

MELFUSION: Synthesizing Music from Image and Language Cues using Diffusion Models

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 Project page - https://schowdhury671.github.io/melfusion_cvpr2024/

Abstract

Music is a universal language that can communicate emotions and feelings. It forms an essential part of the whole spectrum of creative media, ranging from movies to social media posts. Machine learning models that can synthesize music are predominantly conditioned on textual descriptions of it. Inspired by how musicians compose music not just from a movie script, but also through visualizations, we propose MELFUSION, a model that can effectively use cues from a textual description and the corresponding image to synthesize music. MELFUSION is a text-to-music diffusion model with a novel “visual synapse”, which effectively infuses the semantics from the visual modality into the generated music. To facilitate research in this area, we introduce a new dataset MeLBench, and propose a new evaluation metric IMSM. Our exhaustive experimental evaluation suggests that adding visual information to the music synthesis pipeline significantly improves the quality of generated music, measured both objectively and subjectively, with a relative gain of up to **67.98%** on the FAD score. We hope that our work will gather attention to this pragmatic, yet relatively under-explored research area.

1. Introduction

Music is an essential tool for creative professionals and content creators. It can complement and set the mood for an accompanying still image, animation, video, or even text descriptions while creating a social media post. Finding music that matches a specific setting, can indeed be an arduous task. A conditional music generation approach, that can synthesize a music track by analyzing the visual content and the textual description can find a wide range of practical

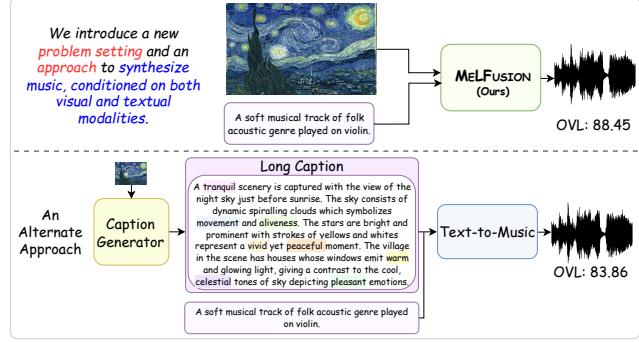


Figure 1. We present MELFUSION, a music diffusion model equipped with a novel “visual synapse”, that can effectively infuse image semantics into a text-to-music diffusion model. This task indeed requires a detailed understanding of the concepts in the image. An alternate approach like using a caption generator to convert image to text space to be further used with existing text-to-music methods leads to a sub-optimal overall audio quality (OVL) score. Our approach can knit together complementary information from both modalities to synthesize high-quality music.

applications in various fields including social media.

Inspired by the progress in generative modeling of images, music generation has also garnered significant attention from the community [1, 46, 73]. Recently, Agostinelli et al. [1], Copet et al. [9] proposed conditioning in the form of melody or humming. While Sheffer and Adi [75] pursue image-guided audio generation. Despite these efforts, music generation conditioned on multiple modalities like text and image, is largely uncharted.

Images are more expressive [19] than text-only information and capture more fine-grained semantic information about various visual aspects. For example, as depicted in Fig 1, to generate a musical track that goes well with a given image, without indeed using it, one has to make the tedious effort of producing long, descriptive captions (either generated by an image captioning model or human annota-

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tors) before employing a typical text-to-music generation model. Moreover, the model has to be supplied with critical attributes like ‘*tranquil*’, ‘*aliveness*’ etc (highlighted in figure) to aptly capture the essence of the image. This poses a major bottleneck in the scalability of such systems especially for social media content creators and necessitates direct image conditioning with textual control in music generation.

Music is indeed different from generic audio. Music contains an arrangement of elements structured to form a coherent and complete entity. These musical elements include melody, harmony, rhythm, dynamics, and form [72, 80]. Unlike audio, music contains harmonies from different instruments forming intricate structures. Prior studies show [11, 17, 24, 60, 84, 91] that the human brain is extremely sensitive to disharmony. As a result, the margin of error especially in producing musical pieces is low compared to generic audio tracks. This makes music generation a harder task as the model should be equipped to control the fine-grained nuances of a composition involving melody, the interplay of the instruments, and genre.

An alternative to generating music would be to retrieve them. Retrieval-based systems [29, 55] struggle to ‘match’ the right track for a given input prompt thereby limiting their practical applicability in open-world scenarios primarily because (a) they tend to search from a pre-existing collection of tracks and (b) finding the correct association between the input prompt and the audio track can be challenging. The problem is inherently complex due to the multifaceted nature of music and the abstract associations between auditory experiences and other sensory modalities.

To overcome these shortcomings, we introduce the first music generation model that can be conditioned on image and text instruction. We observe that the features from a pre-trained text-to-image diffusion model that consumes the DDIM-inverted latent of the image can guide a text-to-audio diffusion model. Our key novelty is to facilitate this information exchange by incorporating a “visual synapse” to the text-to-music model, which includes a set of parameters that learn to combine the signals from both modalities.

We summarise our main contributions below:

(1) We formalize a novel task of generating music that is consistent with a reference image and an associated text prompt.

(2) We present MELFUSION, a novel diffusion model that can address this pragmatic task.

(3) We introduce MeLBench dataset comprising 11,250 \langle image, text, music \rangle triplets. To the best of our knowledge, this is the largest collection of these three modalities. Further, we extend the MusicCaps [1] dataset by supplementing the text, and music pairs with suitable images extracted from corresponding YouTube videos or the web.

(4) In order to quantitatively establish the correspon-

dence between the image-music pairs we propose a new metric IMSM. We demonstrate that the score follows human perception closely, through a user study.

(5) Finally, our exhaustive experimental results reveal that our approach outperforms existing text-to-music generation pipelines on both subjective as well as objective evaluation with a relative gain of up to **67.98%** on FAD score, thereby setting a new benchmark for multi-modal music synthesis.

2. Related Works

Music Generation Approaches: Music generation has garnered significant attention for a considerable amount of time. While some approaches [14, 58, 87] deploy GANs to tackle this task, Ycart et al. [89] introduced recurrent neural networks to model polyphonic music. Bassan et al. [4] proposed an unsupervised segmentation using ensemble temporal prediction errors. Jukebox [13] tackles the long context of raw audio using a multiscale VQ-VAE to compress it to discrete codes, modeling those using autoregressive Transformers. Another stream of work [20, 87] that predicts the MIDI notes to produce music has gained popularity in this space. However, the scope of these approaches is relatively limited as they need additional decoders to produce the musical pieces from the notations.

MusicLM [1] generates high-fidelity music from text descriptions by casting the process of conditional music generation as a hierarchical sequence-to-sequence modeling task. Mubert [57] is an API-based service that employs a Transformer backbone. The encoded prompt is used to match the music tags and the one with the highest similarity is used to query the audio generation API. MusicGen [9] comprises a single-stage transformer LM together with efficient token interleaving patterns. This eliminates the need for hierarchical upsampling. Despite significant progress, none of these approaches utilize the semantic information of images to condition the audio generation.

Diffusion Models for Music Generation: With the prolific success of diffusion models in conditional image generation, there have been recent efforts in music generation using them. Riffusion [18] base their algorithm on fine-tuning a stable diffusion model [67] on mel-spectrograms of music pieces from a paired music-text dataset. This is one of the first text-to-music generation methods. Moüsai [73] is a cascading two-stage latent diffusion model that is equipped to produce long-duration high-quality stereo music. Noise2Music [31] introduced a series of diffusion models, a generator, and a cascade model. The former generates an intermediate representation conditioned on text, while the latter can produce audio conditioned on the intermediate representation of the text. MeLoDy [46] pursues an LM-guided diffusion model by reducing the forward pass bottleneck and applies a novel dual-path diffusion mode. We

find that the visual guidance that is incorporated into our approach significantly enhances the music generation quality when compared to all these approaches. We elaborate this further in Sec. 4.4.

Diffusion Models for Audio Generation: Diffusion-based methods [32–34, 45, 47, 63] achieve remarkable results in speech synthesis too. FastDiff [32] deploys time-aware location-variable convolutions of diverse receptive field patterns to efficiently model long-term time dependencies with adaptive conditions. AudioLDM [48] is a text-to-audio system that is built on a latent space to learn continuous audio representations from contrastive language-audio pretraining (CLAP) embeddings. Ghosal et al. [23] simplifies the architecture of AudioLDM, and uses FLAN-T5 [8] as the text encoder. Another line of work [21, 86] involves text-conditional discrete diffusion models to generate discrete tokens as a representation for spectrograms. However, the quality of the sound produced by such methods leaves room for improvements in terms of both subjective and objective qualities, thereby limiting their practical usability. In contrast to these approaches, our method generates music samples conditioned on visual and textual signals.

3. Synthesizing Music from Image and Text

We propose to learn a conditional distribution $\mathcal{M}(\mathbf{w}|\mathbf{I}, \mathbf{Y})$, that can generate music waveforms \mathbf{w} from an image \mathbf{I} and a paired textual description \mathbf{Y} . We materialize \mathcal{M} as MEL-FUSION, a diffusion model that can succinctly interleave the semantic cues from the image and textual modality while generating acoustically pleasing music.

Fig. 2 provides an overview of our approach. On a high level, our novel methodology consists of two sub-components: 1) an approach to extract relevant visual information from the image conditioning \mathbf{I} and 2) a method to induce this conditioning into the text-to-music generative model, in a parameter efficient way. We describe each of these in the subsequent subsections.

