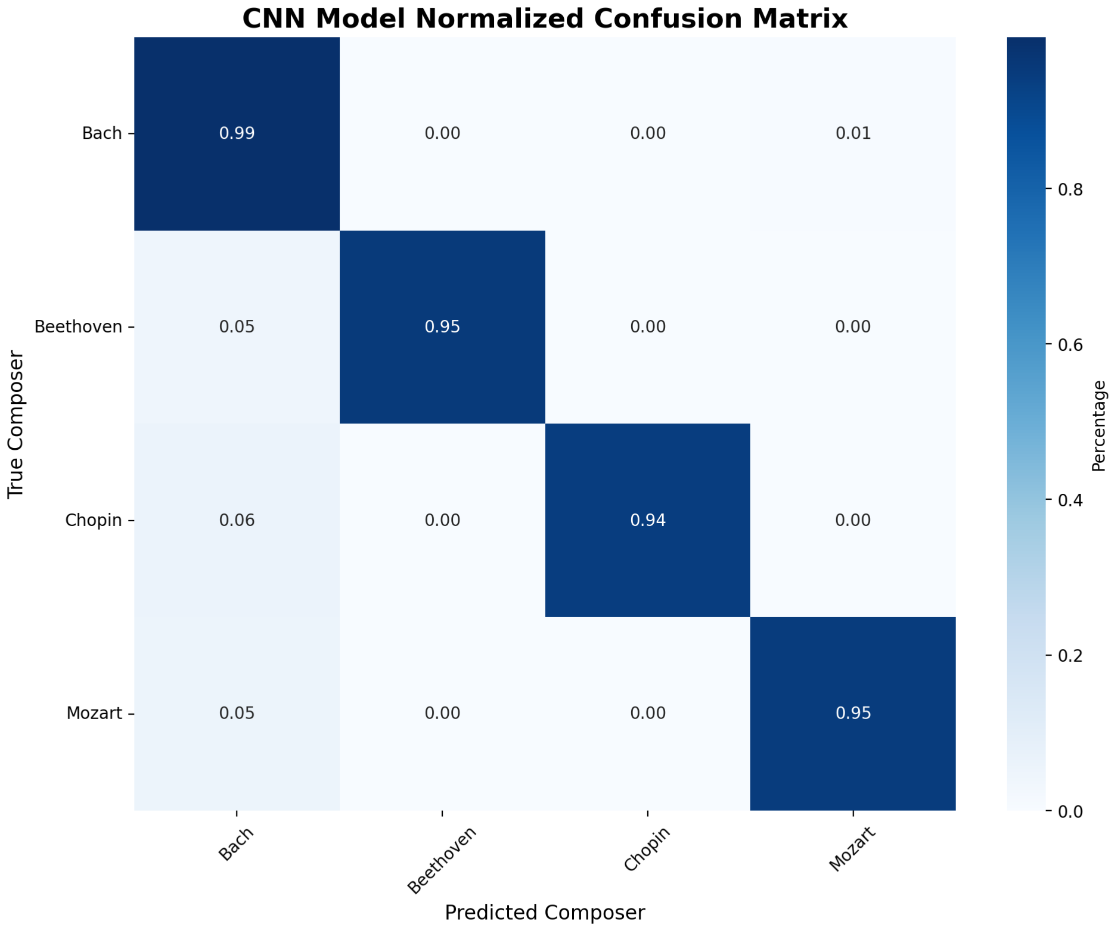
[39]:

```
# ------------------------------
# Confusion Matrix
# ------------------------------
plt.figure(figsize=(10, 8))

# Get unique classes present in the validation set
unique_labels = np.unique(np.concatenate([all_true_labels, all_predictions]))
actual_composer_names = [label_to_composer[i] for i in unique_labels]

print(f"Classes present in validation set: {unique_labels}")
print(f"Corresponding composers: {actual_composer_names}")

# Generate confusion matrix with all possible labels
cm = confusion_matrix(all_true_labels, all_predictions, labels=unique_labels)

# Create a DataFrame for better visualization
cm_df = pd.DataFrame(cm, index=actual_composer_names,
 ↪columns=actual_composer_names)

# Plot heatmap
sns.heatmap(cm_df, annot=True, fmt='d', cmap='Blues', cbar_kws={'label':
 ↪'Count'})
plt.title('CNN Model Confusion Matrix', fontsize=16, fontweight='bold')
plt.xlabel('Predicted Composer', fontsize=12)
plt.ylabel('True Composer', fontsize=12)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
```

```
plt.tight_layout()
plt.show()

# Calculate and display normalized confusion matrix
plt.figure(figsize=(10, 8))
cm_normalized = confusion_matrix(all_true_labels, all_predictions,␣
 ↪labels=unique_labels, normalize='true')
cm_norm_df = pd.DataFrame(cm_normalized, index=actual_composer_names,␣
 ↪columns=actual_composer_names)

sns.heatmap(cm_norm_df, annot=True, fmt='.2f', cmap='Blues', cbar_kws={'label':␣
 ↪'Percentage'})
plt.title('CNN Model Normalized Confusion Matrix', fontsize=16,␣
 ↪fontweight='bold')
plt.xlabel('Predicted Composer', fontsize=12)
plt.ylabel('True Composer', fontsize=12)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```

