

MAFW: A Large-scale, Multi-modal, Compound Affective Database for Dynamic Facial Expression Recognition in the Wild

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ABSTRACT

Dynamic facial expression recognition (FER) databases provide important data support for affective computing and applications. However, most FER databases are annotated with several basic mutually exclusive emotional categories and contain only one modality, e.g., videos. The monotonous labels and modality cannot accurately imitate human emotions and fulfill applications in the real world. In this paper, we propose MAFW, a large-scale multi-modal compound affective database with 10,045 video-audio clips in the wild. Each clip is annotated with a compound emotional category and a couple of sentences that describe the subjects' affective behaviors in the clip. For the compound emotion annotation, each clip is categorized into one or more of the 11 widely-used emotions, i.e., anger, disgust, fear, happiness, neutral, sadness, surprise, contempt, anxiety, helplessness, and disappointment. To ensure high quality of the labels, we filter out the unreliable annotations by an Expectation Maximization (EM) algorithm, and then obtain 11 single-label emotion categories and 32 multi-label emotion categories. To the best of our knowledge, MAFW is the first in-the-wild multi-modal database annotated with compound emotion annotations and emotion-related captions. Additionally, we also propose a novel Transformer-based expression snippet feature learning method to recognize the

compound emotions leveraging the expression-change relations among different emotions and modalities. Extensive experiments on MAFW database show the advantages of the proposed method over other state-of-the-art methods for both uni- and multi-modal FER. Our MAFW database is publicly available from <https://mafw-database.github.io/MAFW>.

CCS CONCEPTS

• **Computing methodologies** → **Computer vision**; • **Human-centered computing** → **HCI design and evaluation methods**.

KEYWORDS

Dynamic compound affective database, single and multiple expressions, multi-modal, Transformer, in the wild

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1 INTRODUCTION

In recent years, facial expression recognition (FER) has become a hot research topic in the fields of human-computer interaction (HCI) systems, multimedia analysis and processing, intelligent robots, and so on [4, 11, 14, 33]. Despite the progress, most the existing methods and databases are developed based on six basic emotions (i.e., happiness, sadness, fear, surprise, disgust, and anger) proposed by P. Ekman [13] and contain only a single modality, e.g., videos. Since the monotonous labels and modality are significantly different from the real-world human emotions in the wild, FER techniques are

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Table 1: Summary of existing dynamic facial expression databases.

Database	#Sample	Source	Expression annotation	Is in-the-wild?	#Annotation Times	Modality
CK+ [28]	327	Lab	6 expressions+neutral and contempt	No	-	Video
MMI [31]	2900	Lab	6 expressions+neutral	No	-	Video
BP4D [39]	328	Lab	6 expressions+embarrassment and pain	No	-	Video&Audio
Aff-Wild2 [8]	84	Web & YouTube	6 expressions+neutral	Yes	3	Video&Audio
AFEW 7.0 [7]	1,809	54 movies	6 expressions+neutral	Yes	2	Video&Audio
CAER [22]	13,201	79 TV dramas	6 expressions+neutral	Yes	3	Video&Audio
EmoVoxCeleb [1]	22,496	Interview videos from YouTube	6 expressions+neutral and contempt	Yes	Auto	Video&Audio
DFEW [20]	16,372	1500 movies	6 expressions+neutral	Yes	10	Video&Audio
		1,600 movies & TV dramas	11 single expressions			Video
Our MAFW	10,045	20,000 short videos from reality shows, talk shows, news, etc 2,045 clips from [7], [20], and [1]	32 multiple expressions emotional descriptive text	Yes	11	Audio Text

still far from the real-world applications [15, 24]. In order to enhance the real-world use of FER technology, it is essential to construct a sizable, in-the-wild dynamic affective database encompassing compound emotions and modalities.

