Multi-Task Multi-Modal Self-Supervised Learning for Facial Expression Recognition

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Abstract

Human communication is multi-modal; e.g., *face-to-face interaction involves auditory signals (speech) and visual signals (face movements and hand gestures). Hence, it is essential to exploit multiple modalities when designing machine learning-based facial expression recognition systems. In addition, given the ever-growing quantities of video data that capture human facial expressions, such systems should utilize raw unlabeled videos without requiring expensive annotations. Therefore, in this work, we employ a multi-task multi-modal self-supervised learning method for facial expression recognition from in-the-wild video data. Our model combines three self-supervised objective functions: First, a multi-modal contrastive loss, that pulls diverse data modalities of the same video together in the representation space. Second, a multi-modal clustering loss that preserves the semantic structure of input data in the representation space. Finally, a multi-modal data reconstruction loss. We conduct a comprehensive study on this multi-modal multi-task self-supervised learning method on three facial expression recognition benchmarks. To that end, we examine the performance of learning through different combinations of self-supervised tasks on the facial expression recognition downstream task. Our model **ConCluGen** outperforms several multi-modal self-supervised and fully supervised baselines on the CMU-MOSEI dataset. Our results generally show that multi-modal self-supervision tasks offer large performance gains for challenging tasks such as facial expression recognition, while also reducing the amount of manual annotations required. We release our pre-trained models as well as source code publicly* [1]*.*

1. Introduction

Facial expression recognition (FER) is a fundamental task for successful everyday human social interaction, and human-computer interaction [1]. Rooted in the context-sensitive and top-down manner of human perception, how we perceive an expression can change with (affective) context and prior knowledge [7, 18, 53], and other various other factors [58]. The same facial expression can be perceived differently depending on the situation and context [5, 16, 47]. A recent review from Maier et al. [39] highlights that to develop FER systems that align with human perception, we should consider contextual cues along with social knowledge. From a human perspective, context is inherently multi-modal, not just what is visually perceptible, as often previously treated in computer vision [31, 33, 59].

Over the last decade, deep learning aproaches have advanced the field of artificial intelligence by utilizing the massive amounts of data generated daily, *e.g.* on the internet. Large quantities of such data are multimodal, such as videos. Even though real-world (in the wild) video data helps train deeper machine-learning models, it also presents multiple challenges. Such data is usually imbalanced, noisy, and, most importantly, unlabeled. Therefore, research in deep learning and computer vision directs attention toward self-supervised learning algorithms, that aim to learn rich data representations without the need for manual labeling processes. Self-supervised learning is a form of unsupervised representation learning where the labels are extracted from the data itself, enabling label-efficient feature learning. Subsequently, the resulting models after the self-supervised learning phase can be used or adapted to downstream tasks, such as facial expression recognition. Given the growing amounts of video data that capture human facial expressions, self-supervision may allow for learning data representations from raw unlabeled video samples. Nevertheless, as mentioned above, FER is a challenging task that

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requires the integration of multi-modal contexts to align with human-level perception, since people their feelings across different modalities (visually, orally, and in other ways). Thus, not only is it essential to include these multiple modalities in learning algorithmss, but we also need to effectively model the interactions across these modalities to enhance FER. In this work, we introduce a multi-task multi-modal self-supervised approach for FER. Employing multiple tasks for self-supervision allows for learning more informative data representations, as each task enhances a certain property in the learned features, and integrating these tasks allows for capturing these complementary properties in the resulting embedding space.

Contributions. The main contributions in this paper are as follows:

- To the best of our knowledge we are the first to employ multi-task multi-modal self-supervised methods for FER.
- Our multi-modal multi-task self-supervised model *ConCluGen* (see Fig. 1) outperforms multiple self-supervised and fully supervised models on FER.
- We provide a comprehensive study on multiple self-supervised learning methods for FER.
- We make all self-supervised models (multi-modal and uni-modal) presented in this study publicly available to the research community as baselines for future studies.

2. Related work

2.1. Self-Supervised Learning

Over the last years, self-supervised learning methods advanced the research in different fields [14, 29, 43, 49], especially in computer vision applications where the amount of unlabeled data is increased rapidly due to social media, *e.g.* YouTube videos, TikTok, and TV-series. The reason is that with self-supervised learning methods, we can learn robust feature representation for the input data without the need for annotations. Such approaches generate the labels for the pretext task automatically from the data itself [32]. Different types of self-supervised methods have been developed: Some are predictive (also called generative) [20], *i.e.* anticipate and/or generate some parts of the data from another part of the data. The others are contrastive, which aim to anticipate the relations between data samples [10]. Some utilize one modality [41], while others draw on multiple modalities [54]. In this paper, we examine different self-supervised approaches and show that especially for complex computer vision applications, such as FER, models can benefit from utilizing multi-modal data in the self-supervised learning techniques.

