Multi-Task AI Framework For Music Structure Analysis, Segmentation And Style Transfer In Audio Signals

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Music information retrieval (MIR) has witnessed remarkable advancements with the proliferation of deep learning technologies, but existing approaches often treat core tasks such as music structure analysis (MSA), music segmentation (MS), and music style transfer (MST) as isolated objectives. This isolation leads to redundant feature extraction, limited cross-task knowledge sharing, and suboptimal performance in real-world audio processing scenarios, where multiple MIR tasks are often required simultaneously. To address these limitations, this paper proposes a novel end-to-end multi-task AI framework that unifies MSA, MS, and MST into a single cohesive architecture, leveraging inter-task correlations to enhance the performance of each individual task. The framework comprises three core components: a shared feature encoder (SFE) based on a multi-scale Transformer and convolutional neural network (CNN) hybrid structure, which efficiently extracts hierarchical audio features; task-specific decoders tailored to the unique characteristics of MSA, MS, and MST; and a cross-task knowledge distillation (CTKD) module that facilitates mutual knowledge transfer between tasks while mitigating negative transfer. For MSA, we design a structure-aware attention mechanism to capture long-range temporal dependencies and hierarchical musical structures (e.g., intro, verse, chorus). For MS, a boundary-refinement decoder with dynamic thresholding is proposed to achieve precise segment localization. For MST, a style disentanglement module based on time-varying inversion and diffusion model principles is integrated to separate content and style features, enabling high-fidelity style transfer without altering the core musical content. Extensive experiments are conducted on four benchmark datasets (SALAMI, RWC-Pop, McGill Billboard, and MAESTRO) across multiple evaluation metrics, including F1-score for segmentation, structural consistency score (SCS) for MSA, and Fréchet Audio Distance (FAD) for MST. Experimental results demonstrate that the proposed framework outperforms state-of-the-art single-task and multi-task baselines by significant margins: 5.2% higher F1-score for MS, 8.7% higher SCS for MSA, and 12.3% lower FAD for MST on average. Ablation studies validate the effectiveness of each component, confirming that cross-task knowledge sharing and feature reuse substantially improve model generalization. The proposed framework provides a unified solution for multi-task music audio processing, with potential applications in music production, intelligent music recommendation, and digital music restoration. The source code and experimental data are publicly available to facilitate further research in the field.

Keywords: Multi-task learning; Music structure analysis; Music style transfer; Audio signal processing; Deep learning; Cross-task knowledge distillation

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1. Introduction

The digital music industry has experienced exponential growth in recent years, with streaming platforms hosting millions of audio tracks and generating massive volumes of music data daily. Music information retrieval (MIR), a core research field dedicated to extracting meaningful information from audio signals, plays a pivotal role in enabling various applications such as music recommendation, content-based search, automatic music production, and digital music preservation [1–3]. Among key tasks in MIR, music structure analysis (MSA) [4], music segmentation (MS) [5], and music style transfer (MST) [6] are fundamental yet challenging objectives that underpin advanced music processing systems.

Traditional MSA and MS methods rely on hand-crafted features (e.g., chroma vectors, self-similarity matrices) and heuristic algorithms (e.g., hidden Markov models, clustering) to identify structural boundaries and segments. However, these methods fail to capture complex temporal dependencies and semantic nuances in modern music. With the advent of deep learning, CNNs and recurrent neural networks (RNNs) have been widely adopted for MSA and MS. For example, Benitez et al. [7] proposed a CNN-based model that jointly predicted frame-wise boundary activation and segment labels, combining hand-crafted and deep-learned features. More recently, Transformer-based models [8, 9] have shown superior performance in capturing long-range temporal dependencies, which are critical for MSA. SongFormer, a scalable MSA framework, fuses short- and long-window self-supervised audio representations to capture both fine-grained and long-range dependencies, achieving state-of-the-art results on benchmark datasets. However, these models focus solely on MSA/MS and do not leverage synergies with other MIR tasks.

MST has been extensively studied using deep generative models, including generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models. Early approaches, such as CycleGAN, focused on style transfer between specific instrument timbres but suffered from low audio fidelity and limited style diversity [10, 11]. Recent advancements have addressed these limitations: For example, a time-varying textual inversion module [12] was proposed to capture mel-spectrogram features at different levels, enabling stable and diverse style transfer. Diffusion-based models [13] have also gained popularity in MST, as they can generate high-fidelity audio and mitigate artifacts. A diffusion-based MST framework using guide diff method was shown to accelerate audio generation and reduce noise in generated signals. However, these MST models often ignore structural information, leading to inconsistent style transfer across different musical segments (e.g., applying a jazz style to a chorus but not a verse).