```
Classes present in validation set: [0 1 2 3]
Corresponding composers: ['Bach', 'Beethoven', 'Chopin', 'Mozart']
```


CNN Model Confusion Matrix
True Composer
Predicted Composer
Bach
Beethoven
Chopin
Mozart
1585
0
1
8
2
41
0
0
7
0
113
0
18
0
0
312
Count
0
200
400
600
800
1000
1200
1400

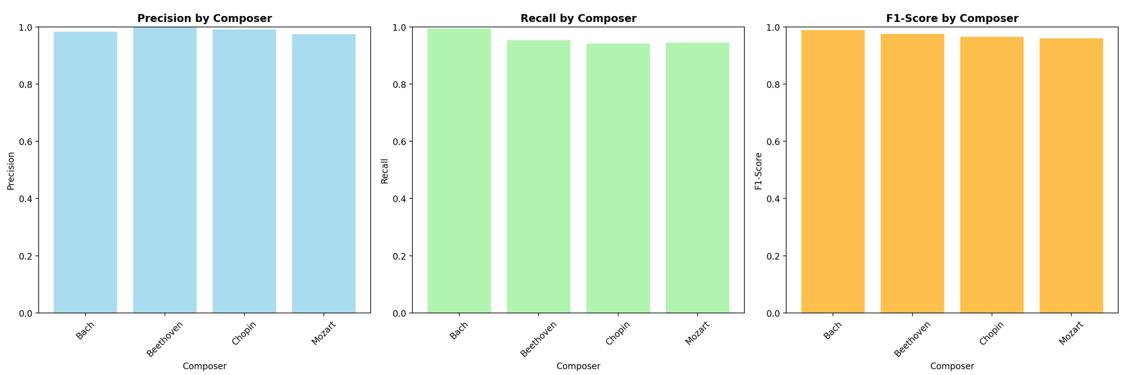


[40]:
```python
# ------------------------------
# Classification Report and Metrics
# ------------------------------
print("=" * 60)
print("DETAILED CLASSIFICATION REPORT")
print("=" * 60)

# Generate classification report using only classes present in validation set
report = classification_report(all_true_labels, all_predictions,
                               target_names=actual_composer_names,
                               labels=unique_labels,
                               output_dict=True)

# Display classification report
print(classification_report(all_true_labels, all_predictions,
                            target_names=actual_composer_names,
                            labels=unique_labels))
```

```python
# Create a DataFrame for metrics visualization
metrics_df = pd.DataFrame(report).transpose()
metrics_df = metrics_df.iloc[:-3, :-1]  # Remove avg rows and support column␣
↪for plotting

