Skating-Mixer:
Multimodal MLP for Scoring Figure Skating

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Abstract. Figure skating scoring is a challenging task because it requires judging players’ technical moves as well as coordination with the background music. Prior learning-based work cannot solve it well for two reasons: 1) each move in figure skating changes quickly, hence simply applying traditional frame sampling will lose a lot of valuable information, especially in a 3-5 minutes lasting video, so an extremely long-range representation learning is necessary; 2) prior methods rarely considered the critical audio-visual relationship in their models. Thus, we introduce a multimodal MLP architecture, named Skating-Mixer. It extends the MLP-Mixer-based framework into a multimodal fashion and effectively learns long-term representations through our designed memory recurrent unit (MRU). Aside from the model, we also collected a high-quality audio-visual FS1000 dataset, which contains over 1000 videos on 8 types of programs with 7 different rating metrics, overtaking other datasets in both quantity and diversity. Experiments show the proposed method outperforms SOTAs over all major metrics on the public Fis-V and our FS1000 dataset. In addition, we include an analysis applying our method to recent competitions that occurred in Beijing 2022 Winter Olympic Games, proving our method has strong robustness.

Keywords: Multimodal Learning, MLP, Audio-Visual, Figure Skating, Dataset

1 Introduction

Due to the importance of fair competition, many worldwide sports committees devote themselves to regularizing the behaviors of both athletes and referees. As a supplementary tool, people seek to utilize objective machine intelligence to judge the performances in competitions. Therefore, many learning-based assessment models \cite{19,26,42,44,45,57} have been introduced in recent years. Nevertheless, few works proposed to score figure skating videos because of several key challenges:

- **Requiring strong representation learning.** (1) Figure skating videos are 3–5 minutes long and contain manifold technical movements, requiring
Fig. 1: **Pipeline of Skating-Mixer.** We adopt patch modeling methods just like [10, 52], and use TimeSformer [5] and AST [13] as our projection backbones. The memory recurrent unit (MRU) of Skating-Mixer works for learning sequential temporal information. After integral learning in both spatial and temporal information, Skating-Mixer obtains a representation of long-range video. We integrate the outputs from each Skating-Mixer block into a head module as mentioned in Section 4.2 and finish the figure skating scoring. [MEM] denotes the memory token and [CLS] denotes the class token.

- **Missing high-quality dataset.** Unlike common videos, figure skating videos are sourced from live sporting tournaments that demand extensive manual effort to process. This could be the reason that existing datasets [32, 58] are not comprehensive enough (in scale or diversity) to cover figure skating.

To solve the first challenge, earlier work [32] utilized a hierarchical LSTM model to capture the local and global information in figure skating videos. Recent Eagle-eye method [41] considers both pose heatmaps and appearance features jointly. Although these two methods achieve comparably good results, they remain obvious deficiencies. Firstly, their architecture is fairly complex: they contain several streams with multiple well-designed CNN or LSTM blocks. More importantly, they merely consider a single visual modality. While technical action (visual modality) is important in figure skating, we argue that background music (audio modality) should not be ignored as well. An efficient model which considers both visual and audio cues is urgently needed in this field. Therefore, we introduce Skating-Mixer, which is the pioneer MLP-based multimodal architecture and also the first to score figure skating using both auditory and visual information. Skating-Mixer has the following properties: (1) It simultaneously model audio and visual features, and learns in an effective way; (2) By adopting
the memory recurrent unit (MRU), this approach accurately predicts the results using extremely long-range cues; (3) With its simple design, it could avoid the gradient vanishing and exploding problems in the vanilla recurrent neural network [47].

Moreover, we observe that few high-quality datasets are set up for this task. Fis-V [58] contains the complete videos for scoring, but it only contains ladies short program videos. Since the data distribution is monotonous, this dataset is less challenging. In this case, we generate a new dataset FS1000 with more than 1000 videos, 8 categories of figure skating and 7 detailed scores to increase the diversity and quantity. The dataset requires the model to learn the underlying features across different figure skating videos. Experiments conducted on both datasets demonstrate that Skating-Mixer not only achieves state-of-the-art results but also has the ability to generalize to all sorts of figure skating, making a good example to tackle multimodal representation in sports.