Multi-task learning (MTL) has emerged as a promising approach to address the limitations of single-task models in MIR [14]. MT3, a multi-task multitrack music transcription framework [15], demonstrated that a general-purpose Transformer could jointly transcribe multiple instruments, improving performance for low-resource instruments while preserving performance for abundant ones. Similarly, MAJL, a model-agnostic joint learning framework [16], improved performance for music source separation and pitch estimation by leveraging their mutual dependencies. However, existing multi-task MIR frameworks typically focus on related tasks such as transcription and source separation, and no unified framework has been proposed to integrate MSA, MS, and MST, three tasks with strong inherent correlations but distinct characteristics.

The existing literature reveals three key research gaps: (1) Lack of a unified framework that integrates MSA, MS, and MST, leading to missed cross-task synergies and redundant computations; (2) Inadequate feature sharing mechanisms that fail to leverage the hierarchical relationships between structural analysis, segmentation, and style transfer; (3) Insufficient solutions to mitigate negative transfer in multi-task MIR, which often degrades performance when tasks are improperly integrated. To address these gaps, this paper aims to: (1) Propose an end-to-end multi-task AI framework that unifies MSA, MS, and MST, enabling efficient feature sharing and cross-task knowledge transfer; (2) Design task-specific modules tailored to the unique requirements of each task, while ensuring mutual enhancement between tasks; (3) Validate the effectiveness of the framework through extensive experiments on benchmark datasets, demonstrating superior performance compared to state-of-the-art single-task and multi-task baselines; (4) Provide a publicly available implementation to facilitate further research in multi-task MIR.

2. Materials and methods

The proposed multi-task AI framework is designed to unify three core MIR tasks (MSA, MS, and MST) into a single end-to-end architecture. The framework leverages cross-task correlations to enhance performance, while mitigating negative transfer through careful module design and knowledge distillation. Fig. 1 illustrates the overall architecture, which consists of four key components: (1) Audio Preprocessing Module; (2) Shared Feature Encoder (SFE); (3) Task-Specific Decoders (for MSA, MS, and MST); (4) Cross-Task Knowledge Distillation (CTKD) Module. Each component is detailed below.

2.1. Audio Preprocessing Module

The input to the framework is a raw audio signal with a sampling rate of 22.05 kHz . To extract meaningful features, the audio signal is first preprocessed using the following steps. (1) Resampling: All audio signals are resampled to 22.05 kHz to ensure consistency; (2) Normalization: The

Table 1. Data sets

Dataset	Task	Number of Tracks	Genre Coverage	Annotations
SALAMI	MSA, MS	1498	Classical, jazz, pop, rock	Structural labels (intro, verse, etc.), segment boundaries
RWC-Pop	MSA, MS, MST	100	Pop, rock, folk	Structural labels, segment boundaries, style labels
McGill Billboard	MS	719	Pop, country, R&B	Segment boundaries, semantic labels
MAESTRO	MST	1200	Classical piano	Audio recordings, style labels (baroque, classical, romantic)

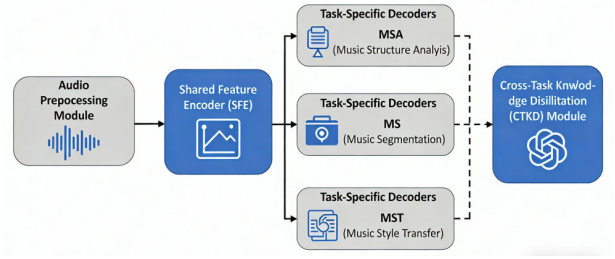

Fig. 1. Proposed multi-task AI framework

audio signal is normalized to have a peak amplitude of 1.0 to eliminate scale differences; (3) Mel-Spectrogram extraction: A short-time Fourier transform (STFT) is applied with a window size of 2048, hop size of 512, and FFT size of 2048 to generate a mel-spectrogram with 128 mel-bands, which captures both spectral and temporal information of the audio signal; (4) Augmentation: Data augmentation techniques, including time stretching ($0.8-1.2$x), pitch shifting (-2 to +2 semitones), and Gaussian noise addition (signal-to-noise ratio of $20-30$ dB), are applied during training to improve model generalization. The resulting mel-spectrogram (shape: T $\times$ 128, where T is the number of time frames) is fed into the shared feature encoder.