Instance-Level Contrastive Learning. Instance-level contrastive learning has been used in multiple domains to improve learned representations from unlabeled data [10, 40]. The main goal of such algorithms is to pull representations of similar objects together and push dissimilar objects far away from each other. Despite recent achievements of instance-level contrastive methods in multiple domains, they still suffer from downsides such as class collision [60]. In downstream classification tasks, instance-level contrastive learning methods lose semantic similarity between images from the same class. To mitigate this effect, some research used graph-based methods with weak supervision to pull similar instances closer to each other [60]. Others used domain knowledge to create semantically aware positive and negative sets for contrastive learning [22]. Moreover, some research focuses on introducing special augmentation techniques that can directly improve a specific downstream task performance rather than focusing on the generality of the self-supervised pre-trained model [51]. Additionally, Doersch and Zisserman [15] study multi-task self-supervised learning for visual representation learning. They jointly learn four simple but diverse self-supervised methods (motion segmentation, colorization, Exemplar task, and relative position). In this paper, we study different self-supervised methods for FER. We also study multi-task self-supervised learning, but in different combinations compared to [15]. We also focus more on multi-modality in multi-task self-supervised learning.

Multi-Modal Self-Supervised Learning. Self-supervised learning techniques have also advanced multi-modal learning. In such an environment, the model can draw on different data modalities to learn robust representation. Some research applies contrastive techniques in a multi-modal setting for multiple modalities together [56], or from two modalities as in CLIP [46] that was first employed for text and audio representation learning, or to learn from visual and audio [42]. Moreover, Taleb et al. [55] applied a multi-modal self-supervised approach on genetic modalities, and Franceschini et al. [19] utilize facial landmarks as an additional modality for FER in videos. Additionally, a body of research work [2, 4, 9] supports multi-modal contrastive learning with multi-modal clustering to ensure that semantically similar modalities are represented close to each other in the embedding space. In this paper, we follow the same direction in our ConCluGen and ConClu models (Sec. 3.6). To the best of our knowledge, we are the first to apply such a technique for FER.

2.2. Facial Expression Recognition

FER is a challenging task in computer vision for multiple reasons, such as overlapping with other facial features such as identity [34], and overlapping between multiple expression labels [6]. Some research focuses on disentangling expression features from other facial features in the input images [21, 35]. Other research focuses on learning a multi-

modal representation for the FER. In [52], Siriwardhana et al. introduced a multi-modal deep learning model for FER with a mechanism for the late fusion of multi-modal SSL features. The proposed technique is based on transformers and attention mechanisms. Our model differs from [52] in that we learn a joint representation space for all input modalities. In [19], the authors used a pairwise contrastive objective function inspired by CLIP [46] to learn unsupervised multi-modal representations from video data paired with text, audio, and facial landmarks. Our model is different from [19] in that we preserve the semantic similarity between all modalities by learning a multi-modal clustering objective that regularizes the pairwise multi-modal contrastive objective.

Other works focus on the late fusion techniques to fuse different representations from different input modalities efficiently into one multi-modal representation that is free of redundant information. The latter is less prone to overfitting in the prediction task [38]. To the best of our knowledge, we are the first to study multi-task multi-modal self-supervised learning for FER. In this work, we study the combination of multiple self-supervised losses, including multi-modal contrastive learning with clustering, instance-based contrastive learning, and generative self-supervised learning.

3. Methodology

In this section, we will explain the self-supervised pre-training techniques that we adopt in this work. Then we will explain our multi-task multimodal self-supervised model.

3.1. Problem Formulation

Each input is an utterance that consists of a segment of a video as a sequence of frames $V = (\mathbf{v}_1, \ldots, \mathbf{v_n})$, a corresponding audio spectrum $A = (\mathbf{a}_1, \ldots, \mathbf{a_m})$, and a corresponding text subtitle $T = (\mathbf{t}_1, \ldots, \mathbf{t_k})$. The task is first to learn a rich representation for the input in an unsupervised manner, then predict the facial expression class of the corresponding input video. Due to the unsupervised nature of our approach, we can build a FER model without the need for a huge dataset. We evaluate the following self-supervised methods on both multi-label and single-label FER using three datasets. Note that that both pretext and downstream tasks are independent. Each input instance I is represented by a triple input $(\mathbf{v_i}, \mathbf{t_i}, \mathbf{a_i})$ where $i \in \{0, N\}$ and N is the total number of input samples. We learn a representation for each modality by mapping each input modality to a lower dimensional space using three separate encoders as follows: A video encoder $F_v(\mathbf{v}) \Rightarrow \mathbf{D_v}$ that maps each video frame sequence to lower dimensional $\mathbf{D_v}$. A text encoder $F_t(\mathbf{t}) \Rightarrow \mathbf{D_t}$ that maps each text subtitle sequence to lower dimensional $\mathbf{D_t}$. Finally, an audio encoder $F_a(\mathbf{a}) \Rightarrow \mathbf{D_a}$ that maps each audio spectrum sequence to lower dimensional $\mathbf{D_a}$. To learn contrastive representations,