Existing dynamic databases are classified into two categories based on the method of collection: laboratory-collected constrained databases and in-the-wild databases [24]. Table 1 reports existing dynamic FER databases and their information. Through event induction, the constrained databases, including CK+ [28], MMI [31], etc., record films of facial expression changes in the lab. These databases with single, limited, and consistent expression changes have seen substantial breakthroughs in FER technology, but they fall short in simulating the complex real-world human emotions. The in-the-wild databases, such as AFEW 7.0 [7] and DFEW [20], are constructed by crawling videos from movies and TV dramas. These databases closely reflect actual life, including a variety of contextual factors and spontaneous expressions. However, they still have the following limitations:

- The labels of the data are monotonous. As shown in Table 1, most existing databases are composed of seven or eight basic mutually exclusive emotional categories, *e.g.*, six basic expressions plus neutral or contempt. Many studies [10, 12, 32, 35, 40] have shown that people usually express multiple emotions simultaneously in real life, along with gestures and vocal changes.
- Video sources are relatively homogeneous and repetitive. As shown in Table 1, videos in CAER [22] and DFEW [20] are from 79 TV dramas and 1,500 movies, respectively, while EmoVoxCeleb [1] is collected from interview programs.
- The modality of the data is relatively monotonous. As shown in Table 1, most existing FER databases contain only video and audio modalities, and very few contain text modalities.

To overcome the above problems, we construct a large-scale compound affective database called MAFW with multiple modalities in the wild, which contains 10,045 video-audio clips. MAFW can be used as a new benchmark for researchers to develop and evaluate their methods for several FER tasks, such as multi-modal emotion recognition, cross-domain FER, emotion captioning, self-supervision FER, etc. Fig. 1 gives typical examples and the corresponding annotations in our MAFW database. Our MAFW has the following three advantages over the existing databases:

- Our MAFW is the first large-scale, multi-modal, multi-label affective database with 11 single expression categories, 32

multiple expression categories, and emotional descriptive texts. To obtain reliable and objective annotation, each clip in MAFW is independently labeled enough often as one or more of the 11 expression categories. Unreliable labels are then removed by an Expectation Maximization (EM) based reliability evaluation algorithm.

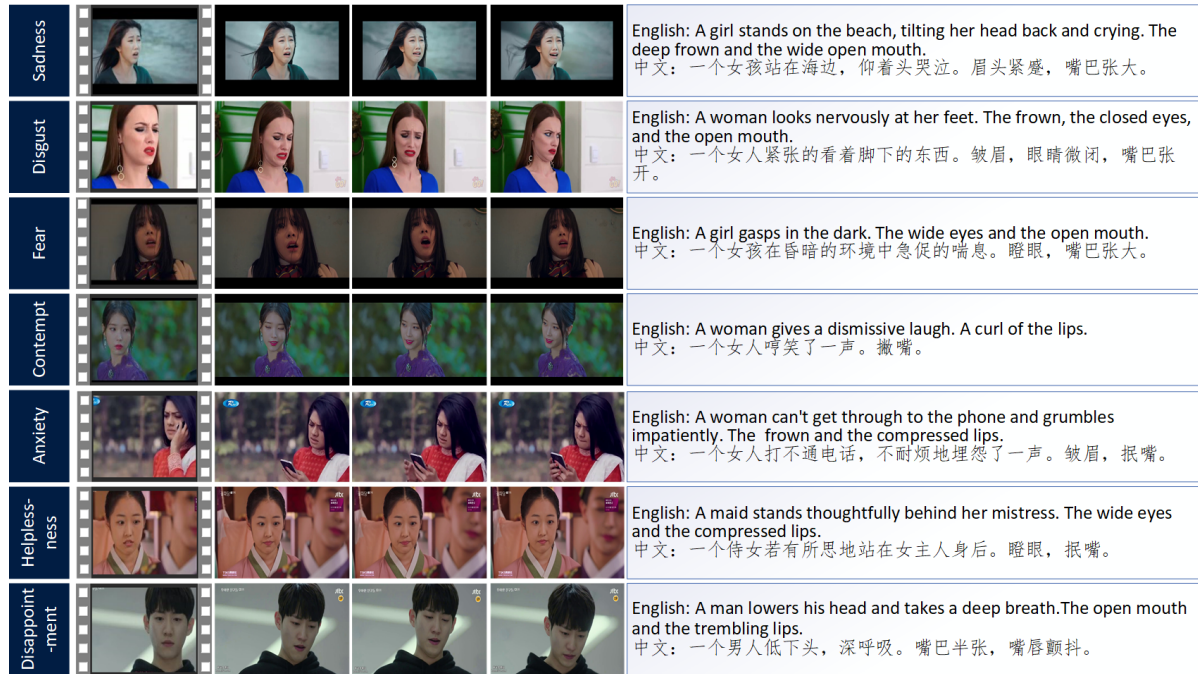
- Unlike most existing multi-modal FER databases that are only labeled with expression category tags, we also provide bilingual descriptive texts on facial expressions and emotions for videos in English and Chinese. The descriptive texts include the information on the environment, body movements, facial unit action, and other emotional elements that can be used for both video emotion captioning and FER.
- Compared to existing databases whose sources are mostly movies and TV shows, MAFW also includes short videos of reality TV, talk shows, news, variety shows, etc.