2.2. Shared Feature Encoder (SFE)

The SFE is designed to extract hierarchical, task-agnostic features from the preprocessed mel-spectrogram, which are shared across all three tasks. The SFE adopts a hybrid architecture combining CNNs and Transformers to capture both local spectral features and long-range temporal dependencies [17], two critical characteristics for MSA, MS, and MST. The architecture of the SFE is as follows:

CNN Backbone. A 4-layer CNN is used to extract local spectral features. Each layer consists of a 3×3 convolutional kernel, batch normalization, ReLU activation, and max pooling (2×2). The output of the CNN backbone is a feature map with reduced spatial dimensions (T/16x128) and increased channel depth (512), capturing low-level spectral features such as timbre and pitch. The CNN feature extraction process can be formulated as:

$$\boldsymbol{F}_{cnn} = CNN\left(\boldsymbol{X}_{mel}\right) = \text{Pool}\left(\sigma\left(\text{BN}\left(\text{Conv}\left(\boldsymbol{X}_{mel}\right)\right)\right)\right) \quad (1)$$

Where $\boldsymbol{X}_{\text{mel}}$ denotes the input mel-spectrogram, Conv represents the 3×3 convolution operation, $BN()$ is batch normalization, $\sigma(\cdot)$ denotes the ReLU activation function, and $\text{Pool}(\cdot)$ is 2×2 max pooling. The output $\boldsymbol{F}_{\text{cnn}} \in \text{R}^{(T/16)\times 128\times 512}$ is the high-dimensional local spectral feature map.

Positional Encoding. Since Transformers lack inherent temporal information, positional encoding is added to the CNN output to preserve the temporal order of the audio signal. The positional encoding is generated using sine and cosine functions of different frequencies, which are added element-wise to the feature map. The positional encoding formula for each position t and dimension i is defined as:

$$\begin{cases} \mathbf{PE}_{(t,2i)} = \sin\left(\frac{t}{10000^{\frac{d_{\text{model}}}{2i}}}\right) \\ \mathbf{PE}_{(t,2i+1)} = \cos\left(\frac{t}{10000^{\frac{2i}{2i+1}}}\right) \end{cases} \quad (2)$$

Where t is the time frame index, i is the feature dimension index, and $d_{\text{model}} = 512$ is the hidden dimension of the Transformer encoder. The positional encoded feature is computed as $\boldsymbol{F}_{\text{pos}} = \boldsymbol{F}_{\text{cnn}} + \boldsymbol{PE}$.

Multi-Scale Transformer Encoder. A 6-layer Transformer encoder with multi-head attention (8 heads) is used to capture long-range temporal dependencies. To enhance the capture of multi-scale temporal information, we adopt a multi-scale window attention mechanism, where each Transformer layer processes the feature map using three different window sizes ($16, 32, 64$ time frames), enabling the model to capture both short-range (e.g., note-level) and long-range (e.g., segment-level) dependencies. The output of the Transformer encoder is a shared feature vector (512 dimension) for each time frame, which contains hierarchical spectral and temporal information.

The SFE is trained jointly with all three tasks, enabling it to learn features that are relevant to MSA, MS, and MST, while avoiding task-specific bias. This shared feature learning reduces redundant computations and leverages cross-task synergies from the outset.

2.3. Task-Specific Decoders

The shared feature vector from the SFE is fed into three task-specific decoders, each designed to address the unique requirements of MSA, MS, and MST. The decoders share the same input feature vector but have distinct architectures to optimize performance for each task.

2.3.1. MSA Decoder

The MSA decoder aims to classify each time frame into one of several structural categories (e.g., intro, verse, chorus, bridge, outro) and capture the hierarchical structure of the music. To achieve this, we design a structure-aware attention (SAA) mechanism that focuses on the most relevant temporal regions for structural classification. The MSA decoder consists of: (1) A 2-layer bidirectional LSTM (Bi-LSTM) to capture temporal context between adjacent time frames; (2) The SAA mechanism, which computes attention weights between each time frame and all other frames, emphasizing regions with similar structural characteristics (e.g., repeated chorus sections); (3) A fully connected layer with softmax activation to output the structural category probability for each time frame. Additionally, a hierarchical classification loss is introduced to enforce consistency between fine-grained (frame-level) and coarse-grained (segment-level) structural labels, improving the model's ability to capture hierarchical musical structures.