we map $\mathbf{D_v}$, $\mathbf{D_t}$, and $\mathbf{D_a}$ representations into three separate projection heads (one for each modality), each consisting of two linear layers, as follows: $J_\mathbf{v}(\mathbf{D_v}) \Rightarrow \mathbf{P_v}$, $J_\mathbf{t}(\mathbf{D_t}) \Rightarrow \mathbf{P_t}$, and $J_\mathbf{a}(\mathbf{D_a}) \Rightarrow \mathbf{P_a}$. After that, to learn the multi-modal clustering, we map the output of the projection heads to one layer clustering head G (see Fig. 1), where $G(\mathbf{D_v}) \Rightarrow \mathbf{g_v}$, $G(\mathbf{D_t}) \Rightarrow \mathbf{g_t}$, and $G(\mathbf{D_a}) \Rightarrow \mathbf{g_a}$. Fig. 1 depicts an overview of this architecture. We named the encoders F *Representation Head* here.

Note that the feature extraction networks in Fig. 1 are fully fixed since we focus on improving the representations obtained from F. This means that in the previous paragraphs, $(\mathbf{v_i}, \mathbf{t_i}, \mathbf{a_i})$ are not the raw data, but the fixed output features extracted from 2D and 3D ResNet ([24] and [3]), DistilBERT [48], and DAVENet [23] respectively.

3.2. Instance-Level (Visual Only) Contrastive Learning

Instance-level contrastive learning methods are self-supervised methods that learn a representation of unlabeled data by discriminating between pairs of instances. They represent similar instances closer to each other in the embedding space, and dissimilar instances far apart. The quality of instance-level contrastive learning methods is influenced by the quality of data augmentations. This is the case because positive pairs for each instance are the augmented version of that instance, and the negative pairs are other instances in the training batch. To implement an instance-level contrastive learning method for video data, we follow the spatial augmentation process in the work of Qian et al. [45] that is consistent along the temporal dimension. Thus we will preserve the motion signal across frames, by generating random spatial augmentations across videos not across frames. We applied the following augmentations: random cropping with resizing, random horizontal flipping, color jitter, random grayscale, and Gaussian blur. Finally, we apply InfoNCE loss given as follows:

$$\ell_{\text{NCE}} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp(sim(\mathbf{P}_\mathbf{v}^i, \mathbf{P}_\mathbf{v}^{'i})/\tau)}{\sum_{k=1}^{2K} 1_{[k \neq i]} \exp(sim(\mathbf{P}_\mathbf{v}^i, \mathbf{P}_\mathbf{v}^k)/\tau)} \tag{1}$$

where τ is the positive temperature parameter, $\mathbf{P_v}$ is the representation of video frames, and sim is a similarity function. By minimizing ℓ_{NCE} we are minimizing the distance between the instance $\mathbf{P_v}$, and its augmented versions $\mathbf{P_v}'$, and maximize the distance between other instances.

3.3. Multi-Modal Contrastive Learning

To train a network that can project all modality inputs to the same embedding space, we learn a Masked Margin Softmax (MMS) loss [26] between each input modality. Masked Margin Softmax (MMS) loss maximizes the similarity of correctly paired modalities and minimizes the similarity of
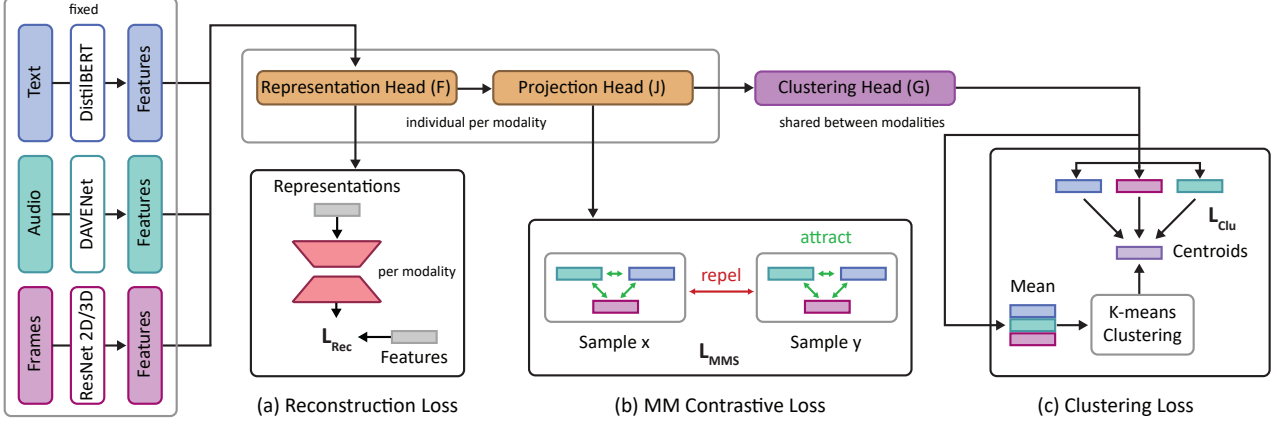
Figure 1. Overview of the architecture of the multi-task multi-modal self-supervised method. The backbone feature extractors process the input modalities in blocks, which we average over the time domain. The resulting temporal features are stored on disk, *i.e.* the backbones are fully fixed. The 3-layer representation head produces the representations we want to use in downstream training. The three losses are: (a) A reconstruction loss which reconstructs the features of each modality individually. (b) The multi-modal contrastive loss encourages the representations from the projection head for modalities belonging to the same input to be represented closer to each other. (c) The multi-modal clustering loss which drives the modalities of a sample towards the centroids computed by k-means clustering. The latter uses the mean of the modalities to compute these centroids.