3.1. Extracting Visual Guidance

Latent diffusion models (LDMs) for text-to-image generation [67] have had phenomenal success in generating high-quality images that are well-grounded in their textual conditioning. We hypothesize that the latent representations and their transformations encode rich semantic knowledge, that can guide our audio diffusion model. In our exploration, we make use of a pre-trained Stable Diffusion model [67]. It contains a VQ-VAE [81] for encoding and decoding the image to the latent space, a text encoder, and a UNet [68] that carries out the diffusion process on the latent. The UNet contains an encoder, a bottleneck layer, and a decoder. Each encoder and the decoder further contain a set of blocks with cross-attention layers, self-attention layers, and convolutional layers. Given any intermediate latent image feature

$\mathbf{f} \in \mathbb{R}^{(w \times h) \times d}$, a single self-attention [82] operation consist of $\mathbf{Q} = \mathbf{W}^q \mathbf{f}$, $\mathbf{K} = \mathbf{W}^k \mathbf{f}$, $\mathbf{V} = \mathbf{W}^v \mathbf{f}$:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}, \quad (1)$$

where d_k is the dimension of the query and key features. During cross-attention, the key and value matrices operate on the external text conditioning $\mathbf{c} \in \mathbb{R}^{s \times d_k}$: $\mathbf{K} = \mathbf{W}^k \mathbf{c}$, $\mathbf{V} = \mathbf{W}^v \mathbf{c}$. Here, \mathbf{W}^q , \mathbf{W}^k and \mathbf{W}^v are the attention weight matrices that transform either the image features or text conditions into the output of each block.

We want to transfer over the semantic information that is present within these attention layers corresponding to the image \mathbf{I} into the music LDM. For this, we first invert \mathbf{I} into the latent space using DDIM Inversion [77] to get \mathbf{z}_T^I . This will guarantee that we will be able to generate \mathbf{I} from \mathbf{z}_T^I . Next, we do the reverse diffusion steps using a pre-trained text-to-image LDM starting from \mathbf{z}_T^I and save the *self-attention features* $\mathbf{K} = \mathbf{W}^k \mathbf{f}$, $\mathbf{V} = \mathbf{W}^v \mathbf{f}$, to be injected into the music LDM. The intuition behind leveraging the self-attention features is that they control the feature transformations responsible for generating the visual semantics of the image. This is mathematically evident from Eq. (1). In the subsequent section, we elaborate on how we construct the “synapse” that can transfer the guidance information from \mathbf{I} to the music-diffusion model.

3.2. Text-to-Music LDM with Visual Synapse

Inspired by recent text-to-audio [23, 48] generation approaches, our text-to-music model is also formulated as a latent diffusion model. During training, the music waveform \mathbf{w} is first converted to a spectrogram $\mathbf{s} \in \mathbb{R}^{E \times F}$, which is a visual representation obtained via Fourier Transformation on \mathbf{w} . E and F denote the number of time slots and frequency slots respectively. Then we encode \mathbf{s} using Audio-VAE [48] to get a latent representation $\mathbf{z}_1^M \in \mathbb{R}^{C \times E/r \times F/r}$, where C is the number of channels and r is the compression level.

The forward diffusion process involves corrupting \mathbf{z}_1^M using a Markovian noise process q , which gradually adds noise to \mathbf{z}_1^M through \mathbf{z}_T^M over T steps with the following Gaussian function:

$$q(\mathbf{z}_t^M | \mathbf{z}_{t-1}^M) = \mathcal{N}(\mathbf{z}_t^M; \sqrt{1 - \beta_t} \mathbf{z}_{t-1}^M, \beta_t \mathbf{I}), \quad (2)$$

where β_t is a predetermined variance schedule. This iterative sampling process can be approximated by a deterministic non-Markovian process as follows [77]:

$$q(\mathbf{z}_t^M | \mathbf{z}_1^M) = \mathcal{N}(\mathbf{z}_t^M; \sqrt{\gamma_t} \mathbf{z}_1^M, (1 - \bar{\gamma}_t) \mathbf{I}) \quad (3)$$

$$= \sqrt{\gamma_t} \mathbf{z}_1^M + \epsilon \sqrt{(1 - \bar{\gamma}_t)}, \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \quad (4)$$

where $\gamma_t = 1 - \beta_t$ and $\bar{\gamma}_t = \prod_{r=0}^t \gamma_r$.

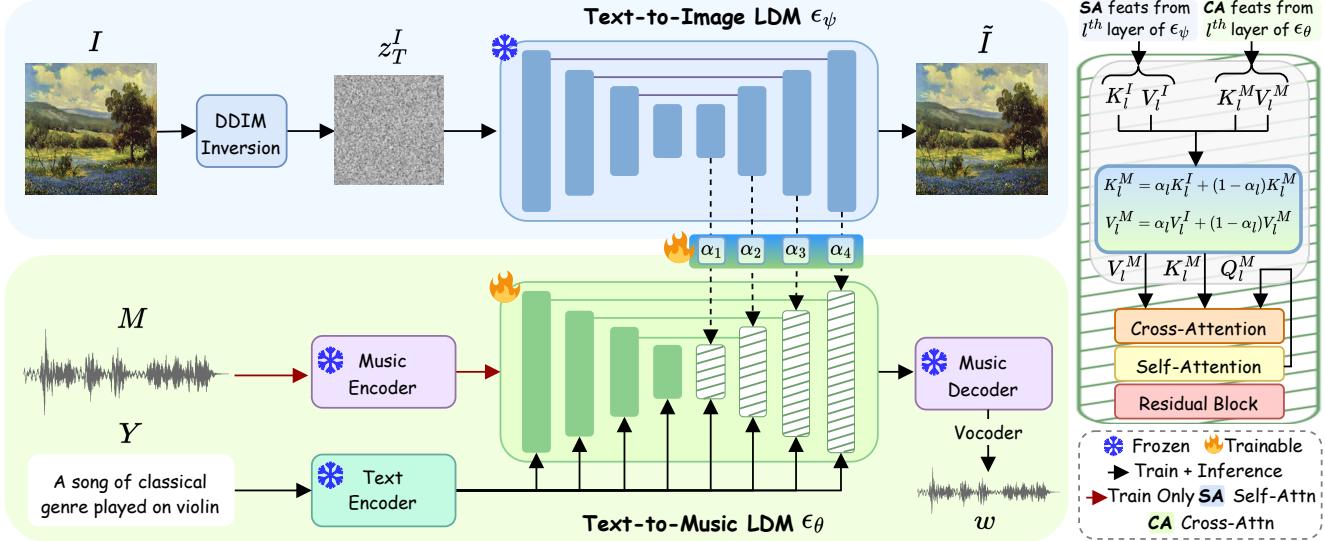


Figure 2. Our approach **MELFUSION** generates music waveform w conditioned on an image I and a given textual instruction Y . Visual semantics from I is instilled into a text-to-music diffusion model (bottom green box) using a pre-trained and frozen text-to-image diffusion model (top blue box). The image I is first DDIM inverted into a noisy latent z_T^I . The self-attention features from the decoder layers of the text-to-image LDM that consumes z_T^I are infused into the cross-attention features of text-to-music LDM decoder layers, modulated by learned α parameters. This fusion operation that happens in the decoder (green stripes) is detailed on the right side of the figure. The music encoder projects the spectrogram representation of the music to the latent space, and the music decoder retrieves back the spectrograms. Finally, a vocoder generates the waveform w from the spectrograms. Please refer to Sec. 3 for more details.

In the reverse diffusion process, an LDM $\epsilon_\theta(\cdot, \cdot, \cdot)$ (implemented as a UNet), learns to de-noise $z_T^M \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ to recover z_1^M . The architecture of the UNet is kept exactly similar to the text-to-image UNet described in Sec. 3.1. To incorporate the additional guidance from image conditioning the *cross-attention* key and value features K_l^M and V_l^M in each of the decoder layer l of the UNet is modified as follows:

$$K_l^M = \alpha_l K_l^I + (1 - \alpha_l) K_l^M \quad (5)$$

$$V_l^M = \alpha_l V_l^I + (1 - \alpha_l) V_l^M, \quad (6)$$

where K_l^I and V_l^I are the *self-attention* features for the corresponding layer l of the image conditioning LDM from Sec. 3.1. Most importantly, the convex combination between these features is modulated by *learned layer specific α parameters*. We find that this simple formulation elegantly incorporates the image guidance into the text-to-music diffusion model without hampering its expressivity. As the α parameters facilitate the information exchange between the text-to-audio and text-to-image diffusion models, analogous to how a synapse in a nervous system facilitates the transfer of electrical and chemical signals between neurons, we refer to this handshake as the *visual synapse of a text-to-music LDM*.

Finally, the parameters of the LDM θ and the α parameters are trained end-to-end with the following loss function:

Algorithm 1 MELFUSION: Training

Input: Image: I ; Text: Y ; Music: M ; Pre-trained Text-to-Image LDM: $\epsilon_\psi(\cdot, \cdot, \cdot)$; Image Encoder: $\mathcal{E}^I(\cdot)$; Music Encoder: $\mathcal{E}^M(\cdot)$; Text Encoder: $\mathcal{T}^M(\cdot)$; Text-to-Music LDM: $\epsilon_\theta(\cdot, \cdot, \cdot)$; Number of Diffusion Steps: T .

Output: Trained Text-to-Music LDM: $\epsilon_\theta(\cdot, \cdot, \cdot)$, Learned mixing coefficient α , for each decoder layer l of LDM: $\{\alpha_l\}$.