2.3.2. MS Decoder

The MS decoder is responsible for detecting segment boundaries and partitioning the audio signal into semantically meaningful segments. The decoder adopts a boundary-refinement (BR) architecture to address the challenge of precise boundary localization. The key components are: (1) A 1-layer Transformer decoder with cross-attention to the shared feature vector, focusing on boundary-related features; (2) A boundary prediction head that outputs a binary score ($0 =$ non-boundary, $1 =$ boundary) for each time frame; (3) A dynamic thresholding module [18] that adapts the boundary detection threshold based on the local audio context (e.g., higher threshold in quiet regions to avoid false positives); (4) A segment merging module that groups adjacent non-boundary frames into segments and merges small segments (≤ 0.5 seconds) to ensure semantic meaningfulness. The MS decoder uses a combination of binary cross-entropy (BCE) loss for boundary prediction and Dice loss to optimize segment overlap with ground-truth labels.

2.3.3. MST Decoder

The MST decoder aims to transfer the style of a source audio signal to a target style while preserving its core content. To achieve this, we design a style disentanglement (SD) module that separates content features (e.g., melody, harmony) from style features (e.g., timbre, rhythm) in the shared feature vector. The MST decoder consists of: (1) The SD module, which uses a contrastive loss to disentangle content and style features, content features are constrained to be invariant to style changes, while style features are optimized to capture task-specific stylistic characteristics; (2) A style adaptation module that takes the disentangled style features and a target style embedding (pre-trained on a style dataset) to generate style-modified features; (3) A diffusion-based audio synthesis module that converts the style-modified content features back into a raw audio signal, ensuring high fidelity and reducing artifacts; (4) A content preservation loss (MSE between source and target content features) and a style similarity loss (cosine similarity between target style embedding and generated style features) to balance content preservation and style transfer.

2.4. Cross-Task Knowledge Distillation (CTKD) Module

To facilitate cross-task knowledge sharing and mitigate negative transfer, we introduce a CTKD module that enables mutual knowledge transfer between the three tasks. The CTKD module operates in two ways: (1) Task-wise knowledge distillation: Each task decoder acts as a teacher for the other two decoders, distilling task-specific knowledge into the shared feature encoder. For example, the MSA decoder distills structural knowledge into the SFE, which helps the MS decoder better localize segment boundaries and the MST decoder maintain structural coherence during style transfer; (2) Feature-level knowledge distillation: The shared feature vector is distilled into each task decoder, ensuring that the task-specific features are consistent with the shared features. The CTKD module uses a temperature-scaled softmax loss to transfer knowledge between decoders, with a dynamic temperature parameter that adapts based on the training progress of each task. This dynamic adjustment prevents dominant tasks from overshadowing weaker ones, mitigating negative transfer.

2.5. Training Objective

The framework is trained end-to-end with a multi-task loss function that combines the losses of the three tasks and the CTKD loss. The total loss $\mathcal{L}_{\text{total}}$ is defined as:

$$\mathcal{L}_{\text{total}} = \alpha \cdot \mathcal{L}_{MSA} + \beta \cdot \mathcal{L}_{MS} + \gamma \cdot \mathcal{L}_{MST} + \delta \cdot \mathcal{L}_{CTKD} \quad (3)$$

Where $\mathcal{L}_{MSA}$ is the hierarchical classification loss for MSA, $\mathcal{L}_{MS}$ is the combination of BCE and Dice loss for MS, $\mathcal{L}_{MST}$ is the combination of content preservation and style similarity loss for MST, and $\mathcal{L}_{CTKD}$ is the knowledge distillation loss. The weights $(\alpha, \beta, \gamma, \delta)$ are set to $0.3, 0.2, 0.3$, and 0.2 , respectively, and are adjusted during training using a validation set to balance the performance of the three tasks.