In addition to MAFW, we also propose a novel Transformer-based expression snippet feature learning method (T-ESFL) to effectively model subtle intra-snippet and inter-snippet expression movements for discovering movement-sensitive emotion representation, thus obtaining robust uni- and multi-modal FER. Furthermore, we establish four benchmark evaluation protocols for MAFW. Extensive experiments show the advantages of T-ESFL over other state-of-the-art deep learning methods, for both uni- and multi-modal FER.

2 RELATED WORK

Constrained dynamic FER databases The constrained databases are usually captured from a small group of individuals in a fixed indoor setting, with emotion frequently occurring during video viewing and event elicitation. For example, CK+ [28] collected six basic expressions from 123 individuals under laboratory conditions. BP4D [39] collected eight expressions from 41 individuals in eight different scenarios, including one-to-one interviews (evoking pleasure), suddenly hearing a voice (evoking surprise), and so on. Despite being spontaneous, the constrained expression databases are limited by a single environment, simple settings, the number of individuals, and the cost of production, making it difficult to simulate the real-world human emotions.

In-the-wild dynamic FER databases Dynamic FER databases in the wild are usually collected from online sources like TV episodes, movies, and other media. AFEW 7.0 [7] and DFEW [20] collect 1,800 and 16,372 facial expression video clips from movies, respectively.



(a) Examples of the single expressions in MAFW.



(b) Examples of the multiple expressions in MAFW.

Figure 1: Examples of the compound expressions and the bilingual descriptive texts from MAFW. (a) The single expressions in MAFW, (b) the multiple expressions in MAFW. Due to space limitations, we only show a small number of frames in these clips.

13,201 facial expression video clips from TV dramas are included in CAER [22]. Although these databases are created using real-world films, they all have the same restrictions, such as just offering basic and single expression labels and using movie or television clips as their sources.

Compound FER databases Recent studies in psychology and cognition have revealed that people frequently express compound emotions at once [12, 35]. This suggests that the existing FER databases with single, basic expression labels are not conducive to understand human emotions. In CVPR2017, Deng *et al.* [25]

presented the first static compound FER database, namely RAF-DB, that contains 7-class single expressions and 12-class multiple expressions. In ACL2018, Zadeh *et al.* [2] presented a dynamic database, CMU-MOSEI, supporting multiple labels consisting of six basic expressions. Compared to these compound FER databases, our MAFW has more basic emotion categories, reliable multi-label emotion categories, and richer modalities.

3 MAFW DATABASE

3.1 Data Collection

The pipeline of data collection in MAFW is shown in Fig. 2. The MAFW has two main data sources. The first data sources are movies, TV dramas, and short videos from some reality shows, talk shows, news, variety shows, etc., on Bilibili and Youtube websites. We develop a crawler program to crawl over 1,600 HD movies, TV dramas, and over 20,000 short videos. These videos come from China, Japan, Korea, Europe, America, and India and cover various themes, e.g., variety, family, science fiction, suspense, love, comedy, and interviews, encompassing a wide range of human emotions. To ensure the diversity of the data, we only randomly download one episode of the same TV series, as well as select no more than three facial expression clips in an episode or short video. The second data source, inspired by [38], uses videos from already-existing public databases to supplement some unusual categories, including 1,097 videos from DFEW [20], 98 videos from AFEW 7.0 [7], and 850 videos from EmoVoxCeleb [1].

With the crawled audio-video clips, we first use FaceDetector [18, 23] to detect the clips containing faces, then manually remove the unqualified clips to obtain 10,045 usable clips.



Figure 2: Overview of the construction of MAFW.

