Interactive Audio-text Representation for Automated Audio Captioning with Contrastive Learning

Chen Chen¹, Nana Hou¹⁺, Yuchen Hu¹, Heqing Zou¹, Xiaofeng Qi, Eng Siong Chng¹

¹School of Computer Science and Engineering, Nanyang Technological University, Singapore

chen1436@e.ntu.edu.sg

Abstract

Automated Audio captioning (AAC) is a cross-modal task that generates natural language to describe the content of input audio. Most prior works usually extract single-modality acoustic features and are therefore sub-optimal for the cross-modal decoding task. In this work, we propose a novel AAC system called CLIP-AAC to learn interactive cross-modality representation with both acoustic and textual information. Specifically, the proposed CLIP-AAC introduces an audio-head and a text-head in the pre-trained encoder to extract audio-text information. Furthermore, we also apply contrastive learning to narrow the domain difference by learning the correspondence between the audio signal and its paired captions. Experimental results show that the proposed CLIP-AAC approach surpasses the best baseline by a significant margin on the Clotho dataset in terms of NLP evaluation metrics. The ablation study indicates that both the pre-trained model and contrastive learning contribute to the performance gain of the CLIP-AAC model.

Index Terms: Automated audio captioning, cross-modal translation, pre-trained model

1. Introduction

Automated Audio Captioning (AAC) aims to generate descriptive sentences for audio inputs as a cross-modal translation task. It serves as a core module in many real-world applications, such as producing text labels for sound search engines [1] and assisting the hearing impaired to access audio content [2].

Most AAC approaches typically adopt encoder-decoder structures [3], where the audio encoder extracts acoustic features from raw audio inputs, and the text decoder generates corresponding descriptive captions. Recent work [4] observed that it is difficult to train a strong encoder for audio inputs because the supervision only comes from captions, which is quite limited. To overcome such problem, prior studies [2, 5, 6, 7, 8, 9] proposed transfer learning to pre-train audio encoders on AudioSet [10] for better acoustic features. However, such acoustic features only contain audio information, which has no text information as a bridge for decoders and thus leads to misalignment of audio-text information [11].

In the computer vision field, recent work [12] proposed a novel image-text pre-trained model, known as CLIP, which was trained with millions of image-text pairs and can therefore offer better features rich in semantics and visuals for cross-modal task [13]. The prior study is the source of inspiration for this work.

In this paper, we propose a novel encoder-decoder method, named CLIP-AAC, to learn the cross-modality embeddings with both acoustic and textual information for the AAC task. Specifically, the encoder in CLIP-AAC consists of an audio-head and a text-head, which are designed to learn the audio embeddings and text embeddings from audio inputs and corresponding captions. Furthermore, we propose contrastive learning to enhance the correspondence between audio-text embeddings. As a result, the extracted features can learn both audio and textual information, which are then fed into the decoder to generate descriptive sentences. At the training stage, the caption provides supervision for both features extraction and token prediction. At the inference stage, as the caption input is not available, the text-head of the encoder is discarded. Experimental results show that the proposed CLIP-AAC approach surpasses strong baselines on the Clotho dataset in terms of NLP evaluation metrics. The ablation study indicates that both the pre-trained model and contrastive learning contribute to the performance gain of the CLIP-AAC model.

The rest of this paper is organized as follows. In section 2, we introduce the proposed CLIP-AAC architecture. In section 3, experimental settings and evaluation metrics are presented. Section 4 reports and analyzes the result of the experiments. Section 5 concludes the study.

2. CLIP-AAC Architecture

We now introduce the proposed CLIP-AAC architecture, which consists of three modules: the encoder, the contrastive learning module and the decoder, as illustrated in Figure 1.

2.1. Audio-head and Text-head of Encoder

Given the $N$ audio-text pairs, we denote the AAC dataset as $D = \{(a_i, t_i)\}, i \in \{1, 2, ..., N\}$, where $a$ is the time-domain audio clip and $t$ is the caption to describe this audio. In a typical AAC model, the encoder $Enc$ is designed to convert the audio signal to the audio embedding $A = Enc(a)$. Such approach usually extracts single-modality acoustic features and are therefore sub-optimal for the cross-modal decoding task.