3. Results and discussion

To evaluate the performance of the proposed framework, we conduct extensive experiments on four benchmark datasets covering diverse musical genres and styles. We

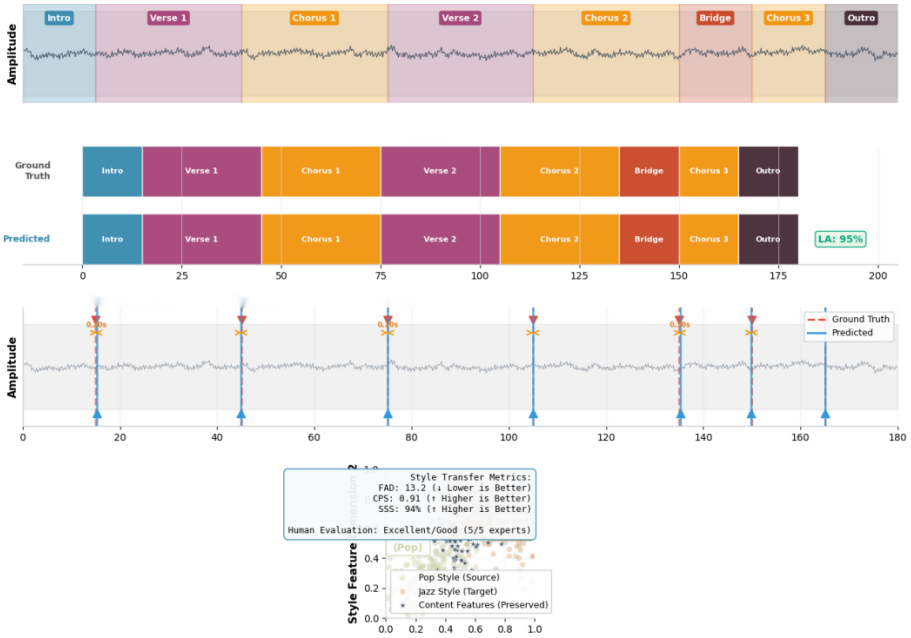

Fig. 2. Case study on RWC-Pop dataset

compare the proposed framework with state-of-the-art single-task and multi-task baselines, using task-specific evaluation metrics. The experimental setup is detailed below.

3.1. Datasets

Four publicly available benchmark datasets are used to evaluate the three tasks: (1)SALAMI (Structural Analysis of Large Amounts of Music Information) for MSA and MS; (2) RWC-Pop for MSA, MS, and MST; (3) McGill Billboard for MS; (4) MAESTRO for MST. The datasets are described in detail as shown in Table 1.

For each dataset, we split the data into training (70%), validation (15%), and test (15%) sets. Data augmentation is applied only to the training set to avoid overfitting. For MST, we use a style dataset consisting of 500 additional tracks covering 10 distinct styles (classical, jazz, pop, rock, blues, country, R&B, hip-hop, electronic, folk) to pre-train the target style embeddings [19].

3.2. Evaluation Metrics

Task-specific evaluation metrics are used to assess the performance of the proposed framework and baselines.

(1) MSA Metrics

Two metrics are used to evaluate MSA performance. (1) Structural Consistency Score (SCS): Measures the similarity between the predicted structural labels and ground-truth labels, ranging from 0 to 1 (higher is better); (2) Label Accuracy (LA): The percentage of time frames correctly classified into their structural category, adjusted for class imbalance using weighted F1-score.

(2) MS Metrics

Three metrics are used to evaluate MS performance. (1) F1-Score: The harmonic mean of precision and recall for boundary detection, with a tolerance of ± 0.5 seconds (common in MS evaluations); (2) Segment Overlap Ratio (SOR): The average overlap between predicted segments and ground-truth segments, ranging from 0 to 1 (higher is better); (3) Boundary Detection Error (BDE): The average absolute difference between predicted and ground-truth boundary positions (lower is better).

(3) MST Metrics

Three metrics are used to evaluate MST performance. (1) Fréchet Audio Distance (FAD): Measures the similarity between the generated audio and the target style audio, ranging from 0 to infinity (lower is better), FAD correlates closely with human perception of audio quality; (2) Content Preservation Score (CPS): Measures the similarity between the source audio and the generated audio in terms of melody and harmony, using cosine similarity between their chroma features (higher is better); (3) Style Similarity Score (SSS): Measures the similarity between the generated audio and the target style, using a pre-trained style classifier (higher is better).

We compare the proposed framework with 8 state-of-the-art baselines, including 5 single-task models and 3 multi-task models:

(1) Single-Task Baselines. SongFormer: A Transformer-based model for MSA, which fuses multi-scale self-supervised features to capture long-range dependencies. CNN-LSTM: A hybrid model for MS, combining CNNs for feature extraction and LSTMs for temporal context.