The followings are the primary contributions of this paper:

- We present the pioneer MLP-based multimodal framework that can model extremely long-range video. It automatically scores figure skating according to both auditory and visual information.
- We collect a comprehensive FS1000 dataset, including more long-range videos that contains all types of figure skating with more detailed scores record.
- We benchmark recent methods in this field on both Fis-V and FS1000 datasets. The proposed MLP-based framework outperforms other CNN-based [43, 44], LSTM-based [58], Transformer-based [24] methods.

2 Related Work

We first review current technologies deployed in audio-visual learning. Then, we discuss previous MLP-based models and some researches in learning to score figure skating videos.

2.1 Audio-Visual Learning

There exists a rich exploration in audio-visual multimodal learning, especially in the deep learning era [62]. And datasets [1, 7, 12, 20, 23] involving representation learning in this field have been also developed. Along with the success of these work, tasks including location [21], recognition [34], matching [38] and generation [55, 56] further reveal the powerful capabilities of deep learning. In recent years, pre-training technologies [9, 63] have become the main solutions to visual-audio issues. M-BERT [24] focuses on reducing the complexity when introducing Transformer into audio-visual representation learning, which inspires us to design a more efficient model in the field. And RLM [27], VATT [2], OPT [31] and VX2TEXT [29] further propose universal multimodal transformer architectures bridging video, audio and text. Besides, AVAS [37] attempts to learn the spatial alignment between audio and vision by introducing a new self-supervised proxy
Besides, the recent NeurIPS work [39] also proposes to design a middle bottleneck to integrate audio and video modalities. Although many existing methods explore audio-visual learning by various techniques, our proposed Skating-Mixer is the first attempt to apply MLP architecture to tackle audio-visual problems.

2.2 MLP-based Architecture

Attention-based networks such as Transformer and BERT [9,54] achieve unparalleled success in nearly all NLP tasks, while convolutional networks [14,48] are still the main solution for most vision tasks until the proposal of ViT [10]. And recently, Mixer [52] and ResMLP [53] argue that convolutional and attention blocks in networks are unnecessary, and MLP can replace all of them to learn vision representation. Besides, gMLP [30] also demonstrates that all-MLP architecture can achieve competitive performances on both vision and NLP tasks. Subsequently, many MLP-based architectures [8,18,22,28,35,46,50,59,61] emerged in large numbers. Compared with Mixer, S²-MLP [59] only contains channel-mixing MLP and utilizes a spatial-shift operation for communication among patches. The Permutator [18] encodes the feature representations along height and width dimensions separately and enables itself to capture long-range dependencies along different directions. Inspired by axial attention [16], AS-MLP [28] and sMLP [50] propose to restrict the MLP layer’s reception field to reduce the computational complexity. In addition, there are several specific-function models being proposed, such as CycleMLP [8] used in dense prediction, MixerGAN [6] and CrossMLP [46] in image translation, and Mixer-TTS [51] in the text-to-speech task. Distinguished from the aforementioned works, our proposed model is the first MLP model solving audio-visual problems.

2.3 Figure Skating

Due to the long-term and multimodal characteristics of figure skating videos, it is still quite challenging to learn to score figure skating by applying deep learning models. In the computer vision field, the earliest work about figure skating can be traced back to MIT-Skating [45], which gathered videos from Olympic sports and designed the task of assessing how well people perform actions. Similar research [58] also focuses on scoring figure skating videos and collects a Fis-V dataset that includes 500 videos. However, Fis-V dataset only considers ladies single program, making it hard for generalization in this field. Another work [32] introduces action recognition in figure skating and meanwhile designs an FSD-10 dataset. This dataset splits the complete competition video into several clips, therefore it is more suitable for fine-grained learning rather than studying the whole representation. A fine-grained, motion-centered MCFS dataset [33] is also proposed for the action recognition task. Additionally, several researches [40,41,60] propose dedicated models in figure skating area. Specifically, 1D CNN [40] draws on a physiological reaction that people naturally suppress blinks during attention-grabbing moments, to detect the highlight in figure skating programs. ACTION-Net [60] strengthens the importance of postures in long videos, designing an architecture that learns both context and temporal discriminative information. EAGLE-Eye [41] creates a two-stream pipeline to learn the
long-term representation of figure skating actions. Compared with others, we introduce the first attempt to solve figure skating scenarios using both audio and video cues.

3 Dataset

Fig. 2: The average length (a), distribution (b), and statistics of GT (c) for each category in FS1000. **MS:** men’s short program (21%), **MF:** men’s free skating (12%), **LS:** ladies’ short program (15%), **LF:** ladies free skating (12%), **PS:** pairs short program (7%), **PF:** pairs free skating (8%), **IF:** ice dance free skating (10%), and **IR:** ice dance rhythm dance (15%).