To alleviate such an issue, we propose an audio-head $Audio_{Enc}$ and a text-head $Text_{Enc}$ for the encoder in CLIP-AAC as shown in Figure 1, which take both audios and captions as inputs to extract corresponding embeddings for each modality.

For audio-head, we employ the ESRResNeXt [14] model which has demonstrated a powerful ability to learn robust Time-Frequency transformation of audios. Firstly, the time-domain signal is converted to a log-power spectrogram using Short-Time Fourier Transform (STFT). Then, we feed the spectrogram into a 2-D convolutional layer with kernel size of $7 \times 7$ and a batch normalization layer. Next, 4 dual-path blocks [15] are stacked to extract deep representation. In each dual-path block, the first path contains 3 stacked bottlenecks [16] with the structure shown in the yellow block. The second path consists of a max-pooling layer, 2 convolutional layers with kernel size...
of 3 × 3 and 1 × 1 respectively, and a batch normalization layer. The outputs of the two paths are multiplied as they have the same shape. Finally, the hidden features are fed into an average pooling layer and a linear layer to generate an audio embedding with a length of \( L \).

For text-head, the caption input \( t \) with any length is firstly converted into a word embedding. Then, a 12-layer Transformer [17] is employed to extract the deep features of input embeddings. Next, a further normalization layer is added after the final attention block [18]. To obtain a text embedding with the same shape as the audio embedding, another linear layer is employed to map the features to embeddings with a length of \( L \).

The parameters of the CLIP-AAC encoder are initialized by AudioCLIP [19], which includes three heads of image, audio and text. We remove the image-head and finetune the text-head and audio-head to adapt the AAC task.

### 2.2. Contrastive learning

We now introduce contrastive learning to learn the correspondence between audio embeddings and text embeddings. Specifically, the audio-head \( \text{Audio}_\text{Enc} \) and text-head \( \text{Text}_\text{Enc} \) are trained jointly 1) to maximize the cosine similarity of audio embeddings \( A_i \) with corresponding text embeddings \( T_k \) in a minibatch of \( b \) pairs, and 2) to minimize the cosine similarity of the audio embeddings \( A_i \) with negative examples. Such negative examples are remaining \( b^2 - b \) mismatched pairs. As shown in Figure 1, we denote the similarities of matched pairs as purple cells that are distributed in the diagonal elements of the grid, while the mismatched pairs are labelled as grey cells in the grid. Such optimization is achieved by contrastive loss [20] over similarity scores, as shown in Algorithm 1.

Given a minibatch of \( b \) audio-text pairs, step 1 to 3 in Algorithm 1 explains the feed forward process of audio and text inputs in the CLIP-AAC encoder. The \( A_i \) and \( T_k \) are the extracted embeddings from audio \( a_i \) and its true caption \( t_k \), respectively. In step 4, for each embedding \( A_i \), we calculate its cosine similarities with every text embedding \( \{ T_1, T_2, ..., T_b \} \) in Eq. (1).

Figure 1: The block diagram of the proposed CLIP-AAC model. The two dashed boxes denote the audio-head and text-head, respectively. “BN” is the batch normalization layer, and “MHA” denotes the multi-head attention mechanism. \( \{ A_1, A_2, ..., A_b \} \) and \( \{ T_1, T_2, ..., T_b \} \) are the audio embeddings and text embeddings extracted from audio-text pairs.