incorrectly paired modalities. In the case of two modalities, text, and video frames. We calculate MMS loss as follows:

$$L_{MMS_{vw}} = L_{wv} + L_{vw} \tag{2}$$

$$L_{vw} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{\mathbf{P_{v_i}} \cdot \mathbf{P_{w_i}} - \delta}}{e^{\mathbf{P_{v_i}} \cdot \mathbf{P_{w_i}}} \sum_{j=1, j \neq i}^{N} e^{\mathbf{P_{v_j}} \cdot \mathbf{P_{w_i}}}} \tag{3}$$

$$L_{wv} = -\frac{1}{N} \sum_{j=1}^{N} \log \frac{e^{\mathbf{P_{v_j}} \cdot \mathbf{P_{w_j}} - \delta}}{e^{\mathbf{P_{v_j}} \cdot \mathbf{P_{w_j}}} \sum_{i=1, j \neq i}^{N} e^{\mathbf{P_{v_i}} \cdot \mathbf{P_{w_j}}}} \tag{4}$$

In the case of three modalities input, we calculate the MMS loss for each modality pair, and the final loss is the sum of all MMS losses between paired modalities.

$$L_{MMS} = L_{MMS_{vh}} + L_{MMS_{vw}} + L_{MMS_{hw}} \tag{5}$$

3.4. Generative Self-Supervised Learning

In this work, we study the impact of the reconstruction objective function on the learned representation from unlabeled data. Either as the only objective function in the proxy task or as a part of multi-task self-supervised training. Since the training data is multi-modal, we follow a similar direction as Chen et al. [9] and perform the reconstruction for each modality individually. The final reconstruction loss is the sum of the reconstruction losses of all modalities. Thus we have 3 encoder-decoder models, Q_f, Q_w, and Q_h for

video, text, and audio respectively. Each decoder receives a feature representation $\mathbf{D}$ from the related reconstruction head. In the following you can see the reconstruction loss for the visual modality:

$$L_{Rec_{\mathbf{v}}} = \mathrm{MSE}(v, Q_v(\mathbf{D_v})) \tag{6}$$

The reconstruction loss is the mean-squared error (MSE) between the output features from the encoder-decoder model and the input features. Such loss penalizes the network for creating outputs (in this case features) different from the input features. The final reconstruction loss over the 3 modalities is given as:

$$L_{Rec} = L_{Rec_v} + L_{Rec_h} + L_{Rec_w} \tag{7}$$

3.5. Multi-Modal Contrastive Learning with Clustering

This method learns a multi-modal representation utilizing the multi-modal contrastive objective function from Sec. 3.3 that encourages modalities of the same instance represented closer to each other in the feature space. Moreover, it preserves the similarity between different instances by learning a multi-modal clustering objective function beside the multi-modal contrastive object function. The objective function that guides the multi-modal learning process consists of two losses: The first one is the multi-modal contrastive loss Eq. (5), the second one is the multi-modal clustering loss that will be elaborated below.

Multi-modal clustering representation learning.
To preserve the similarity between different modalities of similar instances, we formulate a clustering objective function that minimizes the distance between similar modalities. To create the clustering centroids we follow a similar direction of recent work [9] that creates a multi-modal centroid over joint multi-modal representations instead of creating a separate centroid for each modality. Thus, by using the clustering loss, we encourage the audio, visual, and text embeddings of similar videos (that share similar semantic information) to be represented closer to each other in the feature space.