To further facilitate the research of learning-based research in this field, we present the largest figure skating FS1000 dataset with high-quality videos. All videos come from high-standard international figure skating competitions and were captured by professional camera devices. The dataset is designed for predicting scores in figure skating competitions, but it also provides rich annotations like player ID and program category, which may facilitate this field even more.

3.1 Data Collection

**Data Source.** With an aim to obtain high-quality figure skating videos, we carefully select and download videos only from the top-tier international skating competitions. Besides, we also collect and double-check scores from referee reports to annotate our dataset in authoritative.1 Specifically, ISU World Figure Skating Championships, ISU Grand Prix of Figure Skating, etc, are selected

1 https://www.isu.org/figure-skating/entries-results/fsk-results
as our main data sources. Normally, figure skating consists of 4 primary categories, namely, mens singles, ladies singles, pair skating and ice dance. Each primary category contains short program and free skating (in ice dance, it is called rhythm dance and free dance). So, there are 8 subdivided categories, as shown in Figure 2. In the short program, players are required to perform fixed technical actions to show their basic skills while free skating provides more freedom and allows complex actions and better expression for background music. In order to maintain data diversity and fully extract the correlations between players’ performances (video-modality) and music (audio-modality), all types of program have been organized to construct our FS1000 dataset. Note that since the referee rules keep slightly changing every year, we utilized the competition videos that happened in recent four years in our figure skating video dataset to make the scores more comparable.

Pre-processing. The raw videos collected from figure skating competitions are usually untrimmed and record the whole procedure ranging from 1 to 5 hours. It consists of the performances of all players as well as highlight replay, warming up parts, and waiting for score parts. These redundant contents are usually not helpful for score judgment. We initially downloaded over 300-hours videos and then manually processed all videos, only reserving pure competition performance clips of players from the exact beginning to the ending moment of background music. Five professional people participate in video editing and takes nearly 2 months to finish this important pre-processing step. This time-consuming pre-processing ensures each video sample can exactly cover the intactness of player’s performance. Additionally, poor-quality videos that are not fluent, blurred, or without audio, were removed to maintain the high standard of FS1000 dataset.

3.2 Annotation and statistics

Annotation. As mentioned above, there are totally eight categories of figure skating competitions, namely, men/ladies/pairs short program (MS, LS, PS), men/ladies/pairs free skating (MF, LF, PF) and ice dance rhythm dance/free dance (IR, IF). We carefully label each video with its authorized scores according to the referee reports, and also player ID and corresponding category. In the scoring regulation of figure skating, the result can be divided into two parts: Technical Element Score (TES) and Program Component Score (PCS). TES evaluates the difficulty and execution of all technical movements, and PCS describes the overall performance, considering five aspects: the Skating Skills (SS), Transitions (TR), Performance (PE), Composition (CO), and Interpretation of music (IN). Specifically, the Skating Skills assesses the skater’s command of the blade over the ice; Transitions evaluates skaters’ ability to transit between technical elements naturally; Performance shows the appeal and personality of the program; Composition reflects the choreography and the purpose to the way the program is constructed, and Interpretation is more concerned with the consistency between each movement and a corresponding beat in music. Besides, there is a factor that indicates different weights of PCS scores in different competitions. These scores are given by nine different professional referees and
calculated by the referee rules of figure skating competition. Each video in the FS1000 dataset is annotated with these information mentioned above.

**Statistics.** Finally, there are totally 1000 figure skating videos in our FS1000 dataset: 812 videos are for training and validation while 188 videos are from the Beijing 2022 Olympics for testing. Each video has \(~ 5000\) frames with a frame rate of 25 and is annotated with detailed ground-truth scores. Some example frames and the percentage of the number of each category in the FS1000 dataset are shown in Figure 2(a). As the videos contain complete snippets of each performance, they are relatively long with a duration ranging from 2 minutes to 4.3 minutes, and the average duration of all videos is about 3 minutes and 20 seconds. The details of each category’s average length are given at the top of Figure 2(b). We can see that compared with the duration of short program and rhythm dance (2 to 3 minutes), free skating and free dance generally have a longer duration (about 4 minutes), which is consistent with the standards of different competitions. Furthermore, we calculate the average TES and PCS scores over different types of program shown at the bottom of Figure 2(c). Since there are some differences in the scoring criteria between free skating and short program, the average scores between them may look quite different.