Algorithm 1: Pseudocode for Contrastive Loss

**Input:** A minibatch of \( b \) audio-text pairs \( \{ (a_i, t_i) \}, i \in \{ 1, 2, ..., b \} \)

**Output:** Contrastive loss \( L_{cl} \)

1. Initialize the parameters of audio-head \( \text{Audio}_\text{Enc} \) and text-head \( \text{Text}_\text{Enc} \).
2. Initialize temperature parameter \( T \).
3. Extract embeddings from each modality in minibatch:
   \[ A_i = \text{Audio}_\text{Enc}(a_i), A_i \in \mathbb{R}^{1 \times L} \]
   \[ T_i = \text{Text}_\text{Enc}(t_i), E_i \in \mathbb{R}^{1 \times L} \]
4. for \( i \) in 1, 2, ..., \( b \) do
   for \( k \) in 1, 2, ..., \( b \) do
     Calculate cosine similarity between \( A_i \) and \( T_k \)
     \[ \langle A_i, T_k \rangle = \frac{A_i \cdot (T_k)^T}{\|A_i\| \cdot \|T_k\|} \tag{1} \]
   end for
   Calculate cross-entropy based contrastive loss for \( A_i \)
   \[ L_i^{A \rightarrow T} = -\log \frac{\exp(\langle A_i, T_k \rangle / T)}{\sum_{k=1}^{b} \exp(\langle A_i, T_k \rangle / T)} \tag{2} \]
   end for
5. for \( i \) in 1, 2, ..., \( b \) do
   for \( k \) in 1, 2, ..., \( b \) do
     Calculate cosine similarity between \( T_i \) and \( A_k \)
     \[ \langle T_i, A_k \rangle = \frac{T_i \cdot (A_k)^T}{\|T_i\| \cdot \|A_k\|} \tag{3} \]
   end for
   Calculate cross-entropy based contrastive loss for \( T_i \)
   \[ L_i^{T \rightarrow A} = -\log \frac{\exp(\langle T_i, A_k \rangle / T)}{\sum_{k=1}^{b} \exp(\langle T_i, A_k \rangle / T)} \tag{4} \]
   end for
6. Return the contrastive loss \( L_{cl} \)
   \[ L_{cl} = \frac{1}{b} \sum_{i=1}^{b} (\lambda L_i^{A \rightarrow T} + (1 - \lambda) L_i^{T \rightarrow A}) \tag{5} \]
Table 1: BLEUₙ, METEOR, ROUGEₙ, CIDEr, SPICE, and SPIDEr in a comparative study of initialization strategies for the proposed CLIP-AAC encoder. All models are trained with batch size of 8.

| System ID | Initialization | Frozen | BLEUₙ | BLEU₂ | BLEU₃ | BLEU₄ | ROUGEₙ | METEOR | CIDEr | SPICE | SPIDEr |
|-----------|----------------|--------|-------|-------|-------|-------|--------|--------|-------|-------|-------|
| 1         | Random         | No     | 0.421 | 0.246 | 0.159 | 0.070 | 0.312  | 0.105  | 0.060 | 0.059 | 0.060 |
| 2         | Audio-only     | No     | 0.480 | 0.285 | 0.183 | 0.114 | 0.326  | 0.132  | 0.217 | 0.081 | 0.149 |
| 3         | Audio-Text     | Yes    | 0.521 | 0.335 | 0.225 | 0.147 | 0.356  | 0.153  | 0.333 | 0.100 | 0.217 |
| 4         | Audio-Text     | No     | 0.561 | 0.365 | 0.245 | 0.161 | 0.372  | 0.168  | 0.394 | 0.115 | 0.254 |

Since only the true-pair \((A_i, T_i)\) is viewed as positive example, we calculated the cross-entropy loss for each \(A_i\) in Eq (2). Similarly, a symmetric cross-entropy loss for each \(T_i\) is calculated in Eq (3) and Eq (4). Finally, the contrastive loss \(L_{\text{cl}}\) is computed by weight summing these two losses with a weight \(\lambda\). We set \(\lambda = 0.5\) in this work.

2.3. Decoder

The decoder of the proposed CLIP-AAC approach is a typical Transformer [17] with multi-head attention, which has achieved state-of-the-art performance on various cross-modal tasks.