3.2 Data Annotation

Unlike other databases that only give the basic and single emotion annotation, our database offers three different types of emotion annotations for video clips: (1) **single expression label**, i.e., each clip is assigned to a predominant and exclusive expression label, namely anger(AN), disgust(DI), fear(FE), happiness(HA), sadness(SA), surprise(SU), contempt(CO), anxiety(AX), helplessness(HL), disappointment(DS), and neutral(NE) (see Fig. 1(a)); (2) **multiple expression label**, i.e., a clip can be annotated as a multi-label multiple expression category when it is determined to contain multiple emotions (such as "Anger+Disgust" in Fig. 1(b)); (3) **emotional descriptive text**, i.e., each clip is bilingually annotated with a couple of sentences describing the subjects' affective behaviors in the clip. The following details the annotator selection, compound emotion category annotation, and descriptive text annotation, respectively.

Annotator selection Our annotators are college students from different degrees, majors, countries, and genders. To help annotate the emotion category and emotional descriptive text of each video, each annotator is initially trained to recognize expressions using the expression training tool mett¹ proposed by Paul Ekman to gain knowledge of facial action units and emotions. Following the instruction, the experts evaluate each annotator. Finally, for the annotation, 11 skilled annotators are used, each of whom had a test accuracy of at least 90%.

¹<https://www.paulekman.com/micro-expressions-training-tools/>

Compound emotion category annotation To facilitate effective annotation, we create the ExpreLabelTool labeling tool. Each clip is categorized into one or more of the 11 complex emotions using the tool and is labeled by the 11 annotators. On a scale of 0 to 1, the annotators evaluate the self-confidence scores of their annotations (including 11 levels in ExpreLabelTool). The more certain the annotation is, the higher the score. After that, each clip can be obtained as an 11-dimensional vector, where each dimension represents the score of the labeled emotion. We describe later how to select *single* and *multiple* expressions based on this vector.

Descriptive text annotation For each video, except for the neutral emotion, the annotators are required to watch the video carefully and write down the bilingual emotional description according to the pre-established rules. Fig. 1 shows examples of the descriptive texts for emotion captioning in MAFW. The atmosphere, body movements, facial action units, and other emotional details are included in the captions. To ensure the complementarity of the emotional descriptive text, the descriptive text cannot directly use terms with emotional labels, such as "she is angry".

3.3 Metadata

The MAFW is a multi-modal database with text, audio, and video modalities. Each clip data is provided with a single or multiple expression label, an average confidence score for each emotion annotation, and several descriptive sentences (texts) for emotion captioning. We additionally offer three automatic annotations: the frame-level 68 facial landmarks, face regions, and gender. The gender of each person is identified by a CNN model that has been pre-trained on CelebA[26], and the facial landmarks and regions are detected by [3]. After identification and counting, 58.1% of the MAFW database is male and 41.9% is female.

3.4 Annotation Reliability Estimation

Due to the subjectivity difference of annotators, annotation reliability may be highly variable and inconsistent. To get rid of the labels with lower reliability, motivated by [34] and [5], we employ an Expectation Maximization (EM) algorithm to assess each annotator's reliability to achieve high-reliability labels. The algorithm of EM for reliability estimation is shown in Algorithm 1.

Given the labels of N videos annotated by M annotators, we first binarize their labels into a zero-one matrix H_{MN}^k on the emotion category k as:

$$H_{MN}^k = \{h_{ij}^k\}, \quad (1)$$

where h_{ij}^k will be "1", if the i th annotator labels the j th video with emotion category k , otherwise it will be "0".

Our goal is to estimate each annotator's reliability by optimizing the likelihood of their labels. The reliability is formulated as two M -dimensional probability vectors: $\{\alpha_i^k\}$ and $\{\beta_i^k\}$,

$$\alpha_i^k = P(h_{ij}^k = 1 | v_j^k = 1), \beta_i^k = P(h_{ij}^k = 0 | v_j^k = 0), \quad (2)$$

where α_i^k is the reliability probability that the i th annotator correctly labels the emotion category k and β_i^k is the reliability probability that the i th annotator does not label the emotion category k . Note that α_i^k and β_i^k are independent of each other. $v_j^k = \{0, 1\}$

denotes whether the j th video has the label of the emotion category k . We initialize the v_j^k via annotation majority voting.