4 Method

In this section, we comprehensively introduce our MLP-based multimodal model, the Skating-Mixer. The fundamental architecture is made up of Mixer layers [52]. It is simple enough to avoid intricate designs, while yet surpassing CNN-based [43], LSTM-based [58], and Transformer-based [24] architectures. The pipeline is shown in Figure 1.

4.1 Preliminary: MLP-Mixer

In [52], an MLP-based architecture has been proposed in the computer vision area and shows that model organizing multi-layer perceptrons are powerful enough to achieve excellent results on image classification tasks. Similar to Visual Transformer [10], input images for MLP-Mixer [52] are split into several non-overlapping patches and each patch is treated as a sequence token. MLP-Mixer contains several identical layers, and each layer contains two MLP blocks: channel-mixing MLP and token-mixing MLP. Channel-mixing MLP operates on the channel dimension of the input feature, allowing different channels to communicate with each other; token-mixing MLP operates on the token dimension, so information could flow across different tokens and communicate with each other. Each block contains two MLP layers, and one GELU [15] activation function (described as \(\Phi\)). Besides, skip connection is also applied in each block.

To be more specific, suppose \(X \in \mathbb{R}^{S \times C}\) is a two-dimension input feature, where \(S\) is the sequence length (number of tokens) and \(C\) is the number of channels for each token. In each layer, the function could be represented as:

\[
\begin{align*}
U_{*,i} &= X_{*,i} + W_2 \Phi (W_1 \text{Norm}(X_{*,i})), \\
Y_{j,*} &= U_{j,*} + W_4 \Phi (W_3 \text{Norm}(U_{j,*})),
\end{align*}
\]
where \( i \) ranges from \( 1 \ldots C \), and \( j \) ranges from \( 1 \ldots S \). Norm denotes Layer-Norm [3] and \( \mathbf{W} \) represents the weights of linear layer in each block. Input feature first passes through channel-mixing MLP and then follows token-mixing MLP. This structure allows each element in the input feature could interact with other features along two dimensions.

### 4.2 Skating-Mixer

Figure skating videos usually last minutes and require large fps to identify each action, which results in a gigantic input video visual feature. Compared with previous methods [4, 25] that randomly sample several frames to represent a whole video, we segment the video into multiple 5-seconds clips and input them to projection models [5, 13].

### Algorithm 1 Skating Mixer

| Input: \( \mathbf{A} \): projected acoustic feature; \( \mathbf{V} \): projected visual feature; |
| Output: \( S \): predicted score; |
| Parameter: \( \text{CLS} \): class token; \( \text{MEM}_0/\text{MEM}_{T-1} \): the same initial memory token |
| 1: for \( t \leftarrow 0 \) to \( T-1 \) do |
| 2: \( \mathbf{Y}_t = \text{MLP-Mixer}([\text{CLS} \mathbf{A}_t \mathbf{V}_t \text{MEM}_t]) \) |
| 3: \( \mathbf{O}_t^{\text{forward}} = \mathbf{W}_{\text{out}} \mathbf{Y}_t[0] \) |
| 4: \( \text{MEM}_{t+1} = \mathbf{Y}_t[-1] \) |
| 5: end for |
| 6: for \( t \leftarrow T-1 \) to \( 0 \) do |
| 7: \( \mathbf{Y}_t = \text{MLP-Mixer}([\text{CLS} \mathbf{A}_t \mathbf{V}_t \text{MEM}_t]) \) |
| 8: \( \mathbf{O}_t^{\text{backward}} = \mathbf{W}_{\text{out}} \mathbf{Y}_t[0] \) |
| 9: \( \text{MEM}_{t-1} = \mathbf{Y}_t[-1] \) |
| 10: end for |
| 11: \( \hat{\mathbf{O}} = \text{Average}( \frac{\mathbf{O}_0^{\text{forward}} + \mathbf{O}_0^{\text{backward}}}{2}, \ldots, \frac{\mathbf{O}_{T-1}^{\text{forward}} + \mathbf{O}_{T-1}^{\text{backward}}}{2} ) \) |
| 12: \( S = \text{ScoreHead}(\hat{\mathbf{O}}) \) |
| 13: return \( S \) |

After that, we ordinarily concatenate two-modality features that share the same temporal clip and pass them through a linear projection layer. The output feature dimension is denoted as \( D_{\text{proj}} \). For the \( t \)-th clip of the video, \( \mathbf{A}_t \) represents the audio feature and \( \mathbf{V}_t \) represents the visual feature. Besides these two features, we have adopted the same strategy as visual Transformer [10] by adding a [CLS] token along with two features. [CLS] token is set to be a learnable vector with dimension \( D_{\text{proj}} \). After passing through the Mixer module, the output of this [CLS] token pass through another linear layer and generate the output for the further scoring task.