As shown in Figure 1, the tokens of the caption are firstly mapped to word embeddings and then fed into a masked multi-head self-attention layer to obtain hidden features. Subsequently, such hidden features are sent into another cross-attention layer to attentively fuse the audio embedding \(A\) from the audio-head in the encoder. Considering the length of the attention layer to attentively fuse the audio embedding \(A\) from the audio-head in the encoder.

During decoding, the \(m\)-th token \(t_m\) is predicted based on previous tokens \(\{t_0, t_1, ..., t_{m-1}\}\) and audio embedding \(A\), so the output probability of decoder is denoted as \(P_h(t_m | t_0, t_1, ..., t_{m-1}, A)\). The training objective is to maximize the log-likelihood for each predicted token via the cross entropy criterion \(L_{\text{ce}}\):

\[ L_{\text{ce}} = - \sum_{m=0}^{M} \log P_h(t_m | t_0, t_1, ..., t_{m-1}, A) \]  

(6)

Combined with contrastive loss \(L_{\text{cl}}\) in Eq 5, we define the total loss \(L_{\text{total}}\) for the whole neural network as:

\[ L_{\text{total}} = \alpha L_{\text{ce}} + (1 - \alpha) L_{\text{cl}} \]  

(7)

where \(\alpha\) is the coefficient to trade-off each objective.

3. Experiments

3.1. Database

We conduct experiments on the Clotho dataset [21]. The Clotho data is collected from the Freesound archive, and the duration of clips ranges from 15 to 30 seconds. The captions of Clotho are annotated by 5 different annotators so that each audio clip contains 5 captions for diversity. The length of captions ranges from eight to twenty words.

Following the previous works [11], we divided the Clotho dataset into a training set (4884 audio clips with 24420 captions), and a test set (1045 audio clips with 5225 captions). Each audio clip combines one of five captions as an audio-text training pair. At the inference stage, the average performances are calculated between predicted captions and all five captions.

3.2. Network Configuration

At the training stage, the network was optimized by Adam [22]. To prevent the exploding gradients, a small learning rate of \(1 \times 10^{-5}\) is applied to the pre-trained encoder and \(1 \times 10^{-3}\) is applied to the decoder. A warm-up strategy is applied in the first 5 epochs that linearly increases the initial learning rate. The training epoch is set to 40 and the default batch size is 8. In addition, we use label smoothing [23] with \(\epsilon = 0.1\) and dropout with a rate of 0.2 to mitigate the over-fitting problem. During inference, the beam search is applied with a beam size of 3.

3.3. Metrics

We report performances on six metrics, including BLEUₙ [24], METEOR [25], ROUGEₙ [26], CIDEr [27], SPICE [28], and SPIDEr [29].

- BLEUₙ measures the correspondence between generated text and reference text by computing the precision of \(n\)-gram in the text.
- METEOR measures the harmonic mean of precision and recalls based on word-level matches between generated text and reference text.
- ROUGEₙ computes the F-measures based on the longest common sub-sequence.
- CIDEr both considers term frequency inverse document frequency weights of n-grams and the cosine similarity between the generated text and reference text.
- SPICE converts the captions to scene graphs and computes F-score based on tuple in them.
- SPIDEr is the linear combination of CIDEr and SPICE.

The first three metrics are proposed for machine translation systems but are also widely used to evaluate AAC systems in the previous works [1, 2, 4, 11]. The last three metrics are specifically used for captioning task [30, 31, 32]. For all metrics, higher score denotes better performance.