With the above definitions, in the E-step of the EM, the reliability probabilities are used to estimate the posterior probability ϕ_j^k that the j th video correctly is labeled with the emotion category k :

$$\phi_j^k = \frac{p^k \mu_j^k}{p^k \mu_j^k + (1 - p^k) \eta_j^k}, \quad (3)$$

where p^k is the expected probability of the emotion category k and initialized by $\frac{1}{N} \sum_{j=1}^N v_j^k$. μ_j^k and η_j^k are calculated as:

$$\mu_j^k = \prod_{i=1}^M (\alpha_i^k)^{h_{ij}^k} (1 - \alpha_i^k)^{(1-h_{ij}^k)}, \quad (4)$$

$$\eta_j^k = \prod_{i=1}^M (\beta_i^k)^{(1-h_{ij}^k)} (1 - \beta_i^k)^{h_{ij}^k}. \quad (5)$$

In the M-step of the EM, we first update p^k as:

$$p^k = \frac{1}{N} \sum_{j=1}^N \phi_j^k. \quad (6)$$

Then, we update α_i^k and β_i^k by Maximum Likelihood Estimation:

$$\alpha_i^k = \frac{\sum_{j=1}^N \phi_j^k h_{ij}^k}{\sum_{j=1}^N \phi_j^k}, \quad (7)$$

$$\beta_i^k = \frac{\sum_{j=1}^N (1 - \phi_j^k) (1 - h_{ij}^k)}{\sum_{j=1}^N (1 - \phi_j^k)}. \quad (8)$$

Finally, we set $Q(p^k, \alpha^k, \beta^k)$ as the convergence objective in EM algorithm as:

$$Q(p^k, \alpha^k, \beta^k) = \sum_{j=1}^N [\phi_j^k \ln p^k \mu_j^k + (1 - \phi_j^k) \ln (1 - p^k) \eta_j^k]. \quad (9)$$

We can further determine whether $Q(p^k, \alpha^k, \beta^k)$ converges:

$$\frac{|Q(p_{(t+1)}^k, \alpha_{(t+1)}^k, \beta_{(t+1)}^k) - Q(p_{(t)}^k, \alpha_{(t)}^k, \beta_{(t)}^k)|}{|Q(p_{(t)}^k, \alpha_{(t)}^k, \beta_{(t)}^k)|} < \varepsilon, \quad (10)$$

where t denotes the number of iterations and ε is the convergence threshold that is set as 0.000001 empirically. If $Q(p^k, \alpha^k, \beta^k)$ converges, we can obtain the reliability of all annotators, otherwise return the E-step.

Table 2: Cronbach’s alpha scores in the MAFW database.

Emotions	Alpha	Emotions	Alpha	Emotions	Alpha
Anger	0.955	Neutral	0.878	Anxiety	0.729
Disgust	0.824	Sadness	0.948	Helplessness	0.686
Fear	0.934	Surprise	0.920	Disappointment	0.498
Happiness	0.961	Contempt	0.731	Average	0.824

With the reliability estimation, for each emotion category, we retain five high-reliability labels at least. We use Cronbach’s Alpha

[6] scores to measure the consistency of the retained labels. The results in Table 2 show that the retained labels have high consistency and reliability, with an average score of 0.823 on the 11-class emotion categories.

Algorithm 1: Annotation reliability estimation algorithm

Input:

zero-one matrix $\{H_{MN}^k\}_{k=1}^K$ of the emotion category k ;
 M : the number of annotators;
 N : the number of videos;
 K : the number of emotion categories.

Output: the reliability matrices of M annotators on each emotion category $\{\alpha_i^k\}_{i=1}^M, \{\beta_i^k\}_{i=1}^M$.

Initialize:

$\forall k = 1, \dots, K$, initialize true labels $\{v_j^k\}_{j=1}^N$ with majority voting via H_{MN}^k . The initial value of p^k is the expected probability of the emotion label k .

$$p^k := \frac{1}{N} \sum_{j=1}^N v_j^k \quad \alpha_i^k := 0.999999 \quad \beta_i^k := 0.999999$$

for $k=1$ **to** K **do**

Repeat

E-step:

 estimate the posterior probabilities $\{\phi_j^k\}_{j=1}^N$ of N clips with the k th expression as Eq. (3)–(5).