# Plot per-class metrics
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

# Precision
axes[0].bar(range(len(actual_composer_names)), [report[name]['precision'] for␣
↪name in actual_composer_names],
           color='skyblue', alpha=0.7)
axes[0].set_title('Precision by Composer', fontweight='bold')
axes[0].set_xlabel('Composer')
axes[0].set_ylabel('Precision')
axes[0].set_xticks(range(len(actual_composer_names)))
axes[0].set_xticklabels(actual_composer_names, rotation=45)
axes[0].set_ylim(0, 1)

# Recall
axes[1].bar(range(len(actual_composer_names)), [report[name]['recall'] for name␣
↪in actual_composer_names],
           color='lightgreen', alpha=0.7)
axes[1].set_title('Recall by Composer', fontweight='bold')
axes[1].set_xlabel('Composer')
axes[1].set_ylabel('Recall')
axes[1].set_xticks(range(len(actual_composer_names)))
axes[1].set_xticklabels(actual_composer_names, rotation=45)
axes[1].set_ylim(0, 1)

# F1-Score
axes[2].bar(range(len(actual_composer_names)), [report[name]['f1-score'] for␣
↪name in actual_composer_names],
           color='orange', alpha=0.7)
axes[2].set_title('F1-Score by Composer', fontweight='bold')
axes[2].set_xlabel('Composer')
axes[2].set_ylabel('F1-Score')
axes[2].set_xticks(range(len(actual_composer_names)))
axes[2].set_xticklabels(actual_composer_names, rotation=45)
axes[2].set_ylim(0, 1)

plt.tight_layout()
plt.show()

# Overall accuracy
overall_accuracy = accuracy_score(all_true_labels, all_predictions)
```

```python
print(f"\nOverall Model Accuracy: {overall_accuracy:.4f} ({overall_accuracy*100:
↪.2f}%)")
```

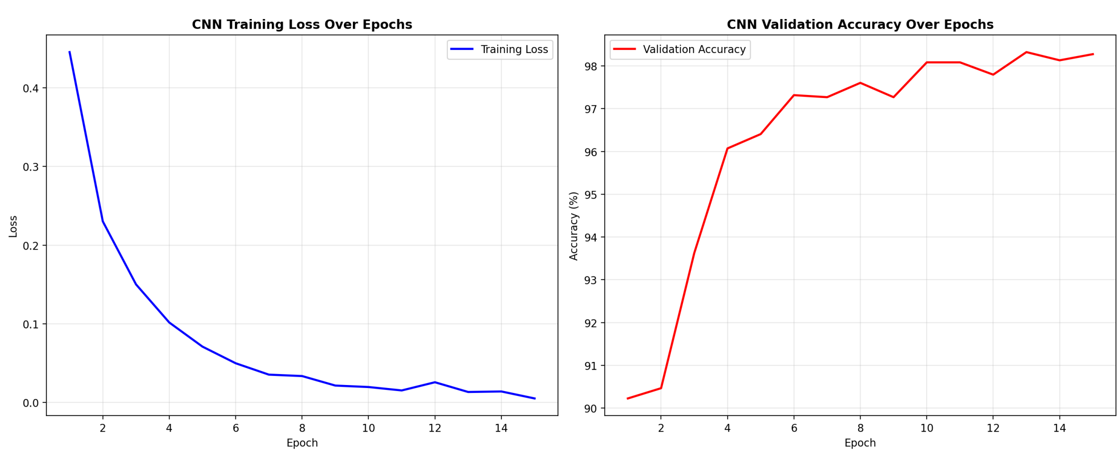
```
============================================================
DETAILED CLASSIFICATION REPORT
============================================================
              precision    recall  f1-score   support

        Bach       0.98      0.99      0.99      1594
   Beethoven       1.00      0.95      0.98        43
      Chopin       0.99      0.94      0.97       120
      Mozart       0.97      0.95      0.96       330

    accuracy                           0.98      2087
   macro avg       0.99      0.96      0.97      2087
weighted avg       0.98      0.98      0.98      2087
```