4. Results

4.1. Effect of Initialization strategies for CLIP-AAC encoder

We first analyze the performances of various initialization strategies for the encoder in the proposed CLIP-AAC approach. As shown in Table 1, system 1 and system 2 only utilize the audio-head in encoders, while system 3 and system 4 combine the proposed audio-head and text-head in encoders. Specifically, “Random” means that the encoder in system 1 is initialized randomly. “Audio-only” denotes that the encoder in system 2 is pre-trained on Audioset. “Audio-Text” depicts that the encoders in system 3 and 4 are initialized with the modified AudioCLIP and then fine-tuned on Audioset. Compared with system 3, the encoder in system 4 is learnable during the training procedure.
Table 2: BLEUn, METEOR, ROUGE1, CIDEr, SPICE, and SPIDEr in a comparative study of the proposed contrastive loss. “α” is the coefficient for contrastive loss, and “B.S.” denotes the batch size during training.

| System ID | α  | B.S.    | BLEU1 | BLEU2 | BLEU3 | BLEU4 | ROUGE1 | METEOR | CIDEr | SPICE | SPIDEr |
|-----------|----|---------|-------|-------|-------|-------|--------|--------|-------|-------|--------|
| 5         | 0  | 8       | 0.551 | 0.358 | 0.241 | 0.158 | 0.369  | 0.162  | 0.368 | 0.109 | 0.239  |
| 6         | 0.1| 8       | 0.556 | 0.359 | 0.240 | 0.156 | 0.367  | 0.165  | 0.379 | 0.113 | 0.247  |
| 7         | 0.2| 4       | 0.565 | 0.365 | 0.246 | 0.160 | 0.371  | 0.163  | 0.372 | 0.109 | 0.241  |
| 8         | 0.2| 8       | 0.561 | 0.365 | 0.245 | 0.161 | 0.372  | 0.168  | 0.394 | 0.115 | 0.254  |
| 9         | 0.2| 16      | 0.572 | 0.379 | 0.257 | 0.169 | 0.379  | 0.171  | 0.407 | 0.118 | 0.263  |
| 10        | 0.3| 8       | 0.561 | 0.366 | 0.248 | 0.165 | 0.374  | 0.166  | 0.380 | 0.114 | 0.247  |

Table 3: BLEUn, METEOR, ROUGE1, CIDEr, SPICE, and SPIDEr in a comparative study of CLIP-AAC and other competitive techniques.

| Method                  | BLEU | BLEU2 | BLEU3 | BLEU4 | METEOR | CIDEr | SPICE | SPIDEr |
|-------------------------|------|-------|-------|-------|--------|-------|-------|--------|
| GRU Baseline [21]       | 0.389| 0.136 | 0.055 | 0.015 | 0.262  | 0.084 | 0.074 | 0.033  | 0.054  |
| PreCNN Transformer [7]  | 0.534| 0.343 | 0.230 | 0.151 | 0.356  | 0.160 | 0.346 | 0.108  | 0.227  |
| CL4AC [1]               | 0.553| 0.349 | 0.226 | 0.143 | 0.374  | 0.168 | 0.368 | 0.115  | 0.242  |
| AT-CNN10 [4]            | 0.556| 0.363 | 0.242 | 0.159 | 0.368  | 0.169 | 0.377 | 0.113  | 0.246  |
| TL + RLSSR [11]         | 0.551| 0.369 | 0.252 | 0.168 | 0.373  | 0.165 | 0.380 | 0.111  | 0.246  |
| CLIP-AAC (ours)         | 0.572| 0.379 | 0.257 | 0.169 | 0.379  | 0.171 | 0.407 | 0.119  | 0.263  |

Figure 2: Visualization of cosine similarity (after softmax) matrix between audio embeddings ($A_1$ to $A_8$) and text embeddings ($T_1$ to $T_8$). (A) and (B) denote the system 8 before and after training, respectively.

We observe from the performances of system 1 that the encoder may not produce good features in deep architectures with random initialization. Compared with system 2, system 3 achieves better performance as the proposed encoder with audio-head and text-head can learn both acoustic and textual information. System 4 further improves performances by making the encoder trainable on the Clotho dataset. We adopt the setting of system 4 for the encoder hereafter.

4.2. Effect of Contrastive Loss

We further report the effect of proposed contrastive loss $L_{cl}$ on CLIP-AAC approach. As shown in Table 2, α is the coefficient to trade-off the contrastive loss $L_{cl}$ and cross-entropy loss $L_{ce}$. B.S. denotes the batch size used at training stage.