- 1: $z_T^I \leftarrow \text{DDIM_Invert}(\mathcal{E}^I(I))$ \triangleright Initialize Image Latent.
- 2: $\{\epsilon_1^M, \dots, \epsilon_T^M\} \leftarrow \text{Forward_Diffusion}(\mathcal{E}^M(M))$ \triangleright Targets.
- 3: $z_T^M \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ \triangleright Initialize Music Latent.
- 4: $c \leftarrow \mathcal{T}^M(Y)$ \triangleright Encoding Text.
- 5: **for** $t \in \{T, \dots, 1\}$ **do** \triangleright For each denoising step.
- 6: **for** each layer l in decoder of LDM **do**
- 7: $K_l^I, V_l^I \leftarrow \text{Self-attention features of } \epsilon_\psi(z_t^I, \emptyset, t)$.
- 8: $K_l^M, V_l^M \leftarrow \text{Cross-attention features of } \epsilon_\theta(z_t^M, c, t)$.
- 9: $K_l^M \leftarrow \alpha_l K_l^I + (1 - \alpha_l) K_l^M$ \triangleright Key update.
- 10: $V_l^M \leftarrow \alpha_l V_l^I + (1 - \alpha_l) V_l^M$ \triangleright Value update.
- 11: $\mathcal{L} \leftarrow \|\epsilon_t^M - \epsilon_\theta(z_t^M, c, t)\|^2$ \triangleright Eq. (7)
- 12: Optimize θ and all α parameters to reduce \mathcal{L} .
- 13: **return** $\epsilon_\theta(\cdot, \cdot, \cdot)$, $\{\alpha_l\}$.

$$\mathcal{L} = \mathbb{E}_{t \sim [1, T], z_1^M, \epsilon_t^M \sim \mathcal{N}(0, 1)} \|\epsilon_t^M - \epsilon_\theta(z_t^M, c, t)\|^2 \quad (7)$$

3.3. Overall Framework

We summarize the overall flow of MELFUSION during training in Algorithm 1. Our key novelty is to introduce a

Algorithm 2 MELFUSION: Sampling

Input: Image: \mathbf{I} ; Text: \mathbf{Y} ; Pre-trained Text-to-Image LDM: $\epsilon_\psi(\cdot, \cdot, \cdot)$; Image Encoder: $\mathcal{E}^I(\cdot)$; Text Encoder: $\mathcal{T}^M(\cdot)$; Trained Text-to-Music LDM: $\epsilon_\theta(\cdot, \cdot, \cdot)$; Learned mixing coefficient α , for each decoder layer l of LDM: $\{\alpha_l\}$; Number of Diffusion Steps: T ; Music Decoder: $\mathcal{D}^M(\cdot)$; Vocoder $\mathcal{V}(\cdot)$.

Output: Music Waveform: \mathbf{w}

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1:  $\mathbf{z}_T^I \leftarrow \text{DDIM\_Invert}(\mathcal{E}^I(\mathbf{I}))$             $\triangleright \text{Initialize Image Latent.}$ 
2:  $\mathbf{z}_T^M \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$                     $\triangleright \text{Initialize Music Latent.}$ 
3:  $\mathbf{c} \leftarrow \mathcal{T}^M(\mathbf{Y})$                           $\triangleright \text{Encoding Text.}$ 
4: for  $t \in \{T, \dots, 1\}$  do           $\triangleright \text{For each denoising step.}$ 
5:   for each layer  $l$  in decoder of LDM do
6:      $\mathbf{K}_l^I, \mathbf{V}_l^I \leftarrow \text{Self-attention features of } \epsilon_\psi(\mathbf{z}_t^I, \emptyset, t)$ .
7:      $\mathbf{K}_l^M, \mathbf{V}_l^M \leftarrow \text{Cross-attention features of } \epsilon_\theta(\mathbf{z}_t^M, \mathbf{c}, t)$ .
8:      $\mathbf{K}_l^M \leftarrow \alpha_l \mathbf{K}_l^I + (1 - \alpha_l) \mathbf{K}_l^M$             $\triangleright \text{Key update.}$ 
9:      $\mathbf{V}_l^M \leftarrow \alpha_l \mathbf{V}_l^I + (1 - \alpha_l) \mathbf{V}_l^M$             $\triangleright \text{Value update.}$ 
10:     $\mathbf{z}_t^M \leftarrow \mathbf{z}_t^M - \epsilon_\theta(\mathbf{z}_t^M, \mathbf{c}, t)$             $\triangleright \text{Reverse Diffusion Step.}$ 
11:     $\mathbf{s} \leftarrow \mathcal{D}^M(\mathbf{z}_0^M)$             $\triangleright \text{Generate Spectrograms.}$ 
12:     $\mathbf{w} \leftarrow \mathcal{V}(\mathbf{s})$             $\triangleright \text{Generate Waveform from Spectrograms.}$ 
13: return  $\mathbf{w}$ .

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channel through which we can guide the text-to-music diffusion model toward the semantic concepts contained in the corresponding image conditioning. This “synapse” is detailed in Line 7 to Line 10. The rest of the algorithm follows the standard LDM training flow.

During inference, we make use of the trained text-to-image and text-to-music diffusion models, along with the learned α parameters. As seen in Lines 8 and 9 in Algorithm 2, the cross-attention features of the text-to-music LDM decoder are updated to incorporate the visual conditioning in each denoising step. Once the denoising (Line 10) is complete, the latent representation is projected back into a spectrogram using the decoder of Audio VAE [48], and then the waveform is generated using HiFi-GAN vocoder [41] in Lines 11 and 12 respectively.

4. Experiments and Results

To complement our newly introduced problem setting which generates music conditioned on visual and textual modality, we introduce a new dataset, a new evaluation metric, and come up with a strong baseline by extending a state-of-the-art text-to-music method to consume image modality. We explain each of these in the subsequent sections.

4.1. Datasets

To the best of our knowledge, there is no publicly available dataset that contains the $\langle \text{Image}, \text{Text}, \text{Music} \rangle$ triplets that are required to train and evaluate MELFUSION. We collect a new dataset MeLBench, which contains 11,250 manually annotated triplets of $\langle \text{Image}, \text{Text}, \text{Music} \rangle$. Further, we extend the MusicCaps [1] dataset which contains $\langle \text{Text}, \text{Music} \rangle$ pairs by adding the corresponding image.

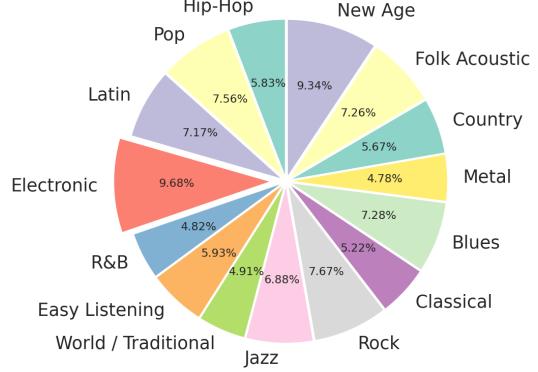


Figure 3. The distribution of different genres in MeLBench.

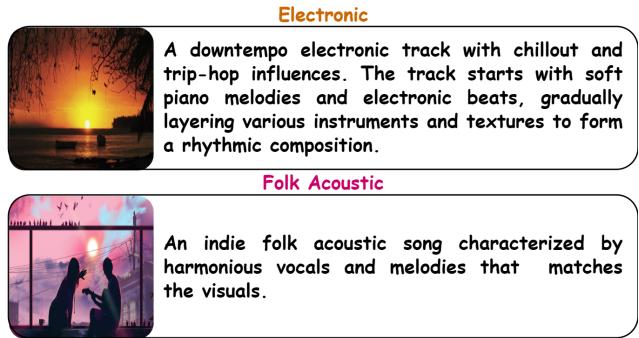


Figure 4. Some image and text pairs from MeLBench. We include more examples in the Appendix.

MeLBench: We hired 18 professional annotators to find 10-second snippets of YouTube videos corresponding to 15 predefined genres. The annotators are trained musicians with at least 5 years of practice. For each of these videos, they were asked to provide (a) a free-form text description for up to three sentences, expressing the composition and (b) any other music-related details such as describing the genre, mood, tempo, singer voices, instrumentation, dissonances, rhythm, etc. A carefully selected frame and music from the snippet along with text description from annotators forms $\langle \text{Image}, \text{Text}, \text{Music} \rangle$ triplets. We perform strict sanity checks to ensure the quality of these triplets in MeLBench. Fig. 4 shows some image and text samples from the dataset and Fig. 3 shows the distribution of different genres in MeLBench. Before annotating YouTube snippets (containing music-albums, art-performance, ensembles etc.), they were asked to check for complementary relevance between visuals and music. Further, we perform manual validation to filter lower-quality samples. We include more examples and more statistics of the dataset in the Appendix.

Extended MusicCaps: MusicCaps [1] is a subset of the AudioSet [22] dataset, which contains music and a corresponding textual description of the same. We carefully choose two images from the web or YouTube that can go

well with each datapoint in MusicCaps, thereby extending $\langle \text{Text}, \text{Music} \rangle$ pairs to $\langle \text{Image}, \text{Text}, \text{Music} \rangle$ triplets. We defer more details to the Appendix.

4.2. Evaluation Metrics

We use objective evaluation and human subjective evaluation metrics to measure the efficacy of MELFUSION.

4.2.1 Objective Evaluation: Following previous works [23, 44, 48], Fréchet Audio Distance (FAD), Fréchet Distance (FD) and KL Divergence scores are used for objective evaluation. FAD [44] is a perceptual metric that is adapted from Fréchet Inception Distance (FID) for the audio domain. It uses a VGG-like backbone [25] for feature extraction. FD is similar to FAD but uses PANNs [43] as the feature extractor. Unlike reference-based metrics, FAD and FD measure the distance between the generated audio distribution and the real audio distribution without using any reference audio samples. On the other hand, KL Divergence [44] is a reference-dependent metric that computes the divergence between the distributions of the original and generated audio samples based on the labels generated by a pre-trained classifier. While FAD is more related to human perception, KL Divergence captures the similarities between the original and generated audio signals based on broad concepts present in them.

FAD, FD, and KL Divergence score captures the ‘goodness’ of generated music, while it doesn’t measure whether the generated music is consistent with the image conditioning. We identify this as a gap and propose IMSM metric.