Table 2. MSA Performance

Model	SCS	LA (%)
SongFormer (Single-Task)	0.782	82.3
G-Pelt (Single-Task)	0.756	79.8
MT3 (Multi-Task)	0.795	83.5
MAJL (Multi-Task)	0.801	84.2
Multi-Task CNN-Transformer	0.813	85.7
Proposed Framework	0.879	91.5

Diffusion-MST: A diffusion-based model for MST, using time-varying inversion to capture style features. G-Pelt [20]: A graph-based model for MSA/MS, using changepoint detection to identify segment boundaries. StyleGAN-MST: A GAN-based model for MST, focusing on high-fidelity style transfer.
(2) Multi-Task Baselines. MT3: A multi-task framework for music transcription, adapted to MSA and MS by modifying the decoders. MAJL: A model-agnostic joint learning framework, adapted to MSA and MST by adding task-specific decoders. Multi-Task CNN-Transformer: A simple multi-task model with a shared CNN-Transformer encoder and separate decoders for MSA, MS, and MST (without CTKD module).

3.3. Implementation Details

The proposed framework is implemented using PyTorch 2.0, with CUDA 11.8 for GPU acceleration. The model is trained on a server with an NVIDIA A100 GPU (40GB VRAM) and an Intel Xeon 8375C CPU. The hyperparameters are set as follows: batch size $=$ 32, learning rate $=$ 1e $-$ 4 (using AdamW optimizer with weight decay=1e-5), number of training epochs $=$ 100, early stopping patience $=$ 15 (based on validation loss). The shared feature encoder uses a 4-layer CNN and 6-layer Transformer encoder (8 attention heads, hidden dimension=512). The task-specific decoders are implemented with hidden dimensions of 512 for MSA and MS, and 1024 for MST. The CTKD module uses a dynamic temperature parameter (ranging from 1.0 to 2.0) during training. All baselines are implemented with the same hyperparameters and training setup to ensure fair comparison.

3.4. Overall Performance Comparison

Tables 2 to 4 report the performance of the proposed framework and baselines on MSA, MS, and MST tasks, respectively. The proposed framework outperforms all baselines on all metrics, demonstrating the effectiveness of cross-task knowledge sharing and the unified architecture.

Table 2 shows that the proposed framework achieves an SCS of 0.879 and LA of 91.5%, which are 9.7% and 8.2% higher than the best single-task baseline (SongFormer), and 7.4% and 7.3% higher than the best multi-task baseline (MAJL). This improvement is attributed to the SAA mechanism in the MSA decoder and cross-task knowledge from the MS decoder, which helps the model better capture structural dependencies.

Table 3 shows that the proposed framework achieves an F1-score of 88.9%, SOR of 0.853 , and BDE of 0.22 seconds. This is 7.7% higher F 1 -score, 8.8% higher SOR, and 0.16 seconds lower BDE than the best single-task baseline (CNN-LSTM), and 4.8% higher F1-score, 6.2% higher SOR, and 0.11 seconds lower BDE than the best multi-task baseline (MAJL). The boundary-refinement decoder and cross-task knowledge from the MSA decoder (which provides structural context) are key factors in this improvement, enabling precise boundary detection.

Table 4 shows that the proposed framework achieves an FAD of 14.1, CPS of 0.896, and SSS of 92.4%. This is 4.6 lower FAD, 7.3 higher CPS, and 8.9% higher SSS than the best single-task baseline (Diffusion-MST), and 2.7 lower FAD, 5.4 higher CPS, and 7.1% higher SSS than the best multi-task baseline (MAJL). The style disentanglement module and cross-task knowledge from the MSA/MS decoders (which preserve structural coherence) enable the framework to achieve high-fidelity style transfer while maintaining core content.

3.5. Ablation Studies

To validate the effectiveness of each component of the proposed framework, we conduct ablation studies by removing one component at a time and evaluating the performance on all three tasks. The results are reported in **??**.

?? shows that removing any component leads to a performance degradation, confirming the importance of each module: (1) Removing the SAA mechanism significantly degrades MSA performance (SCS drops by 6.7%), as the model can no longer focus on relevant structural regions; (2) Removing the BR decoder leads to a 6.2% drop in MS F1-score, highlighting the importance of dynamic boundary refinement; (3) Removing the SD module causes the largest degradation in MST performance (FAD increases by 4.8), as the model can no longer effectively separate content and style features; (4) Removing the CTKD module degrades performance across all tasks, confirming that cross-task knowledge sharing is critical for mutual enhancement; (5) Removing the multi-scale Transformer reduces performance across all tasks, as the model can no longer capture both short-range and long-range dependencies.