As shown in Eq. (8), we compute the multi-modal representation $\mathbf{R_i}$ of each instance as the mean over the representations of each modality associated with that instance. As illustrated in Fig. 1, the clustering loss is performed over the output of the *Clustering Head* which is G (see Sec. 3.1). Assuming we have three modalities (video, text, and audio) as input then the multi-modal representation $\mathbf{R}$ for each instance i is calculated as follows:

$$R_i(\mathbf{g_v^i}, \mathbf{g_t^i}, \mathbf{g_a^i}) = (\mathbf{g_v^i} + \mathbf{g_t^i} + \mathbf{g_a^i})/3 \qquad (8)$$

After estimating the cluster centroids $(\mathbf{C}_1, \ldots, \mathbf{C}_k)$, where k is the number of clusters, we estimate the multi-modal centroids using K-means over the multi-modal representations $\mathbf{R}$ by minimizing the following equation:

$$\sum_{j=1}^{k} \sum_{i=1}^{n} \left| \mathbf{R}_i^{(j)} - \mathbf{C}_j \right| \qquad (9)$$

where $\mathbf{R}_i^{(j)}$ is the multimodal representation that belongs to cluster j with centroid $\mathbf{C}j$. Finally, we learn the Multi-modal clustering loss that minimizes the distance between the multi-modal representations $(\mathbf{R}_1^{(1)}, \ldots, \mathbf{R}_n^{(k)})$ and the cluster centroids $(\mathbf{C}_1, \ldots, \mathbf{C}_k)$. This loss updates all modality encoders to encourage modality embeddings to be presented closer to each other in the feature space. The multi-modal clustering loss encourages the multi-modal representations that belong to the same cluster to be closer to their centroid thus preserving the similarity between multimodal representations.

$$\ell_{\text{Clu}} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{\mathbf{R}_i^j \cdot \mathbf{C}_j - \delta}}{\sum_{k=1}^{K} e^{\mathbf{R}_i^j \cdot \mathbf{C}_k}} \qquad (10)$$

3.6. Multi-Task Self-Supervised Learning

In this section, we analyze the ability to learn rich multimodal representations in a multi-task self-supervised learning fashion. Here we will learn multiple self-supervised tasks simultaneously without supervision, only by leveraging the structure of the multi-modal data. The intuition behind multi-task self-supervised learning is to make the most of the structure of the large unlabeled datasets which leads to rich and better generalized representation learning. In this study, we investigate the following multi-modal task combination:

1. **ConCluGen**: In this model, we jointly learn three self-supervised tasks. The first is multi-modal contrastive learning. The second is online multi-modal clustering. The third is multi-modal reconstruction. The objective function that guides the learning process in ConCluGen model is as follows:

$$L_{ConCluGen} = L_{MMS} + L_{Clu} + L_{Rec} \qquad (11)$$

2. **ConClu**: In this model, we jointly learn two self-supervised tasks. First is multi-modal contrastive learning. The second is online multi-modal clustering. The objective function that guides the learning process in ConClu model is as follows:

$$L_{ConClu} = L_{MMS} + L_{Clu} \qquad (12)$$

3. **ConGen**: In this model, we jointly learn two self-supervised tasks. First is multi-modal contrastive learning. The second is multi-modal reconstruction. The objective function that guides the learning process in ConGen model is as follows:

$$L_{ConGen} = L_{MMS} + L_{Rec} \qquad (13)$$

4. Experiments and Analysis

In this section, we evaluate the previously detailed self-supervised methods on three facial expression recognition datasets [6, 33, 44] . First, we present the datasets used to evaluate our work. Then, we clarify the evaluation metrics (See the Appendix for implementation details). Finally, we analyze and discuss our results.

4.1. Datasets

VoxCeleb2. We pretrain all methods on the large-scale face dataset VoxCeleb2 [11], which is *not* annotated for FER. VoxCeleb2 consists of 145,000 videos of celebrities and also contains audio and subtitles. Since the videos are already focused on the face, we did not perform any cropping. For downstream task, we evaluate the CAER [33], MELD [44] and CMU-MOSEI [6] datasets. We employed a Pytorch MTCNN implementation[2] to crop out the faces (see appendix for details).
CAER. [33] consists of 13,000 videos, containing audio, of the TV series Friends. We automatically inferred subtitles

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from the audio data. Multiple speakers can be visible within one scene. The annotation labels are the 7 basic Ekman expressions [17].

MELD. [44] is a multi-modal dataset providing frames, audio, and subtitles and is also based on the TV series Friends, similarly to CAER. Its 13,000 videos feature single individuals only, cuts in a scene result in a different sample in this dataset. It provides 7 expression labels.

CMU-MOSEI. [6] contains 3,000 videos from YouTube in which people talk mostly directly into the camera. In contrast to CAER and MELD, CMU-MOSEI offers smooth multi-label annotations for 6 emotions on a Likert scale from 0 to 3. We discretize the labels by setting every value greater than 0 to 1.

Evaluation Metrics. For the downstream task we measure accuracy (Acc.), F1 score (F1), precision and recall, all weighted by the class occurences. CAER, MELD and CMU-MOSEI are heavily imbalanced which makes weighting necessary.