Image Music Similarity Metric (IMSM): CLIP score is one of the widely used metrics for measuring the similarity between an image and a corresponding textual description. N pairs of images and texts are passed through respective encoders (pre-trained using CLIP loss [64]) to obtain corresponding feature embeddings which are used to compute CLIP score matrix $\mathcal{A}_{\text{CLIP}} \in \mathbb{R}^{N \times N}$. In a very similar fashion, CLAP scores are computed amongst N audio-text pairs yielding CLAP score matrix $\mathcal{A}_{\text{CLAP}} \in \mathbb{R}^{N \times N}$ [16]. It is worth noting that in both the matrices the columns represent text modality. This motivates us to develop a metric IMSM, which is a measure of the perceptual similarity between given image-music pairs bridged by the text modality. In particular, we use CLIP image and text encoders which are contrastively aligned [64] to compute the image and text feature embeddings. As a second step, we leverage language as the bridging modality by freezing the CLIP text encoder and aligning the music (audio) encoder via contrastive training [16]. Finally, for $\langle \text{Image}, \text{Text}, \text{Music} \rangle$ pairs we obtain IMSM by suitably combining $\mathcal{A}_{\text{CLIP}}$ and $\mathcal{A}_{\text{CLAP}}$ using the given mathematical expression:

$$\mathcal{A}_{\text{IMSM}} = \mathcal{A}_{\text{CLIP}} \mathcal{A}_{\text{CLAP}}^T \quad (8)$$

4.2.2 Subjective Evaluation: Following earlier works in text-to-audio generation [23, 44, 48], we use overall audio quality (OVL) and relevance to image-text inputs (REL) to analyze the results of our subjective user study involving 75 participants. They were presented with 100 randomly generated samples from MELFUSION. Each of the metrics (OVL and REL) is a score between 1-100 with 1 being the lowest. For the OVL score, the users are asked to assign a score based on how perceptually realistic the generated audio is, while the REL score requires them to carefully examine the image and the text prompts before providing a rating based on their relevance with the generated music. We add more details of the user study in the Appendix.

4.3. Baseline Methods

We compare MELFUSION against strong baselines to test its mettle. To the best of our knowledge, there doesn’t exist a music diffusion model that is conditioned on visual and textual modality. Hence, we introduce two baselines: 1) caption the image with Instruct BLIP [10] and then pass it along with the caption to MusicLM [1]. We call this baseline **MusicLM + InstructBLIP**. 2) we adapt a recent text-to-audio diffusion model TANGO [23] into our setting, as explained next. We call its modified version TANGO++. Further, we compare ourselves with 7 other text-to-music approaches. We elaborate on them below:

TANGO++: TANGO [23] is a powerful text-to-audio model based on LDMs. They condition the diffusion model on text embeddings from FLAN-T5 [8] text encoder z_{text} . To facilitate joint conditioning from text and image I , we embed I to the latent space as z_{image} using a ViT [15] based CLIP encoder, and align them together through an Image-Text Contrastive loss. Once they are aligned, both the embeddings are fused and the LDM is jointly conditioned.

Text-to-Music Baselines: To bring out the utility of conditioning on both visual and textual modality, we compare MELFUSION with seven other text-to-music methods too: Riffusion [18], Mubert [57], MusicLM [1], Moûsai [73], Noise2Music [31], MeLoDy [46] and MusicGen [9]. We provide more details of each of these in the Appendix.

4.4. Results

We present exhaustive objective and subjective comparison of MELFUSION with the baseline approaches in Tab. 1. When compared with text-to-music approaches in the first section of the table, our results show the significant utility of adding extra visual conditioning on the generations. The fine-grained contextual information from visual modality is able to supplement the information from the corresponding text, thereby enhancing the quality of music generation. Further, MELFUSION is able to consistently outperform MusicLM + InstructBLIP and TANGO++ (which has

Model	Txt	Img	MusicCaps							MeLBench						
			Objective metrics				Subjective metrics		Objective metrics				Subjective metrics			
			FAD↓	KL↓	FD↓	IMSM↑	OVL↑	REL↑	FAD↓	KL↓	FD↓	IMSM↑	OVL↑	REL↑		
Riffusion [18]	✓	✗	13.40	1.19	-	-	79.48	75.60	14.06	1.42	32.64	-	80.11	76.26		
MuBERT [57]	✓	✗	9.60	1.58	-	-	77.59	77.93	-	-	-	-	-	-		
MusicLM [1]	✓	✗	4.00	1.01	-	-	81.51	82.65	3.62	0.93	23.44	-	83.86	84.27		
Mousai [73]	✓	✗	7.50	1.59	-	-	75.94	77.33	9.13	1.63	31.51	-	75.11	74.32		
Noise2Music [30]	✓	✗	2.13	-	-	-	81.13	79.88	-	-	-	-	-	-		
MeLoDy [46]	✓	✗	5.41	-	-	-	80.61	79.25	-	-	-	-	-	-		
MusicGen [9]	✓	✗	3.40	1.23	-	-	83.57	83.18	3.28	1.21	23.60	-	84.61	83.25		
MusicLM + InstructBLIP [10]	✓	✓	4.12	1.18	25.68	0.55	80.21	79.85	3.88	1.07	24.96	0.63	81.18	82.42		
TANGO++	✓	✓	3.05	1.17	23.91	0.68	84.62	83.96	2.93	1.14	22.16	0.71	85.52	84.81		
MELFUSION (Ours)	✓	✓	1.12	0.89	22.65	0.76	86.78	85.92	1.05	0.72	20.49	0.83	88.45	87.39		
$\Delta_{\text{MELFUSION-MusicGen}}$	-	-	+67.05%	+27.64%	-	-	+3.84%	+3.29%	+67.98%	+40.49%	+13.17%	-	+4.53%	+4.97%		

Table 1. Our proposed approach MELFUSION offers significant gains over state-of-the-art text-to-music methods (first section), and our adapted text-and-image conditioned baselines (second section) across multiple objective and subjective metrics on two datasets. IMSM is applicable only when the model is conditioned on visual modality. We skip comparison with MuBERT, Noise2Music, and MeLoDy on MeLBench dataset as their codebases are not public. Please refer to Sec. 4.4 for more details.

similar conditioning as ours). This highlights the efficacy of our visual synapse, which infuses the right amount of visual conditioning to enable the model to synthesize perceptually congruent music tracks. Captions from InstructBLIP are superfluous and vague when compared to expert-annotated, high-quality MusicCaps captions on which MusicLM is trained. This distributional shift leads to a performance drop as shown in the table. TANGO++ uses contrastive loss to align CLIP image features and FLAN-T5 text features, further, we use simple addition for joint conditioning – these design choices can be sub-optimal.

Our subjective human evaluation in Tab. 1 also suggests that conditioning the music generation on both visual and textual modality improves its perceptual quality.

5. Discussions and Analysis

5.1 Analyzing the Design Choice of α parameters: α parameters introduced in Eq. (6) controls how the self-attention features from the blocks within the text-to-image diffusion model interact with the cross-attention features from the text-to-music diffusion model. MELFUSION has one alpha parameter per block within the decoders of both diffusion models. We vary this design choice in Tab. 2. Attaching the synapse in the decoder offers better performance. This is because the decoder controls the major transformations that contribute to generating the image. Further, learning different α per block helps to learn block-specific mixing co-efficient, which slightly improves the performance.

We also perform a sensitivity analysis on the learning rate (LR) used while learning α parameters in Tab. 3. Based on this analysis, we use a LR of $1e-5$ in our experiments.

5.2 Efficacy of Conditioning on both Modalities: In order to study the contribution of each modality on MELFUSION, we train three different variations of the model by selectively turning off visual conditioning and textual con-

Encoder	Decoder	Extended MusicCaps			MeLBench		
		FAD↓	KL↓	FD↓	FAD↓	KL↓	FD↓
Same α for all blocks.							
✓	✗	3.22	1.23	24.01	2.01	1.01	21.96
✓	✓	2.71	1.13	23.31	1.27	0.87	21.04
✗	✓	2.79	1.14	23.44	1.29	0.87	21.13
Different α for each block.							
✓	✗	2.03	1.10	23.36	1.92	0.93	21.28
✓	✓	1.13	0.94	22.81	1.07	0.76	20.53
✗	✓	1.12	0.89	22.65	1.05	0.72	20.49

Table 2. We systematically analyze our design choice of learnable α parameters. We vary the position of the synapse: encoder or decoder and also study whether we need the same or different α parameters for each block within them.

Learning Rate	Extended MusicCaps			MeLBench		
	FAD↓	KL↓	FD↓	FAD↓	KL↓	FD↓
0.5e-6	3.12	1.21	23.26	2.01	1.14	21.95
0.5e-4	1.38	0.95	22.81	1.39	0.88	20.86
1e-6	2.56	1.17	23.11	1.86	1.10	21.71
1e-5	1.12	0.89	22.65	1.05	0.72	20.49

Table 3. Sensitivity analysis on the learning rate for α parameters.

Text	Image	Extended MusicCaps			MeLBench		
		FAD↓	KL↓	IMSM↑	FAD↓	KL↓	IMSM↑
✓	✗	3.07	1.21	-	3.11	1.19	-
✗	✓	5.62	1.54	-	4.16	1.37	-
✓	✓	1.12	0.89	0.76	1.05	0.72	0.83

Table 4. Conditioning independently on each of the modalities leads to inferior music generation performance in this experiment.

ditioning. We report the results in Tab. 4. We see significant improvement when conditioning on both modalities. This highlights how complementary semantic information from each modality can compose better music.