```
Overall Model Accuracy: 0.9828 (98.28%)
```

[41]:
```python
# ------------------------------
# Training and Validation Curves
# ------------------------------
fig, axes = plt.subplots(1, 2, figsize=(15, 6))

# Training Loss Curve
epochs_range = range(1, len(cnn_train_losses) + 1)
axes[0].plot(epochs_range, cnn_train_losses, 'b-', label='Training Loss',␣
↪linewidth=2)
axes[0].set_title('CNN Training Loss Over Epochs', fontweight='bold')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
axes[0].grid(True, alpha=0.3)
```

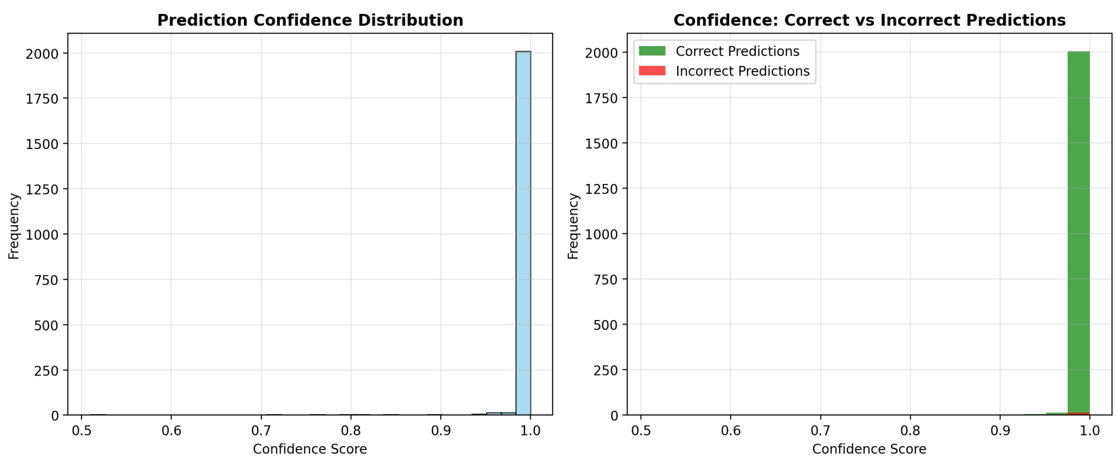
```python
axes[0].legend()

# Validation Accuracy Curve
axes[1].plot(epochs_range, cnn_val_accuracies, 'r-', label='Validation Accuracy', linewidth=2)
axes[1].set_title('CNN Validation Accuracy Over Epochs', fontweight='bold')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Accuracy (%)')
axes[1].grid(True, alpha=0.3)
axes[1].legend()

plt.tight_layout()
plt.show()

# Print training summary
print("=" * 60)
print("TRAINING SUMMARY")
print("=" * 60)
print(f"Total Epochs Trained: {len(cnn_train_losses)}")
print(f"Final Training Loss: {cnn_train_losses[-1]:.4f}")
print(f"Final Validation Accuracy: {cnn_val_accuracies[-1]:.2f}%")
print(f"Best Validation Accuracy: {max(cnn_val_accuracies):.2f}%")
print(f"Best Epoch: {cnn_val_accuracies.index(max(cnn_val_accuracies)) + 1}")

# Check for overfitting indicators
best_epoch = cnn_val_accuracies.index(max(cnn_val_accuracies)) + 1
final_epoch = len(cnn_val_accuracies)
if final_epoch - best_epoch > 5:
    print(f"  Potential overfitting detected: Best accuracy was at epoch {best_epoch}, but training continued to epoch {final_epoch}")
else:
    print("  No significant overfitting detected")
```



```
============================================================
TRAINING SUMMARY
============================================================
Total Epochs Trained: 15
Final Training Loss: 0.0052
Final Validation Accuracy: 98.28%
Best Validation Accuracy: 98.32%
Best Epoch: 13
 No significant overfitting detected
```

[42]:
```python
# ------------------------------
# Model Performance Analysis
# ------------------------------