4.2. Evaluation Results

In this section, we start with evaluating our model ConCluGen that we pretrained on VoxCeleb2 dataset against FER benchmarks and baselines. Then we conduct a detailed study to analyze the efficiency of the features obtained from the self-supervised methods mentioned above.

4.2.1 Benchmarking Against SOTA

In this section we are comparing the multi-task multi-modal self-supervised learning model **ConCluGen** that is pretrained on VoxCeleb, to other multi-modal self-supervised benchmarks [19, 30, 52]. Results in Tab. 1 show that ConCluGen model pretrained on VoxCeleb and finetuned on CMU-MOSEI dataset is outperforming CAE-LR [30], which is a self-supervised model that is trained on CMU-MOSEI dataset. It is also on par with Franceschini et al. [19] model performance, which uses more modalities (facial landmarks) than ConCluGen model for pretraining. It is worth mentioning that both CAE-LR [30], and Franceschini et al. [19] are pretrained on CMU-MOSEI and evaluate the downstream task on this dataset as well. However, ConCluGen model in Tab. 1 is pretrained on VoxCeleb2, and only finetuned on CMU-MOSEI.

Moreover, our ConCluGen model, both with fintuning on the CMU-MOSEI dataset on Tab. 1 and without (*i.e.* simple linear evaluation), are outperforming SSE-FT [52]. SSE-FT is an independently pre-trained SSL model for vision, audio, and text modalities. They perform late fusion using an attention mechanism. Finally, they evaluate the model on CMU-MOSEI dataset without finetuning. Finally, results in Tab. 1 show that ConCluGen model outperforms multiple fully supervised benchmarks [6, 8, 12,

Method	Year	Mod.	Acc.
Self-Supervised Baselines			
SSE-FT [52]	2020	VAT	55.7
CAE-LR [30]	2021	VAT	61.03
Franceschini et al. [19]	2022	VATK	66.70
ConCluGen (ours)	2024	VAT	66.48
Fully Supervised Baselines			
CMIB [38]	2022	VAT	48.2
Huynh et al. [25]	2021	VAT	57.70
Graph-MFN [6]	2018	VAT	62.35
CIA [8]	2019	VAT	62.88
MESM [12]	2021	VAT	66.80
Khare et al. [28]	2021	VAT	66.90
Wen et al. [57]	2021	VAT	82.08
Shenoy and Sardana [50]	2020	VAT	82.77

Table 1. Benchmark evaluations of our model against SOTA methods for CMU-MOSEI dataset. Modalities (*Mod.*) are **V**ideo, **A**udio, **T**ext, (facial) **K**eypoints.

Method	CMU-MOSEI	CAER	MELD
Supervised baseline	57.88	34.43	55.97
ConCluGen (linear eval.)	60.0	37.5	56.6
ConCluGen (finetuned)	66.48	50.75	60.03

Table 2. Comparison of the proposed method and baselines.

25, 38] and is on the par with [12, 28] on CMU-MOSEI.

4.2.2 Supervised Baselines

The supervised baseline shown in Tab. 2 consists of the same multi-model architecture as the ConCluGen model, but with a fully-supervised objective function on the target dataset. Results in Tab. 2 show that both the linear evaluation and the finetuning approach outperform the fully supervised baseline for the three datasets. That highlights the efficiency of the multi-modal self-supervised learning method.

4.2.3 Evaluation of Self-Supervised Tasks

We start with a comparison between individual self-supervised tasks, then we evaluate different permutations of combining different self-supervised tasks, all for facial expression recognition.

Instance-level contrastive learning vs. multi-modal contrastive learning.
Results in Tab. 3, Tab. 4, and Tab. 5 show that the multi-modal contrastive learning method **Multi-Cont** (Sec. 3.3) outperforms the instance level contrastive learning **Instance-Cont** (Sec. 3.2). Thus the self-supervised multi-

Method	Acc.	F1	Prec.	Recall
ConCluGen	60.4	49.6	41.7	70.3
ConClu	57.4	43.9	44.9	60.5
ConGen	53.3	39.2	45.8	58.4
Multi-Cont	56.4	44.4	43.9	63.1
Instance-Cont	41.2	43.3	35.1	77.1
Generative	46.9	49.2	38	87.8
ConCluGen/(vision)	52.4	40.4	38.2	57.3
Multi-Cont Wout/text	42.5	27.3	35.3	53.1
Multi-Cont Wout/audio	53.4	47.4	41.3	75.9

Table 3. Results of different combinations of self-supervised methods on CMU-MOSEI dataset. All metrics are weighted.