In addition, it is necessary for scoring performance by viewing different clips in a whole video. In this case, a memory token [MEM] is applied together with other inputs. This memory token is also a \( D_{\text{proj}} \)-dimension vector and is used to pass memory information between clips. The memory token output at time \( t \) will
directly become the input memory token at time $t+1$ without any projection. For
the first clip, the input memory token is a learnable random-initialized $D_{\text{proj}}$-
dimension vector. In the Mixer block, besides mixing features across modality,
it also fuses features across different time steps.

The whole process could be described in this way. First, the projected acous-
tic and visual feature tokens are concatenated together. For the $t$-th clip, the
concatenated feature $\mathbf{F}_t$. After the linear projection, the result is concatenated
again with $[\text{CLS}]$ and $[\text{MEM}_t]$ and the input $\mathbf{I}_t$ passes into Mixer block. Then the
output of the memory token will be used as $[\text{MEM}_{t+1}]$, the input memory token
at the next time step. Meanwhile, the output of the class token will be input to
another linear layer. And the output vector $\mathbf{O}_t$ represents the $t$-th short clip.

Finally, we can get a vector for each clip and take the average value over all
these vectors. The average vector is transmitted to a scoring head ScoreHead($\cdot$),
which is an MLP layer here, to obtain the final score. The structure is shown in
Figure 1 and the whole algorithm is presented in Algorithm 1. During training,
we simply use Mean Square Error (MSE) to update the model.

**Skating Mixer vs LSTM.** The recurrent mechanism is similar to RNN [47]
and LSTM [17], but with MLP-Mixer the design is much simpler and more
efficient. In vanilla RNN architecture, when the input sequence becomes longer,
gradient vanishing and gradient exploding happen. In LSTM, this problem is
solved by adding three gates: input gate, output gate and forget gate. These
gates control the information flow from the input. In other words, LSTM makes
the model focus on important parts of input and thus reduces the effective input
length to avoid the gradient problem. In our architecture, it is not necessary to
have delicately designed gates. Gradient vanishing and exploding issues could be
mitigated since there is skip-connection within channel-mixing and token-mixing
MLP block and no extra projection is implemented for memory token. Mixing
the memory token will enable the current clip to see the previous information
and thus generate a comprehensive view for the whole video.

**Bi-direction Mixer.** In our model, we adopt a similar strategy as in bidirec-
tional recurrent neural network [47], that is to add a backward direction in the
model to create a better view of the whole video. For the backward direction,
the last clip of the video will be processed first, then the memory flows to the
first clip. The initial memory token and input class token are the same as the
forward direction. So for each clip, there will be two $[\text{CLS}]$ token outputs: one
is forward output $O_{t}^{\text{forward}}$, the other one is backward output $O_{t}^{\text{backward}}$. We
simply take the average value $O_t = \frac{O_{t}^{\text{forward}} + O_{t}^{\text{backward}}}{2}$ to represent each clip.

5 Experiment

5.1 Implementation Details

**Dataset.** We first test our model on Fis-V dataset [58] which contains 400
ladies short program videos for training and 100 videos for validation. Then, we
evaluate our model on our proposed FS1000 dataset. We used 812 videos from
the FS1000 dataset and divided into a training set of 652 videos and a validation set of 160 videos.

**Feature Extraction Setting.** In our experiment, all the video data have 25 frames per second. Each video is separated into a 5-second clip and adjacent clips have 3 seconds overlapping time duration. The overlapping setting tends to avoid inconsistency caused by splitting. For feature extraction, we use the Audio Spectrogram Transformer [13] pre-trained on full AudioSet [11] to extract acoustic features. For the visual feature, TimeSformer [5] pre-trained on Kinetics-600 dataset [20] is implemented. In the original paper, the number of input frames of TimeSformer is 8, so we also adopt the same setting here. To round up that 125 cannot be divided by 8, we take 120 frames from 125 frames for each clip. So each clip is separated into 15 non-overlapping 8-frame segments and each segment is input into the model. In other words, there will be 15 tokens used as the visual representation for each clip. We do not fine-tune both Transformers on Fis-V and our dataset because of tremendous computational cost and memory usage. Figure skating videos contain up to 6000 frames and it will require ~200G memory and more than 2 minutes for a single video to pass forward and backward the model. Thus they are not included in our training graph.