5.3 Sensitivity Analysis: Tab. 5 reports the sensitivity analysis of changing the number of denoising steps T and the

Guidance	Varying Steps				Varying Guidance				
	Steps	FAD \downarrow	KL \downarrow	FD \downarrow	Steps	Guidance	FAD \downarrow	KL \downarrow	FD \downarrow
7	50	2.59	1.97	27.45	400	2	1.47	1.13	24.64
	200	1.35	1.12	25.22		7	1.12	0.89	22.65
	400	1.12	0.89	22.65		20	1.51	1.18	24.92
	600	1.09	0.88	22.57		30	1.63	1.29	25.38
	800	1.07	0.77	22.48		50	1.58	1.34	24.87

Table 5. Sensitivity analysis on the number of denoising steps T , and the strength of classifier-free guidance.

Text prompt length (in words)	Image	Objective metrics			Subjective metrics	
		FAD \downarrow	KL \downarrow	FD \downarrow	OVL \uparrow	REL \uparrow
$\geq 8 \leq 13$	\times	5.28	1.35	25.81	82.86	82.54
$\geq 14 \leq 19$	\times	3.13	1.20	23.11	85.25	85.16
≥ 20	\times	3.02	1.19	22.65	86.04	85.96
≤ 7	\checkmark	1.86	0.87	21.36	87.13	86.21

Table 6. Performance of MELFUSION with varying verbosity of text prompts collected from MeLBench.

strength of classifier-free guidance during inference. Similar to the findings from Ghosal et al. [23], increasing T helps to generate more pleasing music. This can be attributed to enhanced refinement from more denoising. CFG strength of 7 gives the best result, and we use it in our experiments.

5.4 Verbose Text versus Image Conditioning: The visual synapse infuses fine-grained semantics from the image into text-to-music diffusion models. Another alternative to infuse such semantics would be to use verbose text descriptions. To study this, we remove the visual synapse from MELFUSION and train a music generation model conditioned only on text. Then, we vary the length of text prompts and report results in Tab. 6. Interestingly, we find that using image conditioning with a small text prompt outperforms using lengthier prompts. This underscores the utility of visual conditioning and the ability of visual synapses to modulate the LDM effectively.

5.5 Effect of visual-cues: We analyse the effect of using a different image and the same text prompt (please refer to the project page). When we change from the walkway image to the blue forest, the music becomes more calm and distant. We change the image to an abandoned amusement park, carnival orchestra, foggy seaside concert and forest at night. We observe a prevalence of eerie ambient sound echoing through the deserted park, occasional circus-inspired motifs, distant sounds of waves and foghorn-like effects and atmospheric strings imitating rustling leaves respectively.

5.6 Comparison with Text-to-Audio Methods: We include a comparison of MELFUSION with text-to-audio generation approaches in Tab. 7. We finetune their pre-trained checkpoints on our benchmark datasets for this experiment. The complementary information from both modalities allows our approach to outperform these methods too.

5.7 Effectiveness of IMSM: We conduct a user study with 64 participants to check whether the proposed IMSM metric is indeed capturing the relatedness between generated mu-

Method	MusicCaps			MeLBench		
	FAD \downarrow	KL \downarrow	FD \downarrow	FAD \downarrow	KL \downarrow	FD \downarrow
AudioLDM [48]	2.29	1.29	24.07	1.86	1.42	22.49
TANGO [23]	1.96	1.17	23.31	1.93	1.18	21.92
MELFUSION	1.12	0.89	22.65	1.05	0.72	20.49

Table 7. While comparing MELFUSION with state-of-the-art text-to-audio approaches, we see significant improvement in quality.

sic and the conditioning image. We randomly choose 300 samples from Extended MusicCaps and MeLBench each. We compute the IMSM score, and also ask users for their image-music similarity on a scale of [0,1], for these samples. The average score from IMSM metric and the users for Extended MusicCaps and MeLBench are (0.76, 0.71) and (0.83, 0.85) respectively. The high correlation underscores the validity and usefulness of IMSM metric.

5.8 Using IMSM to Measure Purity of the Datasets: We compute the IMSM scores for all image-music pairs present in both Extended MusicCaps and MeLBench datasets and obtain a score of 0.91 and 0.93 respectively. The purpose of this is to quantitatively establish that the curated samples are perceptually in sync and are meaningful. The high values of the IMSM scores demonstrate that the curated image samples are highly perceptually similar and have ample association with the musical compositions.

6. Conclusion and Future Works

We explore the utility of infusing image semantics into a text-to-music diffusion model, enabling us to generate music, consistent with both visual and textual semantics in this work. To the best of our knowledge, ours is the first effort towards such a multi-conditioned music generation. We develop MELFUSION with a novel “visual synapse” to effectively infuse the image semantics into music generation, introduce a new dataset MeLBench, and propose a new evaluation metric. We conduct exhaustive experimental analysis on MeLBench and a modified version of MusicCaps [1] and compare MELFUSION against 7 text-to-music methods, and a modified baseline. The results suggest: 1) the extra information from the image conditioning significantly boosts music generation quality 2) our “visual synapse” is effective in modulating and infusing the required semantic information into the generative process.

MELFUSION can be an essential tool for a creative professional or a social-media content creator who needs to generate music that can go well with their multi-modal post (consider a user posting about their recent picnic – their photos can be the image conditioning while a short description of the trip can be the textual input to MELFUSION). Creating music with semantic lyrics that can go well with a video can be some interesting open-ended follow-up works.

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Appendix

In this appendix we provide additional information on the following:

- A** More Details on TANGO++
- B** Problem Motivation Revisited
- C** Other Baseline Approaches
- D** Implementation Details
- E** More Experimental Analysis
- F** Dataset Details
- G** User Study Details
- H** Inspiration from Conditional Image Generation
- I** Related Audio Concepts

A. More Details on TANGO++

Our modified baseline model TANGO++ comprises an early-fusion approach, where we align the visual and the textual modalities through an Image-Text Contrastive (ITC) loss. As the generated music is conditioned on both modalities, bringing them to a common latent space is imperative to the success of the system. The text input is passed through the FLAN-T5 text encoder which we keep as frozen. For image encoding we use ViT [15]. We project the visual and the textual inputs to a common embedding space and align them using ITC loss. The diffusion model is conditioned on this hybrid embedding to produce audio signals. It is then converted into spectrograms using the decoder and then passed through a HiFi GAN vocoder to produce the music signal. The expression for ITC loss (\mathcal{L}_{ITC}) is as follows:

$$\begin{aligned} \mathcal{L}_{\text{ITC}} = & -\frac{1}{2N} \sum_{j=1}^N \log \left[\underbrace{\frac{\exp(\langle z_j^I, z_j^T \rangle / \tau)}{\sum_{l=1}^N \exp(\langle z_j^I, z_l^T \rangle / \tau)}}_{\text{Contrasting images with the texts}} \right] \\ & -\frac{1}{2N} \sum_{l=1}^N \log \left[\underbrace{\frac{\exp(\langle z_l^I, z_l^T \rangle / \tau)}{\sum_{j=1}^N \exp(\langle z_j^I, z_l^T \rangle / \tau)}}_{\text{Contrasting texts with the images}} \right] \quad (9) \end{aligned}$$

where $\langle \cdot, \cdot \rangle$ denotes inner product, and τ is the temperature parameter. z^I and z^T refer to the image and text latent representations respectively.

B. Problem Motivation Revisited



Figure 5. A mock-up of a social media post that contains an image and associated textual content. Our approach MELFUSION, can consume such image-textual pairs as input and synthesize music that can go well with them.

Social media platforms have become ubiquitous and provide a channel for everyone to express their creativity and share their happenings with the world. It is very common for users to upload an image, and write an associated text with it (Fig. 5). Adding music to these social media posts enhances its visibility and appeal. Instead of retrieving music from an existing database, our approach MELFUSION, will be able to generate music tracks that are custom-made, conditioned on the uploaded image and its description. We note that ours is the first approach that operates in this pragmatic setting, to generate music conditioned on both visual and textual modality.

C. Other Baseline Approaches

In addition to our proposed baseline approach, we compare MELFUSION against the following methods. Note that these are text-to-music generation methods unlike our approach and don't support multi-conditioning in input prompts. Hence a direct comparison might not be entirely fair. In most cases these methods don't support introducing an additional modality conditioning as a result we compare our approach against these baselines directly to study the

benefits of MELFUSION.

Riffusion [18] base their algorithm on fine-tuning a Stable Diffusion model [67] on mel spectrograms of music pieces from a paired music-text dataset. This is one of the first text-to-music generation methods. Mubert [57] is an API-based service that employs a Transformer backbone. The encoded prompt is used to match the music tags and the one with the highest similarity is used to query the audio generation API. It operates over a relatively smaller set as it produces a combination of audio from a predefined collection. MusicLM [1] generates high-fidelity music from text descriptions by casting the process of conditional music generation as a hierarchical sequence-to-sequence modeling task. They leverage the audio-embedding network of MuLan [29] to extract the representation of the target audio sequence. Moūsai [73] is a cascading two-stage latent diffusion model that is equipped to produce long-duration high-quality stereo music. It achieves this by employing a specially designed U-Net facilitating a high compression rate. Noise2Music [31] introduced a series of diffusion models, a generator, and a cascader model. The former generates an intermediate representation conditioned on text, while the later can produce audio conditioned on the intermediate representation of the text. MeLoDy [46] pursues an LM-guided diffusion model by reducing the forward pass bottleneck and applies a novel dual-path diffusion mode. MusicGen [9] comprises a single-stage transformer LM together with efficient token interleaving patterns. This eliminates the need for hierarchical upsampling.

D. Implementation Details

Our text-to-music LDM contains 3 encoder blocks and 3 decoder blocks, similar to Ghosal et al. [23]. Empirically we find that finetuning from its pre-trained checkpoint helps convergence. FLAN-T5 [8] is used as the text encoder. MELFUSION is trained for 30 epochs using AdamW optimizer [54]. We attach our visual synapse only on the decoder layers of the LDM. Similar to earlier works [23, 48], we find that using classifier-free guidance improves the result. Our training takes 42 hours on 4 NVIDIA A100 GPUs.