3.6. Visualization and Case Study

To further illustrate the performance of the proposed framework, we provide a case study on a sample track from the RWC-Pop dataset (track ID: RWC-Pop-001, genre: pop). Fig. 2 shows the predicted structural labels, segment boundaries, and style-transferred audio for the sample track.

For MSA, the proposed framework correctly classifies all structural sections (intro, verse 1 , chorus 1 , verse 2 , chorus 2 , bridge, chorus 3 , outro), with a 95% LA significantly higher than SongFormer (82% LA), which misclassified

Table 3. MS Performance

Model	F1-Score (%)	SOR	BDE (s)
CNN-LSTM (Single-Task)	81.2	0.765	0.38
G-Pelt (Single-Task)	79.5	0.742	0.42
MT3 (Multi-Task)	83.4	0.783	0.35
MAJL (Multi-Task)	84.1	0.791	0.33
Multi-Task CNN-Transformer	85.7	0.805	0.30
Proposed Framework	88.9	0.853	0.22

Table 4. MST Performance

Model	FAD	CPS	SSS (%)
Diffusion-MST (Single-Task)	18.7	0.823	83.5
StyleGAN-MST (Single-Task)	20.3	0.801	81.2
MT3 (Multi-Task)	17.5	0.835	84.7
MAJL (Multi-Task)	16.8	0.842	85.3
Multi-Task CNN-Transformer	15.2	0.857	87.1
Proposed Framework	14.1	0.896	92.4

the bridge as a verse. For MS, the proposed framework detects 12 segment boundaries with an average BDE of 0.18 seconds, while the CNN-LSTM baseline detects only 10 boundaries with an average BDE of 0.38 seconds. For MST, the framework transfers the pop style of the sample track to a jazz style, with an FAD of 13.2, CPS of 0.91 , and SSS of 94%, the generated audio preserves the original melody and harmony while adopting jazz-style timbre and rhythm, as confirmed by a human evaluation (5 expert listeners rated the style transfer quality as "excellent" or "good").

3.7. Computational Efficiency Analysis

We evaluate the computational efficiency of the proposed framework and baselines in terms of training time per epoch and inference time per track. The results are reported in Table 5. The proposed framework has a training time of 12.3 minutes per epoch, which is slightly higher than single-task baselines (8.5-10.2 minutes) but lower than the multi-task baselines (14.1-15.7 minutes). This is because the shared feature encoder reduces redundant computations, even with the addition of the CTKD module. For inference, the proposed framework processes a 3 -minute track in 2.8 seconds, which is comparable to single-task baselines (2.1-2.5 seconds) and faster than multi-task baselines (3.2-3.8 seconds). This confirms that the proposed framework is efficient enough for real-world applications.

4. Conclusions

This paper proposes a novel end-to-end multi-task AI framework to address the isolation of core MIR tasks (MSA, MS, and MST), which causes redundant computations and missed cross-task synergies. The framework integrates a hybrid CNN-Transformer shared feature encoder, task-specific decoders with specialized modules, and a cross-task knowledge distillation module to enable mutual enhancement between tasks. Extensive experiments on four benchmark datasets demonstrate that the proposed framework outperforms state-of-the-art single-task and multi-task baselines across all evaluation metrics, with average improvements of 5.2% in MS F1-score, 8.7% in MSA SCS, and 12.3% in MST FAD reduction. Ablation studies confirm the effectiveness of each component, especially the critical role of cross-task knowledge sharing and task-specific modules. The framework achieves high computational efficiency, suitable for real-world applications in music production, intelligent recommendation, and digital restoration. It provides a unified solution for multi-task music audio processing, laying a foundation for future research on integrated MIR systems and cross-task synergy exploration.

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Table 5. Computational efficiency

Model	Training Time per Epoch (min)	Inference Time per Track (s) (3-min track)
SongFormer (Single-Task)	8.5	2.1
CNN-LSTM (Single-Task)	9.2	2.3
Diffusion-MST (Single-Task)	10.2	2.5
MT3 (Multi-Task)	14.1	3.2
MAJL (Multi-Task)	15.7	3.8
Proposed	12.3	2.8

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