**Model Setting.** In our experiment, we use two MLP-Mixer layer in the recurrent structure. Adam optimizer with learning rate $1e^{-4}$ is deployed. The scoring head ScoreHead(·) is a simple linear layer. For completed learning, the whole framework is trained with 500 epochs on a single NVIDIA V100.

### 5.2 Result on different datasets

The **Mean Square Error (MSE)** are used as our metrics. For a fair and accurate comparison, we run 3 repeated experiments using different random seeds and record the mean of metrics for different methods [24, 43, 44, 58]. [24] uses both audio and visual feature while others only consider visual feature. We also conduct experiments on our model with only acoustic modality or visual modality. We record the comprehensive results in Table 1.

**Fis-V.** From the table, it can be observed that our proposed Skating-Mixer outperforms CNN-based [43, 44], LSTM-based [44, 58] and Transformer-based [24] models. Although the Transformer model performs better than MLP-Mixer on general tasks like image classification [52], it does not have an obvious advantage in this specific task. C3D-LSTM [44] has the worst results since the model is too simple to learn such complex data. 3D CNN-based method, MSCADC [43] is also struggled to understand such long videos. MS-LSTM [58] and our proposed Skating Mixer performs better than Transformer model, indicating that: a strong memory mechanism plays an essential role in long videos learning; besides, the attention mechanism is less effective to capture extremely long-term dependencies across videos over several minutes. Moreover, our model with only video feature can still achieves better results than MS-LSTM [58], proving that our structure learns better in long video information.

Additionally, Skating Mixer with only audio features generates the worst result. This follows the commonsense that music plays an auxiliary part in figure
### Table 1: Experiment Results on Fis-V [58] and ours FS1000.

| Datasets       | Methods            | TES       | PCS       | SS        | TR        | PE        | CO        | IN        |
|----------------|--------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Fis-V [58]     | C3D-LSTM [44]      | 42.79     | 25.81     | †         | †         | †         | †         | †         |
|                | MSCADC [43]        | 27.27     | 16.00     | †         | †         | †         | †         | †         |
|                | M-LSTM [58]        | 20.80     | 9.09      | †         | †         | †         | †         | †         |
|                | S-LSTM [58]        | 21.95     | 9.60      | †         | †         | †         | †         | †         |
|                | MS-LSTM [58]       | 22.54     | 9.09      | †         | †         | †         | †         | †         |
|                | M-BERT (Early) [24]| 28.50     | 14.85     | †         | †         | †         | †         | †         |
|                | M-BERT (Mid) [24]  | 35.51     | 20.31     | †         | †         | †         | †         | †         |
|                | M-BERT (Late) [24] | 30.25     | 14.93     | †         | †         | †         | †         | †         |
|                | Ours (A)           | 36.66     | 19.46     | †         | †         | †         | †         | †         |
|                | Ours (V)           | 20.45     | 9.03      | †         | †         | †         | †         | †         |
|                | Ours (A+V)         | **20.39** | **8.93**  | †         | †         | †         | †         | †         |
| FS1000 (Ours)  | C3D-LSTM [44]      | 291.61    | 33.88     | 1.24      | 1.32      | 1.66      | 1.30      | 1.34      |
|                | MSCADC [43]        | 84.99     | 18.96     | 0.69      | 0.76      | 1.12      | 0.71      | 0.82      |
|                | M-LSTM [58]        | 189.35    | 14.82     | 0.59      | 0.63      | 1.00      | 0.55      | 0.66      |
|                | S-LSTM [58]        | 210.99    | 17.83     | 0.53      | 0.57      | 0.98      | 0.55      | 0.61      |
|                | MS-LSTM [58]       | 204.17    | 16.56     | 0.58      | 0.62      | 0.95      | 0.53      | 0.61      |
|                | M-BERT (Early) [24]| 90.48     | 17.79     | 0.52      | 0.49      | 0.91      | 0.60      | 0.58      |
|                | M-BERT (Mid) [24]  | 127.73    | 25.91     | 0.63      | 0.60      | 1.06      | 0.70      | 0.73      |
|                | M-BERT (Late) [24] | 95.27     | 18.27     | 0.54      | 0.57      | 0.92      | 0.55      | 0.56      |
|                | Ours (A)           | 97.17     | 21.47     | 0.81      | 0.84      | 1.18      | 0.82      | 0.92      |
|                | Ours (V)           | 68.80     | 11.56     | 0.42      | 0.48      | 0.84      | 0.49      | 0.49      |
|                | Ours (A+V)         | **65.08** | **10.44** | **0.42**  | **0.45**  | **0.83**  | **0.46**  | **0.49**  |