E. More Experimental Analysis

E.1. Choice of Text-to-Image Diffusion Model

Model	MusicCaps			MeLBench		
	FD ↓	KL ↓	FAD ↓	FD ↓	KL ↓	FAD ↓
Stable Diffusion V1.2	1.84	1.52	22.88	1.49	1.14	21.44
Stable Diffusion V1.3	1.62	1.29	22.72	1.34	1.03	21.02
Stable Diffusion V1.4	1.31	1.13	22.67	1.20	0.91	20.53
Stable DiffusionV1.5	1.12	0.89	22.65	1.05	0.72	20.49

Table 8. MELFUSION with different versions of Stable Diffusion.

We study the effect of employing different variants of the text-to-image Stable Diffusion model (V1.2 through V1.5) in Tab. 8. We note that the best results are obtained with the latest variant. This brings to light that our proposed visual synapse is able to cascade the usage of better text-to-image models into improving the quality of music generation. The Stable Diffusion V1.4 and V1.5 checkpoints were initialized with the weights of the Stable Diffusion V1.2 checkpoint and subsequently fine-tuned on 225k steps at resolution 512×512 on the LAION dataset and 10% dropping of the text-conditioning to improve classifier-free guidance sampling.

E.2. Performance with Different Text Encoders

Model	MusicCaps			MeLBench		
	FAD ↓	KL ↓	FD ↓	FAD ↓	KL ↓	FD ↓
BERT [12]	2.82	2.23	24.73	2.91	1.94	22.13
RoBERTa [52]	2.35	2.02	24.09	2.17	1.87	21.95
T5-Small [65]	1.98	1.79	23.68	1.89	1.66	21.23
T0 [71]	1.42	1.25	22.96	1.32	1.19	20.76
CLIPText	1.24	0.94	22.78	1.16	0.91	20.58
FLAN-T5 [8]	1.12	0.89	22.65	1.05	0.72	20.49

Table 9. Performance of MELFUSION with different text encoders

In Tab. 9 we compare the performance of MELFUSION under different text encoders. We note that the best results are achieved when an instruction-tuned text encoder is employed (FLAN-T5 [8]) over other non-instruction-based models, which correlates with the findings in Ghosal et al. [23]. This is very closely followed by the ClipText [64] encoder.

E.3. Variation Across Genres

Genre name	Objective metrics				Subjective metrics	
	FD ↓	KL ↓	FAD _{VGG} ↓	IMSM ↑	OVL ↑	REL ↑
Pop	22.47	0.78	1.21	0.95	86.31	90.10
Rock	21.11	0.95	0.85	0.81	88.41	84.92
Hip-Hop/Rap	19.73	0.65	1.24	0.69	83.05	88.78
Electronic Dance Music	20.03	1.06	0.93	0.72	85.39	86.18
Country	19.56	0.89	0.88	0.98	89.94	87.22

Table 10. A study on the diversity analysis of MELFUSION. We evaluate the performance of our model on generating musical tracks of five different genres on MeLBench.

Tab 10 reports the performance of MELFUSION across the 5 most popular genres (chosen through a study undertaken by [28]) on the genre-wise test set collected from MeLBench. We find a steady performance of our approach across different genres substantiating the ability of the model to capture the musical nuances like the composition of the instruments, track progression, sequence of instruments introduced, rhythm, tonality, tempo, and beats.

Due to the highly subjective nature of the problem, we also perform a human evaluation by subject matter experts. To this end, we employ 7 individuals formally trained in music to independently listen and report OVL and REL scores considering the aforementioned aspects to assess the quality of genre-wise samples. We report the mean OVL and REL values from all the evaluators on a subset of the corresponding genre-wise test splits. We find that the overall performance of our method is highly encouraging as reported in Tab 10.

E.4. Ablating choice of layers

When we fuse subset of Decoder Blocks, we see drop in performance in Tab. 11, as coupling becomes weak. We also ablate encoder and decoder layer separately (refer to Tab. 2 of main paper). Learned α values for each blocks (0.37, 0.59 and 0.63 respectively) improves over $\alpha=0.5$ on all metrics, thus avoiding an extra hyper-parameter to tune. With a few layers to account for dimension mismatch, visual synapse can scale to different architectures and avoid layer-to-layer correspondence. We will explore this in a future work.

Decoder Block	Extended MusicCaps			MeLBench		
	FAD ↓	KL ↓	FD ↓	FAD ↓	KL ↓	FD ↓
1	1.79	1.12	22.97	1.71	1.02	21.20
1,2	1.53	1.05	22.76	1.27	0.86	20.93
1,2,3	1.12	0.89	22.65	1.05	0.72	20.49

Table 11. Ablation of different decoder blocks

E.5. On conditioning image

MELFUSION generates music from complementary information from text and image modalities. While selecting images randomly, we have lower FAD/KL/FD scores of 6.38/1.73/26.45 and 8.33/1.57/28.64 on the extended MusicCaps and MeLBench datasets respectively, as it gets conditioned on random image semantics. We see similar trend in the baselines too, and MELFUSION still outperforms them. Retrieving or generating image from conditioning text, will also have similar effect due to semantic similarity in both conditioning domains.

E.6. Alternate visual conditioning

We compare alternate conditioning from ViT features and ControlNet here. The semantics contained in these representations are inferior to those from text-to-image models (similar to findings in [88]). Further, our visual synapse effectively adapts them by learning to modulate the representations, specific to music synthesis. Moreover compared to the generalist model (that consumes multiple modalities) in AudioLDM2 [49], our specialist synaptic model gener-

OVL Range	Reasons
0-25	Discordant sound, unpleasant, poor quality, mismatched genre, not cohesive, repetitive melody, distractive background noise, unpleasant timbre, lack of contrast.
26-50	Unappealing instrumentation, lack of emotional resonance, unusual degree of dissonance, complex narrative, unrelated theme, abrupt transition, unbalanced sound levels.
51-75	Inconsistent mood, uninteresting chord progression, uneven transition between sections, has a nostalgic appeal, cinematic quality, spirituality.
76-100	Exudes calmness, cohesive, pleasing sequence of notes, well balanced combinations, engaging rhythmic pattern, evoke a sense of groove, nice arrangement of instruments, strong sense of expression, authentic, vibrant texture, catchy, intuitive and natural flow.

Table 13. Subjective analysis on generated samples

ates better music. Also, their feature concatenation strategy is inferior to our visual synapse, as evident from Tab. 12.

Model	Extended MusicCaps			MeLBench		
	FAD ↓	KL ↓	FD ↓	FAD ↓	KL ↓	FD ↓
CLIP ViT Feats [64]	1.83	1.15	23.03	1.77	1.04	21.48
Control Net [92]	1.65	1.09	22.94	1.25	0.85	20.91
AudioLDM2 [49]	1.77	1.13	22.96	1.74	1.02	21.42
Ours	1.12	0.89	22.65	1.05	0.72	20.49

Table 12. Comparison against different visual conditioning

E.7. Subjective analysis

We complement our OVL scores with subjective descriptions, where we ask the evaluators to justify the score, stratify them based on OVL scores, and report the most frequent reasons in Tab. 13.

E.8. Learnable versus Fixed α Parameters

Fusion parameter α	Extended MusicCaps			MeLBench		
	FAD ↓	KL ↓	IMSM ↑	FAD ↓	KL ↓	IMSM ↑
$\alpha = 0$	3.07	1.21	-	3.11	1.19	-
$\alpha = 0.10$	2.98	1.17	0.51	3.03	1.07	0.56
$\alpha = 0.50$	1.17	0.93	0.71	1.12	0.79	0.77
$\alpha = 0.90$	4.96	1.38	0.85	4.11	1.29	0.89
$\alpha = 1.0$	5.62	1.54	-	4.16	1.37	-
Learnable α	1.12	0.89	0.76	1.05	0.72	0.83

Table 14. Analyzing the effect of having fixed versus learnable α .

We study the impact when α is kept frozen as compared to being learnable here. The first five entries in Tab. 14 denote the cases where the value of α is unaltered during training and kept constant at 0, 0.10, 0.50, 0.90, and 1.0 respectively. Experimental results demonstrate that a learnable value of α produces significantly better results as compared to the fixed counterpart, as the model has the flexibility to learn them to effectively balance between both the conditioning modalities.