Method	Acc.	F1	Prec.	Recall
ConCluGen	56.6	53.1	58.5	56.6
ConClu	58	54.7	57.6	58
ConGen	57.4	52.7	57.1	57.4
Multi-Cont	57.2	54.1	57.6	57.2
Instance-Cont	46.3	32.1	25.3	46.3
Generative	52.1	40.9	37.5	52.1
ConCluGen/(vision)	31.0	26.3	28.7	31
Multi-Cont Wout/text	48.1	31.4	24.3	48.1
Multi-Cont Wout/audio	54.3	46.9	58.2	54.3

Table 4. Results of different combinations of self-supervised methods on MELD dataset. All metrics are weighted.

Method	Acc.	F1	Prec.	Recall
ConCluGen	37.5	26.1	34.8	37.5
ConClu	36.6	24	29.4	36.6
ConGen	35.8	22.5	32.3	35.8
Multi-Cont	34.6	22.3	30.7	34.6
Instance-Cont	34.6	17.8	12	34.6
Generative	37.3	23.9	45.3	37.3
ConCluGen/(vision)	36.1	21.9	32.5	36.1
Multi-Cont Wout/text	23.2	16.8	13.9	23.2
Multi-Cont Wout/audio	35.1	19.3	24	35.1

Table 5. Results of different combinations of self-supervised methods on CAER dataset. All metrics are weighted.

modal contrastive method can learn better representations than the instance-level contrastive method (uni-modal). The confusion matrices for the MELD dataset in Fig. 2 indicate the quality of the classification performance of Multi-Cont model Fig. 2c across different emotion classes over Instance-Cont model Fig. 2d. See the Appendix for the confusion matrices of the CAER dataset. Moreover, we conduct an experiment to evaluate which modality is more

informative to be learned along with the visual modality. Results in Tab. 3, Tab. 4, and Tab. 5 consistently show that the model can benefit more from text modality.

Contrastive learning with clustering.
Results on Tab. 4, and Tab. 5 show that learning online multi-modal clustering task along with multi-modal contrastive task during the pre-training phase, such as in **ConClu** model (Sec. 3.5), improves the results on the downstream task of FER for both MELD and CAER. Tab. 3 shows that the results are comparable between both models on CMU-MOSEI dataset. The hypothesis behind such a model is that by supporting the contrastive method with distance-based clustering, we can better capture semantic structures from the data. Fig. 2b shows how the quality of the classification in ConClu model enhanced over emotion classes on MELD dataset over Multi-Cont model (Fig. 2c).

Generative self-supervised learning vs. contrastive self-supervised learning.
To answer this question we compare the generative multi-modal model **Generative** (Sec. 3.4) that reconstructs each modality representation separately, to both multi-modal contrastive learning method **Multi-Cont** and instance-level contrastive **Instance-Cont**. Results on CMU-MOSEI and CAER datasets in Tab. 3 and Tab. 5 show that the generative loss is a robust objective function as a proxy task for FER. On the other hand, results for MELD dataset in Tab. 4 show that the **Generative** model is outperforming **Instance-Cont** but not the **Multi-Cont** model.

Multi-task multi-modal self-supervised learning.
In the previous section, results showed how powerful the generative objective function is as a proxy task compared to contrastive objective functions on some datasets. On the other hand, results in Tab. 3, Tab. 4, Tab. 5, show that for all datasets, minimizing a reconstruction loss along with a multi-modal contrastive loss **ConGen** leads to models that underperform the model that we pre-trained using only the multi-modal contrastive objective function.
Finally, we evaluate the model that learns using the multi-task multi-modal self-supervised objective function **ConCluGen** Sec. 3.6. Results in Tab. 3, and Tab. 5, show that for all datasets except for MELD Tab. 4, ConCluGen model is outperforming all other models.

How informative is the individual modality representation when learning the multi-modal multi-task self-supervised model ConCluGen?
To answer this question we evaluate the results using only the visual representation from the multi-modal multi-task model **ConCluGen** to the results of **Instance-Cont** model that only utilizes the vision modality during pretraining. Tab. 5, and Tab. 3, show that **ConCluGen/(vision)** is outperforming the model that we pre-trained using the instance

(a) ConCluGen Model.   (b) ConClu Model.   (c) Multi-Cont Model.   (d) Instance-Cont Model.

Figure 2. Confusion metrics for MELD dataset over different self-supervised models.

level contrastive method. On the other hand, results in Tab. 4 show that we need to utilize the three modalities that are learned by **ConCluGen** model, to outperform the **Instance-Cont** model.

5. Conclusion and Future Work

In this work, we employed a multi-task multi-modal self-supervised method for facial expression recognition on three different in-the-wild datasets. Our **ConCluGen** model outperforms several multi-modal self-supervised as well as supervised baseline models. We conduct an extensive experimental study to evaluate the performance of pre-trained models with multiple self-supervised tasks.