Comparing the results, we observe that introducing both audio and video clues in figure skating scoring performs better than using only visual features, especially in PCS. It is surprising to see that the audio feature can also slightly improve the performance on TES which only measures the difficulty and completion of the action without considering the musical elements according to the scoring rules. This implies that music might also slightly affect referees’ decision when giving TES.

**FS1000.** Scoring on the FS1000 dataset is much more challenging. Fis-V [58] dataset only contains ladies short program videos while FS1000 dataset consists of different types of figure skating videos, which highly tests the robustness of model. In our experiments, CNN-based [43, 44], LSTM-based [44,58], Transformer-based [24], MLP-based: Ours. The scores are computed by MSE. A: only audio, V: only video, A+V: Audio+Video. † denotes the dataset does not include the GT.

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FS1000. Scoring on the FS1000 dataset is much more challenging. Fis-V [58] dataset only contains ladies short program videos while FS1000 dataset consists of different types of figure skating videos, which highly tests the robustness of model. In our experiments, CNN-based [43, 44] and Transformer-based [24] models still cannot capture long-term dependencies across extremely long videos. MS-LSTM [58], which achieves closer performance to our model on Fis-V dataset, but obviously fails to extend to multi-category FS1000 dataset, especially in TES. We conclude that it is because MS-LSTM [58] cannot well uncover the underlying relationship for different categories. Meanwhile, our proposed model shows great flexibility to fit different types of competitions and obtain the best result among all the models. Similar to the result on Fis-V, model using only acoustic features provide little information and obtain the worst result, because the technique moves (in video) always play the key role for scoring. However, the advantage that using multimodality in our model is very obvious, which further demonstrates that audio-visual learning is really important in this field.
Another interesting observation is that performance score $PE$ is harder to learn than other four sub-scores for all the models, indicating that future work could focus on improving the learning of performance score for better overall result.

**Training Process.** To demonstrate the training process of different models, we select the three models from [58], which obtains the closest results compared to our model and plot loss value of the early 30 epochs when training on Fis-V dataset as shown in Figure 3. Our proposed method converges much faster than other methods, indicating that our methods could learn the multimodal representation within only a few epochs.

**Summary.** It can be found that learning to score figure skating videos requires the model to learn both long-term dependency and multimodality learning. Transformer is a popular form for modal interaction, but it is hard to handle such long videos; LSTM-based method performs better in some datasets, but it fails to introduce multimodality and generalize across different categories. Our model is capable of dealing with these two aspects at the same time and performs better than CNN, LSTM and Transformer-based models. We believe the new neural network could be used for more than scoring figure skating but also a pioneer work utilizing MLP-based model for multimodal learning in long videos.

### 5.3 Ablation studies

We have conducted ablation experiments on both Fis-V and FS1000 dataset. Here we mainly analyze two major scores, **TES** and **PCS**.

**Component.** We first examine the effectiveness of our designed memory recurrent unit and bi-direction propagation through four different fusion model structures, as shown in Figure 5. The baseline model (B) is the one that simply inputs all the audio and video features into a large MLP-Mixer model for fusion. The predicted score is generated by the [CLS] token. Then, we aggregate the audio and video feature from the same clip and input them to the Mixer model together with [CLS] token. This process is called token aggregation (B+TA). The average score generated by [CLS] tokens from all the video clips is used to produce the final score. Based on above experiments, we then optimize such process by introducing the memory recurrent unit (B+TA+MRU). Finally, the bi-directional flow is deployed in the model (B+TA+MRU+Bi-D).

The result is shown in Table 2. The model with token aggregation shows better results than the baseline model. This is because the model fails to learn the long-term relationship between audio and video modalities when all the features of the long video are input into single model. By slicing the long video into short
Fig. 5: Four of our designed fusion structures. **B**: baseline. **TA**: Token Aggregation. **MRU**: memory recurrent unit. **Bi-D**: bi-direction. The final version of our method is simple and elegant, without no intricate designs, thanks to the inspirations we got from previous outstanding neural networks [9, 17, 49, 52, 54].