From system 5, 6, 8 and 10, we observe that performances improve as the coefficient α increases, indicating that the contrastive learning strategy can learn more audio and text information. We obtain best performances when α for $L_{cl}$ is set as 0.2. Furthermore, system 7-9 improve performances by increasing the batch size B.S. because a large batch size can increase the diversity of negative audio-text pairs for training. Best performances are obtained with B.S. of 16.

To further show the contribution of the contrastive loss, we visualize the cosine similarity matrix of audio-text embeddings after the softmax function in system 8. The diagonal elements denote the cosine similarity of true audio-text pairs in Figure 2. We observe that the proposed pre-trained CLIP-AAC encoder can catch some correspondence between true audio-text pairs before training. After training, such correspondence is significantly enhanced by proposed contrastive learning. Therefore, we draw a conclusion that the CLIP-AAC encoder can provide high-quality embeddings for cross-modal decoding.

4.3. Benchmark against other competitive methods

Table 3 summarizes the comparison between the proposed CLIP-AAC and other competitive techniques in terms of BLEU, METEOR, ROUGE1, CIDEr, SPICE, and SPIDEr. We conduct experiments on the Clotho dataset. Except for the GRU baseline [21], all encoders in the other five techniques are pre-trained on AudioSet. The GRU baseline is trained from scratch. We observe that the proposed CLIP-AAC obtained the best performances for all metrics.

5. Conclusions

In this paper, we propose CLIP-AAC to learn interactive cross-modality representation with both acoustic and textual information for AAC tasks. Specifically, we introduce an audio-head and text-head in the encoder to capture audio-text correspondence. Furthermore, we also propose a contrastive learning strategy to optimize the CLIP framework. Experimental results show the proposed CLIP-AAC outperforms the best baseline by a large margin in terms of all metrics.

6. Acknowledgements

This research is supported by the National Research Foundation, Singapore under its AI Singapore Programme (AISG Award No: AISG-100E-2018-006). The computational work for this article was partially performed on resources of the National Supercomputing Centre, Singapore (https://www.nscc.sg).
7. References

[1] X. Liu, Q. Huang, X. Mei, T. Ko, H. L. Tang, M. D. Plumbley, and W. Wang, “Cl4ac: A contrastive loss for audio captioning,” arXiv preprint arXiv:2107.09990, 2021.

[2] X. Mei, Q. Huang, X. Liu, G. Chen, J. Wu, Y. Wu, J. Zhao, S. Li, T. Ko, H. L. Tang et al., “An encoder-decoder based audio captioning system with transfer and reinforcement learning,” arXiv preprint arXiv:2108.02752, 2021.

[3] K. Drossos, S. Adavanne, and T. Virtanen, “Automated audio captioning with recurrent neural networks,” in 2017 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA). IEEE, 2017, pp. 374–378.

[4] X. Xu, H. Dinkel, M. Wu, Z. Xie, and K. Yu, “Investigating local and global information for automated audio captioning with transfer learning,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 905–909.

[5] X. Xu, Z. Xie, M. Wu, and K. Yu, “The siju system for dcase2021 challenge task 6: audio captioning based on encoder pre-training and reinforcement learning,” DCASE2021 Challenge, Tech. Rep., Tech. Rep., 2021.

[6] Y. Wu, K. Chen, Z. Wang, X. Zhang, F. Nian, S. Li, and X. Shao, “Audio captioning based on transformer and pre-training for 2020 dcase audio captioning challenge,” DCASE2020 Challenge, Tech. Rep., 2020.

[7] K. Chen, Y. Wu, Z. Wang, X. Zhang, F. Nian, S. Li, and X. Shao, “Audio captioning based on transformer and pretrained cnn,” in Proceedings of the Detection and Classification of Acoustic Scenes and Events Workshop, 2020, pp. 21–25.