# Analyze prediction confidence
model_cnn.eval()
confidence_scores = []
prediction_probabilities = []

with torch.no_grad():
    for X_val, y_val in cnn_val_loader:
        X_val = X_val.to(device)
        outputs = model_cnn(X_val)
        probabilities = torch.softmax(outputs, dim=1)
        max_probs, _ = torch.max(probabilities, dim=1)

        confidence_scores.extend(max_probs.cpu().numpy())
        prediction_probabilities.extend(probabilities.cpu().numpy())

confidence_scores = np.array(confidence_scores)
prediction_probabilities = np.array(prediction_probabilities)

# Plot confidence distribution
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.hist(confidence_scores, bins=30, alpha=0.7, color='skyblue',␣
 ↪edgecolor='black')
plt.title('Prediction Confidence Distribution', fontweight='bold')
plt.xlabel('Confidence Score')
plt.ylabel('Frequency')
plt.grid(True, alpha=0.3)

# Correct vs Incorrect predictions confidence
correct_mask = (all_predictions == all_true_labels)
correct_confidence = confidence_scores[correct_mask]
```

```
incorrect_confidence = confidence_scores[~correct_mask]

plt.subplot(1, 2, 2)
plt.hist(correct_confidence, bins=20, alpha=0.7, label='Correct Predictions',␣
 ↪color='green')
plt.hist(incorrect_confidence, bins=20, alpha=0.7, label='Incorrect␣
 ↪Predictions', color='red')
plt.title('Confidence: Correct vs Incorrect Predictions', fontweight='bold')
plt.xlabel('Confidence Score')
plt.ylabel('Frequency')
plt.legend()
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("=" * 60)
print("CONFIDENCE ANALYSIS")
print("=" * 60)
print(f"Average Confidence (All): {np.mean(confidence_scores):.4f}")
print(f"Average Confidence (Correct): {np.mean(correct_confidence):.4f}")
print(f"Average Confidence (Incorrect): {np.mean(incorrect_confidence):.4f}")
print(f"High Confidence Predictions (>0.8): {np.sum(confidence_scores > 0.8)}␣
 ↪({np.sum(confidence_scores > 0.8)/len(confidence_scores)*100:.1f}%)")
print(f"Low Confidence Predictions (<0.5): {np.sum(confidence_scores < 0.5)}␣
 ↪({np.sum(confidence_scores < 0.5)/len(confidence_scores)*100:.1f}%)")
```




```
============================================================
CONFIDENCE ANALYSIS
============================================================
Average Confidence (All): 0.9940
```

```
Average Confidence (Correct): 0.9962
Average Confidence (Incorrect): 0.8733
High Confidence Predictions (>0.8): 2062 (98.8%)
Low Confidence Predictions (<0.5): 0 (0.0%)
```

[43]:

```python
# ------------------------------
# Error Analysis
# ------------------------------
print("=" * 60)
print("ERROR ANALYSIS")
print("=" * 60)

# Find misclassified examples
misclassified_indices = np.where(all_predictions != all_true_labels)[0]
print(f"Total misclassified samples: {len(misclassified_indices)} out of␣
↪{len(all_predictions)}")

# Analyze confusion patterns using actual labels present
print("\nMost Common Misclassification Patterns:")
for true_label in unique_labels:
    for pred_label in unique_labels:
        if true_label != pred_label:
            count = np.sum((all_true_labels == true_label) & (all_predictions␣
↪== pred_label))
            if count > 0:
                percentage = count / np.sum(all_true_labels == true_label) * 100
                if percentage > 10:  # Only show significant patterns
                    true_composer = label_to_composer[true_label]
                    pred_composer = label_to_composer[pred_label]
                    print(f"  {true_composer} → {pred_composer}: {count} times␣
↪({percentage:.1f}%)")