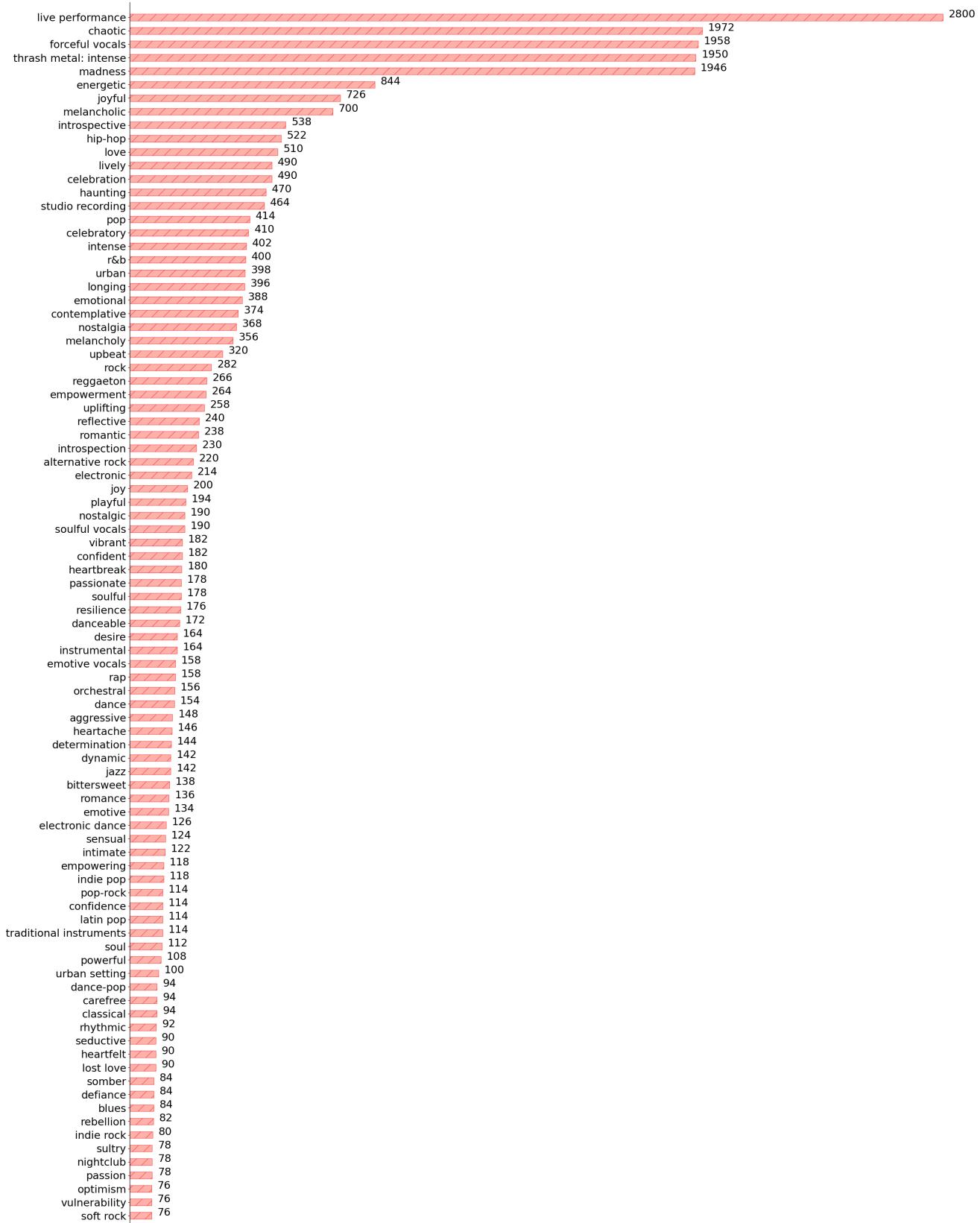


Figure 6. Frequency of top 90 words from MeLBench

New-Age



The track falls within the alternative hip-hop and pop genres. It incorporates electronic beats, synthesizers, and rap-style vocals, creating a contemplative yet catchy composition.

Classical



The baroque composition is executed by a string orchestra, the instruments involved include violins, violas, cellos, and a double bass.

Latin



The track is nestled within the Latin Trap genre. Electronic beats and synthesizers form the backbone of the composition, initiating a rhythmic and engaging melody.

R & B



The track embodies the essence of Indie R&B/Soul, weaving soulful vocals and gentle guitar melodies. The composition contains a background chorus enhancing the emotional depth of the song.

Easy-Listening



The composition features acoustic guitar chords as the foundational instrument, accompanied by soft, melodic strings or subtle orchestration. The composition begins with a gentle guitar introduction and gradually builds as additional instruments are layered in. The track belongs to the chanson genre.

Metal



The track fits into the post-grunge and alternative metal genres. Its composition follows a sequence of instruments, typically kicking off with heavy electric guitars and aggressive, anguished vocals, creating a powerful and emotionally charged atmosphere. As the song progresses, this intensity remains, with drums and bass joining in to maintain the heavy and relentless sound. The vocals are delivered with a raspy and aggressive tone.

Rock



The music track falls under the rock and roll genre and prominently features instruments like electric guitar, bass, drums, and keyboards, with a driving rhythm that propels the composition forward. The vocals are delivered with a confident and energetic tone, fitting the overall spirited nature of the song.

Jazz



The track falls under the traditional jazz genre. It features a harmonious blend of traditional jazz instruments like trumpet, saxophone, piano, and double bass, creating a melodious and timeless musical composition.

World-Traditional



The music track belongs to the world-traditional genre. It features acoustic instruments such as the acoustic guitar, accordion, and a string instrument being introduced in a distinct sequence, creating a haunting and memorable melody.

Hip-Hop



The instrumentation features a mix of electronic beats, piano chords, and smooth vocal delivery, creating a laid-back and introspective composition with subtle chattering noises in the background.

Pop



The song can be classified as a country-rock or country-pop-rock song. It prominently features electric guitars, drums, and horns in a sequence that creates an upbeat and energetic composition.

Blues



The track features powerful electric guitars, drums, bass, keyboards, and possibly horns, creating an emotive and intense musical composition. The vocals are emotive and soulful, conveying determination and strength, resonating with the song's themes of struggle and resilience. The track belongs to blues rock genre.

Country



The track is a country ballad composed of acoustic guitar, pedal steel guitar, and a rhythm section, arranged to form a mournful and wistful composition.

Figure 7. Samples from MeLBench.

Genre	Subgenre
Hip-Hop	Alternative Hip Hop, Rap, Pop Rap, Trap, Melodic Rap, Gangster Rap, Southern Hip Hop, Urban Contemporary, Crunk, German Hip Hop, Rap Conscient, Italian Hip Hop, East Coast Hip Hop, Hardcore Hip Hop, Alt Hip Hop, Dirty South Rap, Russian Hip Hop, Polish Trap, Underground Hip Hop, Funk Carioca, West Coast Rap, Cloud Rap
Pop	Dance Pop, Pov- Indie, Singer-Songwriter Pop, Mexican Pop, J-Pop, Latin Arena Pop, Indie Pop, Modern Country Pop, Art Pop, Alt Z, Indietronica, New Wave Pop, Spanish Pop, Italian Adult Pop, Electropop, Turkish Pop, Reggae Fusion, Post-Teen Pop, Hip Pop, Ccm, Indonesian Pop, Pop Nacional
Latin	Latin Pop, Trap Latino, Urbano Latino, Reggaeton, Musica Mexicana, Rock En Espanol, Norteno, Sierreno,R&B Francais, Reggaeton Colombiano, Sad Sierreno, Mp, Sertanejo, Tropical, Latin Alternative, Banda, Corrido, Grupera, Ranchera, Trap Brasileiro, Rap Conciencia, Urbano Espanol
Electronic	Edm, Pop Dance, Uk Dance, Electronica, Electro House, House, German Dance, Tropical House, Downtempo, Brostep, Stutter House, Progressive House, Slap House, Big Room, Chill House, New French Touch, Dancefloor Dnb, Chillhop, Pop Edm, Lo-Fi Beats, Trance, Metropolis
R&B	Soul, Indie Soul, Quiet Storm, Neo Soul, Funk, Alternative R&B, Disco, Pop Soul, Afrobeats, Bedroom R&B, Dark R&B, Reggae, British Soul, Contemporary R&B, Hi-Nrg, Classic Soul, Uk Contemporary R&B, Motown, New Jack Swing, Gospel, Roots Reggae, Philly Soul
Easy listening	Adult Standards, Chanson, Soundtrack, Show Tunes, Hollywood, Movie Tunes, Cartoon, Japanese Soundtrack, Broadway, Deutscher Disney, Swing, British Soundtrack, Lounge, Preschool Children's Music, Scorecore, Romantico, Classic Girl Group, Children's Music, Electro Swing, French Soundtrack, French Movie Tunes, Classic Soundtrack
World / traditional	Folkmusik, Modern Bollywood, Filmi, Pop Urbane, World, Afroswing, Dancehall, World Worship, Entehno, Sufi, Naija Worship, Classic Bollywood, Nouvelle Chanson Francaise, Modern Reggae, Laiko, Classic Oppn, UK Dancehall, South African Pop Dance, Chutney, Celtic, Manila Sound, Azontobeats
Jazz	Vocal Jazz, Bossa Nova, Dinner Jazz, Contemporary Post-Bop, Jazz Fusion, Nu Jazz, Background Jazz, Smooth Jazz, Jazz Funk, Contemporary Vocal Jazz, Jazz Piano, Jazztronica, Hard Bop, Smooth Saxophone, Cool Jazz, Nz Reggae, Soul Jazz, Torch Song, Folore Salento, Indie Jazz, Contemporary Jazz, Brazilian Jazz
Rock	Permanent Wave, Modern Rock, Classic Rock, Mellow Gold, Album Rock, Soft Rock, Pop Rock, Alternative Rock, Hard Rock, Folk Rock, New Wave, New Romantic, Indie Rock, Heartland Rock, Latin Rock, Art Rock, Blues Rock, Dance Rock, Country Rock, Alternative Dance, Pop Punk, Punk
Classical	Orchestral Soundtrack, Compositional Ambient, Classical Performance, Javanese Dangdut, Italian orchestra, Orchestral Performance, Neo-Classical, Orchestra, Classical Piano, British Orchestra, Choral Opera, Indian Classical, Hungarian Classical, Epicore, Impressionism, Chamber Orchestra, Historically Informed Performance, Violin, Baroque Ensemble, Symphonicky Orchestra, Japanese Guitar
Blues	Electric Blues, Jazz Blues, British Blues, Modern Blues, Malian Blues, Rebel Blues, Acoustic Blues, Rhythm And Blues, Doo-Wop, Traditional Blues, Soul Blues, Louisiana Blues, Garage Rock Revival, Indie Quebecois, New Orleans Blues, Texas Blues, Country Blues, Australian Garage Punk, Chicago Blues, Delta Blues, Memphis Blues, Slack-Key Guitar
Metal	Alternative Metal, Post-Grunge, Nu Metal, Rap Metal, Groove Metal, Power Metal, Melodic Metalcore, Metalcore, Skate Punk, Glam Metal, Thrash Metal, Speed Metal, Death Metal, Funk Metal, Screamo, Nerdcore Brasileiro, Industrial Metal, Comic Metal, Symphonic Metal, Deathcore, Gothic Metal, Progressive Metal
Country	Contemporary Country, Agronejo, Arrocha, Country Road, Sertanejo Universitario, Outlaw Country, Nashville Sound, Pop Rap Brasileiro, Pagode Novo, Arrochadeira, Forro, Forro De Favela, Funk 150 Bpm, Progressive Bluegrass, Black Americana, Axe, Bandinhos, Funk Ostentacao, Alternative Country, Piseiro, Jam Band, Classic Texas Country
Folk/ acoustic	Singer-Songwriter, Neo Mellow, Indie Folk, New Americana, Stomp And Holler, British Singer-Songwriter, Melancholia, Lilith, Turbo Folk, Countrygaze, Neo-Psychedelic, Pop Folk, Turkish Folk, Ambient Folk, Modern Indie Folk, Rune Folk, Indian Folk, Fantasy, Alternative Americana, Ska Punk, Vbs, German Indie
New age	Rain, Color Noise, Sleep, Sound, Healing Hz, Solfeggio Product, Indie Game Soundtrack, Ocean, Environmental, Water, Piano Cover, Acoustic Guitar Cover, Lullaby, High Vibe, Instrumental Worship, Atmosphere, Background Music, Ambient Worship, Binaural, Brain Waves, Background Piano, Fourth World