[8] X. Mei, X. Liu, Q. Huang, M. D. Plumbley, and W. Wang, “Audio captioning transformer,” arXiv preprint arXiv:2107.09817, 2021.

[9] Q. Kong, Y. Cao, T. Iqbal, Y. Wang, W. Wang, and M. D. Plumbley, “Panns: Large-scale pretrained audio neural networks for audio pattern recognition,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 28, pp. 2890–2894, 2020.

[10] J. F. Gemmeke, D. P. Ellis, D. Freedman, A. Jansen, W. Lawrence, R. C. Moore, M. Plakal, and M. Ritter, “Audio set: An ontology and human-labeled dataset for audio events,” in 2017 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2017, pp. 776–780.

[11] A. Koh, F. Xue, and E. S. Chng, “Automated audio captioning using transfer learning and reconstruction latent space similarity regularization,” arXiv preprint arXiv:2108.04692, 2021.

[12] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark et al., “Learning transferable visual models from natural language supervision,” in International Conference on Machine Learning. PMLR, 2021, pp. 8748–8763.

[13] R. Mokady, A. Hertz, and A. H. Bermano, “Clipcap: Clip prefix for image captioning,” arXiv preprint arXiv:2111.09734, 2021.

[14] A. Guzhov, F. Raue, J. Hees, and A. Dengel, “Essrene (x) t-rbsp: Learning robust time-frequency transformation of audio,” in 2021 International Joint Conference on Neural Networks (IJCNN). IEEE, 2021, pp. 1–8.

[15] A. Guzhov, F. Raue, and Hee, “Essresnet: Environmental sound classification based on visual domain models,” in 2020 25th International Conference on Pattern Recognition (ICPR). IEEE, 2021, pp. 4933–4940.

[16] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[17] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” Advances in neural information processing systems, vol. 30, 2017.

[18] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever et al., “Language models are unsupervised multitask learners,” OpenAI blog, vol. 1, no. 8, p. 9, 2019.

[19] A. Guzhov, F. Raue, J. Hees, and A. Dengel, “Audioclip: Extending clip to image, text and audio,” arXiv preprint arXiv:2106.13043, 2021.

[20] Y. Zhang, H. Jiang, Y. Miura, C. D. Manning, and C. P. Langlotz, “Contrastive learning of medical visual representations from paired images and text,” arXiv preprint arXiv:2010.00747, 2020.

[21] K. Drossos, S. Lipping, and T. Virtanen, “Clotho: An audio captioning dataset,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 736–740.

[22] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[23] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Re-thinking the inception architecture for computer vision,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 2818–2826.

[24] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “Bleu: a method for automatic evaluation of machine translation,” in Proceedings of the 40th annual meeting of the Association for Computational Linguistics, 2002, pp. 311–318.

[25] C.-Y. Lin, “Rouge: A package for automatic evaluation of summaries,” in Text summarization branches out, 2004, pp. 74–81.

[26] A. Lavie and A. Agarwal, “Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments,” in Proceedings of the second workshop on statistical machine translation, 2007, pp. 226–231.

[27] R. Vedantam, C. Lawrence Zitnick, and D. Parikh, “Cider: Consensus-based image description evaluation,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 4566–4575.

[28] P. Anderson, B. Fernando, M. Johnson, and S. Gould, “Spice: Semantic propositional image caption evaluation,” in European conference on computer vision. Springer, 2016, pp. 382–398.

[29] S. Liu, Z. Zhu, N. Ye, S. Guadarrama, and K. Murphy, “Improved image captioning via policy gradient optimization of spider,” in Proceedings of the IEEE international conference on computer vision, 2017, pp. 873–881.

[30] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, “Show and tell: A neural image caption generator,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3156–3164.

[31] L. Zhou, Y. Kalantidis, X. Chen, J. J. Corso, and M. Rohrbach, “Grounded video description,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 6578–6587.

[32] Q. You, H. Jin, Z. Wang, C. Fang, and J. Luo, “Image captioning with semantic attention,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 4651–4659.