# Sample some misclassified examples
if len(misclassified_indices) > 0:
    print(f"\nSample Misclassified Examples:")
    sample_size = min(10, len(misclassified_indices))
    sample_indices = np.random.choice(misclassified_indices, sample_size,␣
↪replace=False)

    for i, idx in enumerate(sample_indices):
        true_composer = label_to_composer[all_true_labels[idx]]
        pred_composer = label_to_composer[all_predictions[idx]]
        confidence = confidence_scores[idx]
        print(f"  {i+1}. True: {true_composer}, Predicted: {pred_composer},␣
↪Confidence: {confidence:.3f}")

# ------------------------------
```

```python
# Model Summary and Recommendations
# ------------------------------
print("\n" + "=" * 60)
print("MODEL PERFORMANCE SUMMARY")
print("=" * 60)

best_composer_idx = np.argmax([report[name]['f1-score'] for name in actual_composer_names])
worst_composer_idx = np.argmin([report[name]['f1-score'] for name in actual_composer_names])

print(f"  Overall Accuracy: {overall_accuracy*100:.2f}%")
print(f"  Best Performing Composer: {actual_composer_names[best_composer_idx]} (F1: {report[actual_composer_names[best_composer_idx]]['f1-score']:.3f})")
print(f"   Worst Performing Composer: {actual_composer_names[worst_composer_idx]} (F1: {report[actual_composer_names[worst_composer_idx]]['f1-score']:.3f})")
print(f"  Training Epochs: {len(cnn_train_losses)}")
print(f"  Best Validation Accuracy: {max(cnn_val_accuracies):.2f}%")

# Check which composers are missing from validation set
all_composer_names = [label_to_composer[i] for i in range(len(composer_to_label))]
missing_composers = set(all_composer_names) - set(actual_composer_names)
if missing_composers:
    print(f"   Missing composers in validation set: {', '.join(missing_composers)}")

print(f"\n  RECOMMENDATIONS:")
if overall_accuracy < 0.8:
    print("   • Consider training for more epochs or adjusting learning rate")
    print("   • Try data augmentation techniques or feature engineering")
    print("   • Experiment with different model architectures")
if max(cnn_val_accuracies) - cnn_val_accuracies[-1] > 5:
    print("   • Model may be overfitting - consider early stopping or regularization")
if np.mean(confidence_scores) < 0.7:
    print("   • Model predictions lack confidence - consider ensemble methods")
if missing_composers:
    print(f"   • Collect more data for missing composers: {', '.join(missing_composers)}")
print("   • Collect more training data for underperforming composers")
print("   • Analyze feature importance to understand model decisions")
```

```
============================================================
ERROR ANALYSIS
============================================================
```

```
Total misclassified samples: 36 out of 2087

Most Common Misclassification Patterns:

Sample Misclassified Examples:
  1. True: Mozart, Predicted: Bach, Confidence: 0.741
  2. True: Bach, Predicted: Chopin, Confidence: 0.802
  3. True: Mozart, Predicted: Bach, Confidence: 0.509
  4. True: Bach, Predicted: Mozart, Confidence: 0.956
  5. True: Mozart, Predicted: Bach, Confidence: 1.000
  6. True: Chopin, Predicted: Bach, Confidence: 0.972
  7. True: Mozart, Predicted: Bach, Confidence: 0.941
  8. True: Mozart, Predicted: Bach, Confidence: 1.000
  9. True: Bach, Predicted: Mozart, Confidence: 0.964
  10. True: Mozart, Predicted: Bach, Confidence: 0.570

============================================================
MODEL PERFORMANCE SUMMARY
============================================================
 Overall Accuracy: 98.28%
 Best Performing Composer: Bach (F1: 0.989)
  Worst Performing Composer: Mozart (F1: 0.960)
 Training Epochs: 15
 Best Validation Accuracy: 98.32%

 RECOMMENDATIONS:
 • Collect more training data for underperforming composers
 • Analyze feature importance to understand model decisions
```