M-step:

 update p^k, α_i^k , and β_i^k based on $\{\phi_j^k\}_{j=1}^N$ through the maximum likelihood algorithm as Eq. (6)–(8).

 Calculate $Q(p^k, \alpha^k, \beta^k)$ as Eq. (9).

until $Q(p^k, \alpha^k, \beta^k)$ **converges**

3.5 Single and Multiple Expression Selection

Using the retained high-reliability labels with their self-confidence scores, we can naturally divide the MAFW into two sets, namely the single expression set and the multiple expression set. Fig. 1(a) and Fig. 1(b) show some typical examples from the 11-class single expression and 32-class multiple expression sets, respectively.

Given the self-confidence scores from a high-reliability labeled clip, if no less than half of the annotators have labeled the k th emotion category $C^k = (c_1^k, c_2^k, \dots, c_m^k)$, we then calculate the mean value of the self-confidence scores $c_{mean}^k = \sum_{i=1}^m c_i^k / m$ on the emotion category, and pick out the emotion label k w.r.t $c_{mean}^k \geq 0.5$ as the valid label.

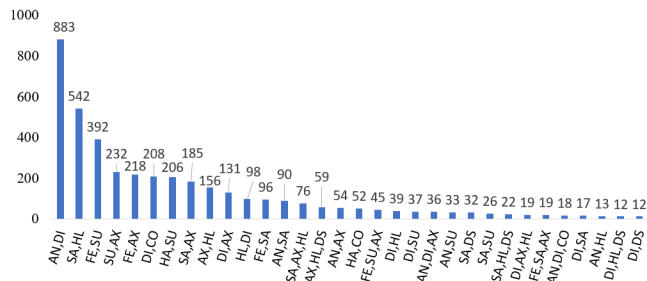
Single expression set For valid-labeled clips with single expression labels, we directly classify them into the single expression set; for clips with multiple expression labels, we select the labels with the highest average confidence score as its predominant single expressions and also classify them into the single expression set, so that the single expression set consists of all 9,172 valid-labeled clips with 11-class emotions. Table 3 reports the distribution of clip amount and clip length per expression category on the single expression set.

Multiple expression set Similarly, we create the multiple expression set from the valid-labeled clips with multiple expression

Table 3: The distribution of clip amount and clip length per single expression on the single expression set.

Expressions	Clips			Total	Percent(%)
	0-2s	2-5s	5s+		
Anger	183	945	262	1390	15.15
Disgust	97	434	108	639	6.97
Fear	139	413	73	625	6.81
Happiness	88	900	254	1242	13.54
Neutral	42	872	224	1138	12.41
Sadness	97	873	500	1470	16.03
Surprise	233	721	118	1072	11.69
Contempt	18	173	45	236	2.57
Anxiety	99	626	191	916	9.99
Helplessness	20	174	68	262	2.86
Disappointment	13	118	51	182	1.98
Total	1029	6249	1894	9172	100.00

labels. To prevent having too few samples in a class, we keep only the multiple expression categories with more than 10 labeled samples, yielding 32-class multiple expressions. As a result, we obtain 4,058 clips with multiple expressions. Fig. 3 shows the distribution of multiple expression categories on the multiple expression set.

**Figure 3: The distribution of the number of multiple expressions on the multiple expression set.**

4 EXPRESSION SNIPPET FEATURE LEARNING WITH TRANSFORMER

In-the-wild FER is a difficult task due to subtle facial expression movements within videos that can be too difficult to be modeled properly by existing methods. In this paper, we propose a novel Transformer-based expression snippet feature learning method (T-ESFL) that can model intra-snippet and inter-snippet expression movements and relations, to obtain movement-sensitive emotion representation. In particular, for intra-snippet modeling, we decompose the modeling of facial movements of the entire video into the modeling of a series of small expression snippets so that enhance the encoding of subtle facial movements of each snippet by gradually attending to more salient information. Meanwhile, for inter-snippet modeling, we introduce a snippet order shuffling and reconstruction learning (SOSR) head and its loss to improve the modeling of subtle motion changes across snippets by training the Transformer to identify shuffled snippet orders. To this end, the

T-ESFL consists of three main components, *i.e.*, expression snippet decomposition, Transformer, and SOSR, as illustrated in Fig. 4.