First, we assess the gains obtained by including multiple data modalities in the self-supervised algorithm, by evaluating the performance of the model pre-trained with a multi-modal contrastive method against a model pre-trained using a contrastive method with the visual modality only, following instance-based state-of-the-art self-supervised algorithms. We found that the multi-modal contrastive method learns more informative representations than the instance-based contrastive (uni-modal method), *i.e.* the resulting model from the multi-modal method outperforms the uni-modal model on the facial expression recognition task. In another related experiment, we discarded the other data modalities from the multi-modal model, and only kept the visual modality part of the model. In this experiment, we found that even only the visual part of the multi-modal still outperforms the instance-based uni-modal model which was trained on the visual modality only. These experiments illustrate the gains obtained when including other data modalities in the self-supervised pre-training stage; the resulting features contain more information about the data - facial expressions in our case. In addition, another noteworthy observation here is that the text modality seems to enrich the resulting representations with more information about facial expressions than the audio modality.

Moreover, in another set of experiments, we evaluate the performance gains when pretraining a model with a self-supervised task that combines both a multi-modal contrastive loss and a multi-modal clustering loss simultaneously. Here, we found that combining a contrastive loss with a distance-based clustering loss encourages the model to learn more semantic structure from the data. This effect is demonstrated clearly in the improved downstream FER performance. We believe that employing a clustering loss in combination with a contrastive loss mitigates the issue of class collision that contrastive learning methods alone could encounter [60], as explained earlier.

Finally, it is noteworthy that performing the self-supervised pre-training phase in a multi-task fashion captures more semantically meaningful representations than performing each task alone. In other words, for a challenging downstream task, such as facial expression recognition in the wild, the representations learned by each individual self-supervised task alone do not seem sufficient, as demonstrated by the superior performance of **ConCluGen** against all other self-supervised models.

In future work, we would like to expand the multi-task multi-modal method for more modalities such as facial landmarks. Additionally, we aim to evaluate our multi-task multi-modal **ConCluGen** on different downstream tasks, such as facial action unit detection, face detection, and sentiment analysis. The code and the pre-trained models implemented in this work are publicly available for the research community as baselines for future studies [3].

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[3] https://github.com/tub-cv-group/conclugen

Acknowledgements

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Supplementary Material

6. Implementation Details

We extract features from the input modalities using pre-trained fixed feature extractors. The frames for the 2D ResNet-152 [24] (ImageNet [13]) are subsampled to 1fps and for the 3D ResNet-101 [3] (Kinetics [27]) to 16fps. The audio is transformed into Mel spectrograms before processing with a DAVENet [23] pretrained on affective audio. For text, we take the last hidden layer of a DistillBERT [48] that was trained for sentiment analysis. To obtain a fixed-size feature vector per modality, we process the inputs sequentially and average the resulting vectors over time. The 2D and 3D frame features are concatenated after averaging. The result is stored on disk, *i.e.* no finetuning of the backbone feature extractors happens. We use AdamW optimizer [36] for both pertaining and downstream training, in combination with cosine annealing with warm restarts [37] as learning rate scheduling. Our batch size is 4096 and the image size is 180 by 180 pixels (cropped or resized). The size of the representations is 4096. More details are given in the supplementary material. We used the following learning rates in our experiments:

Pretraining:

- ConCluGen: lr=0.00009, weight decay=0.00032
- ConClu: lr=0.00009, weight decay=0.00032
- ConGen: lr=0.00036, weight decay=0.00032
- Multi-Cont: lr=0.00036, weight decay=
- Instance-Cont: lr=0.00036, weight decay=00032
- Generative: lr=0.00036, weight decay=0.00032

Downstream: (We chose common hyperparameters that worked well for all methods)

- CAER: lr=0.0061, weight decay=0.08216
- MELD: lr=0.00967, weight decay=0.00004
- MOSEI: lr=0.00996, weight decay=0.00007

For the K-means clustering, we choose a queue size of 4 (*i.e.* 4 batches were considered in the clustering), 8 clusters and started the clustering in epoch 12.

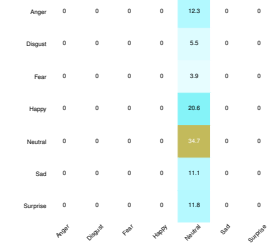## 7. Confusion Matrices for CAER
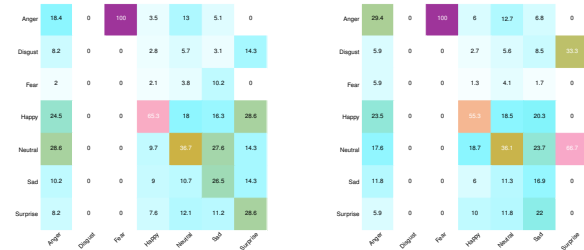
(a) ConCluGen Model.

(b) ConClu Model.

(c) Multi-Cont Model.

(d) Instance-Cont Model.

Figure 3. Confusion metrics for CAER dataset over different models.