Table 15. Genre and sub-genre-wise division of the collected samples. Our dataset encompasses samples from 15 different genres each further divided into 22 sub-genres

F. Dataset Details

F.1. MeLBench Statistics

Type of image	# Pieces	Percentage (%) in Dataset
Natural image	3206	28
Animation	2404	21
Poster	2748	24
Painting / Sketch	3092	27

Table 16. Image categories in MeLBench.

Tab. 16 presents the distribution of the image samples in MeLBench. To maintain a fair balance across different distributions we collect samples from 4 different categories: natural images, animations, posters, paintings/sketches. This ensures that MELFUSION is trained with ample examples from each of these classes and is equipped to tackle images from any of these very frequent and popular classes better. MeLBench comprises 11,250 samples which is $\sim 2x$ larger than the next largest dataset MusicCaps [1].

Fig. 6 presents the frequency of the top 90 words in MeLBench. The annotators were asked to write free-form text descriptions of the musical pieces with an emphasis on the musicality of the samples. We observe that the annotation contains important cues about the nature of the audio track (e.g., ‘live performance’, ‘chaotic’, ‘forceful vocals’, etc). These can supplement a model with useful pieces of information regarding the aesthetics of the composition.

Table 15 contains the genre and sub-genre-wise division of the samples collected in MeLBench. We categorise the collected musical samples into 15 broad categories with each of them having 22 sub-genres to facilitate fine-grained control over the composition through the image (theme) and text-instructions (details on musicality). The samples are divided across different genres roughly equally to maintain a good balance.

Fig. 7 presents one sample from each of the remaining 13 categories (Electronic and Folk Acoustic present in the main paper). As can be seen from the examples, the captions are of varied lengths and the images are from different distributions (natural images, animation, paintings, etc.).

F.3. Extended MusicCaps Data Collection

MusicCaps [1] is a music caption dataset comprising music clips from AudioSet [22] paired with corresponding text descriptions in English. The collection consists of a total of 5,521 examples, out of which 2,858 are from the AudioSet eval and 2,663 are from the AudioSet train split. The authors further tag 1,000 samples as a balanced subset of the dataset - equally divided across genres. All examples in the balanced subset are from the AudioSet eval split. As our setup is not restricted to text and requires joint conditioning in the form of images as well, we supplement this dataset by

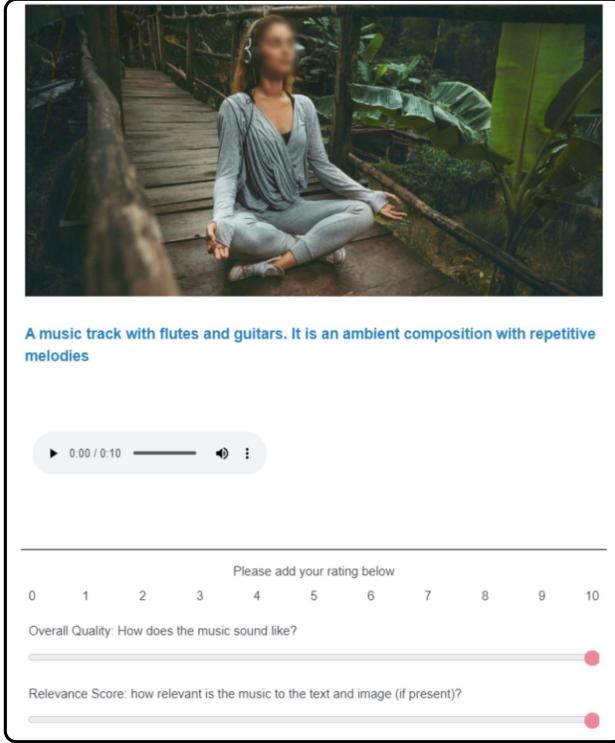


Figure 8. User study interface to collect OVL and REL scores.

collecting 2 carefully chosen image frames for each of the 10-second samples from the corresponding YouTube video or web. As some of the samples are not live anymore, we were able to collect a total of 7,684 samples which we divided into a 60%/20%/20% split for train/validation/test respectively.

G. User Study Details

Fig. 8 presents the user study interface. To obtain the OVL and REL scores, we provide the participants with an image-text pair and the audio sample generated by MELFUSION. For the overall audio quality score (OVL) the participants are instructed to add their score between [1,10] while for the relevance score (REL), they are required to rate the sample based on its similarity with the input image-text pairs.

In Fig. 9 we compare our method against prior text-to-music methods and report the OVL and REL scores in the main paper (Tab. 1). In this case, the participants were presented with only the text-music pairs.

Fig. 10 shows the user study interface for the IMSM score. For this, the participants were presented with image-music pairs and asked to provide their rating between [1,10], with 1 being the lowest. The higher the score, the more perceptually similar the participant has found the image-music pair to be.

Figure 9. User study interface for comparison against prior text-to-music methods

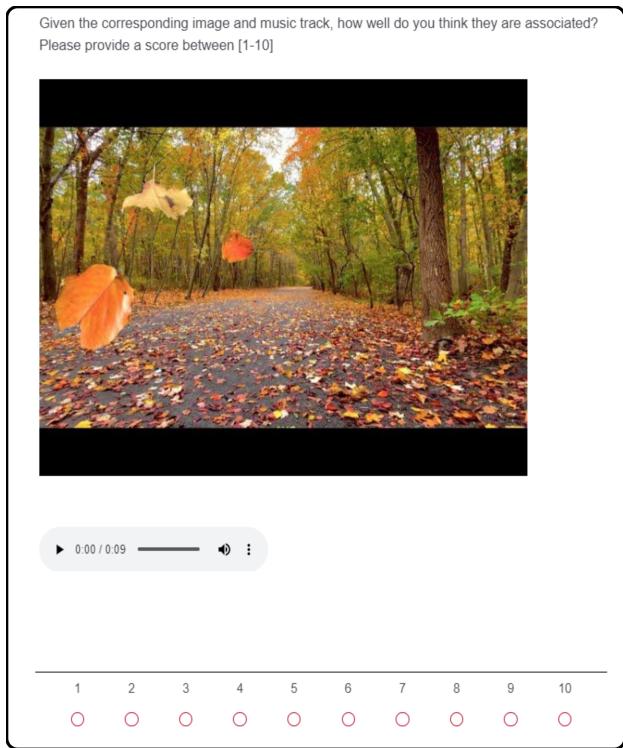


Figure 10. User study interface to obtain IMSM scores

H. Inspiration from Conditional Image Generation

Powered by architectural improvements and the availability of large-scale, high-quality paired training data, conditional image generation methods have made considerable progress in the generative AI space. Promising results from transformer-based auto-regressive approaches [66, 90] were boosted by diffusion model-based methods [59, 67, 70]. These approaches have been naturally extended to generate videos from text prompts too [27, 76, 85]. Latent diffusion models [67] do the diffusion process in the latent space of a pre-trained VQ-VAE [81]. This significantly reduced the compute requirements when compared with image diffusion methods. Ho and Salimans [26] proposed classifier-free guidance to enhance image quality. Text-to-music and text-to-audio methods are heavily inspired by the success of text-to-image generative methods, and so are we.

I. Related Audio Concepts

The Multimodal Variational Auto-encoders (MVAEs) are latent variable generative models to learn more generalizable representations from diverse modalities through joint distribution estimation. Arik et al. [2] pioneered a neural audio synthesis model based on VAEs. Their approach demonstrated promising results in generating realistic audio samples by learning a latent representation of the audio data. Inspired by this VAEs have been widely used in the audio processing domain for speech synthesis [51, 79, 93], audio generation [5, 23, 38], and audio denoising [3, 69].

Vocoders are used for a variety of purposes across different domains due to their ability to manipulate and synthesize audio signals efficiently. Among other prominent applications of vocoder, neural voice cloning [2, 37], voice conversion [50], and speech-to-speech synthesis [36] are very popular. GAN-based vocoders [42] have been employed to generate high-fidelity raw audio conditioned on mel spectrogram. More recently, WaveRNN [40] has been applied for universal vocoding task [39, 53, 62].

Spectrograms are a powerful tool for analyzing time-varying signals such as audio and speech. They provide a visual representation of the frequency content of a signal over time, making them widely used in speech processing [7, 56, 74], music analysis [46, 73], and audio synthesis [6, 23, 35, 48, 83] in general. Audio spectrograms are also massively deployed in different audio visual applications [6, 61, 78].

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