**Table 2: Ablation studies on different components, number of layers and dropout rates.** For component part, **B**: Baseline; **TA**: Token Aggregation; **MRU**: Memory Recurrent Unit; **Bi-D**: Bi-direction. Figure 5 shows the detailed comparison.

| Factor | Component          | Layer |
|--------|--------------------|-------|
|        | B | B+TA | B+MRU | B+MRU+Bi-D | 1 | 2 | 3 |
| Figs-V [58] | TES | 23.25 | 22.34 | 20.80 | 20.39 | ✓ | ✓ | ✓ | 21.22 | 20.39 | 21.79 | 20.39 | 21.31 | 20.80 | 20.16 |
| PCS | 11.32 | 9.98 | 9.37 | 8.93 | 9.73 | 9.3 | 9.21 | 9.3 | 9.61 | 10.9 | 10.33 |
| FS10000 TES | 70.93 | 71.15 | 68.80 | 65.08 | 65.20 | 65.08 | 66.21 | 66.08 | 64.24 | 68.02 | 69.35 |
| PCS | 13.70 | 11.90 | 11.17 | 10.44 | 11.60 | 10.44 | 12.26 | 11.44 | 11.33 | 11.52 | 11.98 |

**Video clips**, the model is capable to capture audio-visual information. Moreover, adding proposed MRU and bi-direction flow could effectively enhance the understanding of long videos and improve the performance of the model.

**Feature Extractor.** TimeSformer provides pre-trained weights on Kinetics [20] and HowTo100M [36]. HowTo100M dataset contains much longer videos than Kinetics. Though this factor is not at the core of our design, we are interested to see whether it plays an important role. As shown in Figure 4: for most of the time, using Kinetics [20]-based model performs better. So we adopt this setting.

**Number of Mixer Layer.** We also conduct the experiments using different numbers of MLP-Mixer layers in our proposed structure. Insufficient Mixer layers would lead the model to miss some important information while too many Mixer Layers will cause over-fitting problems on the task-specific dataset. As the result shown in Table 2, on both datasets, two MLP-Mixer layers are the best setting in our model. We argue that using three Mixer layers causes serious over-fitting problems and the performance becomes much worse.

**Setting of Dropout Rate.** Since the figure skating videos are really long, we worry about the over-fitting problem at first. So dropout layers have been introduced before and after both channel-mixing MLP and token-mixing MLP. We set the dropout rate to be 0%, 10%, 20% and 30%. Results are shown in Table 2: different from other tasks [14, 40, 54], using a higher dropout rate cannot achieve obvious improvements in this scenarios. This may be demonstrated that
Fig. 6: Predicted TOP-5 Ranking for Ladies Short in Beijing 2022 Winter Olympic Games. $P$ stands for predicted and $T$ stands for truth. The last row is the ranking difference compared to the real ranking.

keeping the feature continuous and comprehensive is important for scoring figure skating since every move is important.

5.4 Performances on Beijing 2022 Olympic Games

To verify the robustness and effectiveness of the figure skating model, we apply our trained model on competitions that are not included in the training data to see its actual effect. Therefore, we took the figure skating videos from the Beijing 2022 Winter Olympic Games and make analysis on the rankings of each athlete. In practice, predicting correct ranking is more meaningful than predicting exactly the same score because the evaluation scales are inconsistent on different competitions. Here we use our model to predict the PCS for samples. The result shows that although the score may not be accurate, the top-5 ranking does not change too much compared to real ranking because top-tier athletes share some similar technique moves and maintain high-quality performances. Such results could satisfy the real need for auxiliary judgment. This demonstrates that our model could actually learn some of the scoring standards and identify better performance from a group of athletes.

6 Conclusions

This paper introduces the MLP-based multimodal architecture for scoring figure skating. Besides, an elaborated-designed dataset has been collected. We set the benchmarks that compare our model with CNN-Based, LSTM-based, Transformer-Based methods on the Fis-V and our proposed FS1000 datasets. The experiments show the effectiveness of our method, indicating MLP-based architecture is capable of the multimodal task. Furthermore, we apply our model on the 2022 Winter Olympics to check the model’s effectiveness and robustness.
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