Expression snippet decomposition Formally, given an input FER video clip \mathcal{S} , we first decompose the input into a series of small expression snippets $\mathcal{S} = \{S_1, S_2, \dots, S_n\}$, where S_i represents the i -th snippet and n is the total number of snippets. All the snippets have the same length, and they follow consecutive orders along time. To model subtle expression changes within each snippet, we employ a pre-trained CNN [29] and attention learning to extract snippet features R_i from each S_i , thus augmenting the Transformer’s ability to model intra-snippet expression changes.

Transformer architecture With the snippet features R_i , a Transformer is applied here to model the expression movements across snippets and discover a unified emotion feature for FER. We follow the typical Transformer [37] and apply a multi-head attention-based encoder-decoder pipeline for the processing. In general, the multi-head attention estimates the correlation between a *query* tensor and a *key* tensor and then aggregates a *value* tensor according to correlation results to obtain an attended output.

SOSR learning To make the output representation of the Transformer more sensitive to subtle expression movements, SOSR shuffles the snippet order and makes T-ESFL reconstruct the correct order in a self-supervision learning manner. The order of frames/audio within each snippet is retained. We follow a Jigsaw permutation [30] and shuffle the order pure randomly to deconstruct the normal temporal dependency between the snippets. The shuffled snippets are sent to T-ESFL and predicted the permutation type by using a reconstruction loss L_{rec} . Based on this, we can achieve movement-sensitive emotion representation T for robust FER.

Optimization Objective The total objective function of T-ESFL includes two joint cross-entropy losses and is expressed as $L = L_{cls} + \frac{1}{n} \cdot L_{rec}$. The first one L_{cls} is a FER classification loss, and the second one L_{rec} is the snippet order reconstruction loss. Note that, n is the number of the decomposed snippets.

Multi-modal emotion prediction The T-ESFL is easily extended for multi-modal FER, achieving the state-of-the-art performance on both uni- and multi-modal FER. Specifically, we use the ResNet_LSTM network and DPCNN [21] to extract audio and text emotion features, respectively. Then, we concatenate the audio, text, and movement-sensitive visual representations to identify the final emotion category via a simple fully-connected layer and Softmax operation. We experimentally verified that the use of multi-modal fusion features effectively improves FER in the wild.

5 EXPERIMENTS

The experimental setup of the benchmarks, including experiment protocols, data preprocessing, assessment measures, and implementation information, are first presented in the section. Then, using a variety of labels and modalities, we conducted comprehensive benchmarks and comparison studies on our MAFW.

5.1 Experimental Setup

Data&Protocol To facilitate the FER research from laboratory environments to the real world, we performed four challenging benchmark experiments on MAFW: 11-class uni-modal single expression classification, 11-class multi-modal single expression classification,

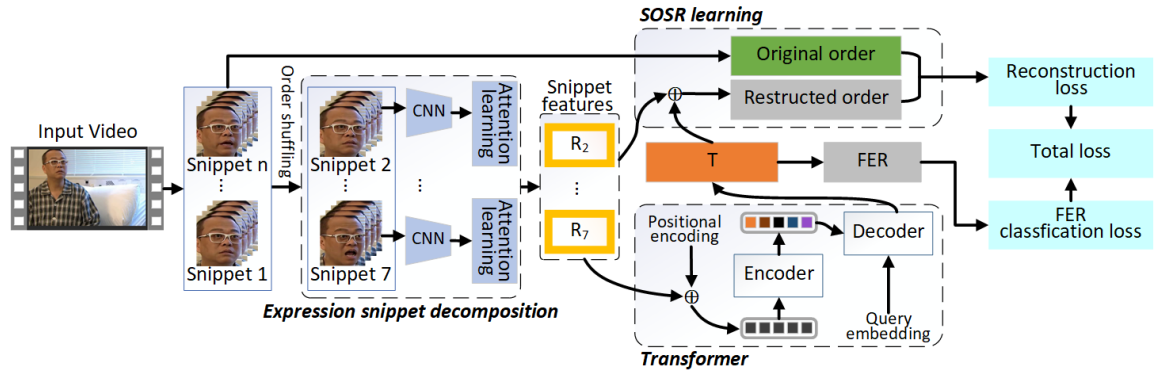


Figure 4: The architecture of T-ESFL for movement-sensitive emotion representation learning. Using untrimmed video clips, we mainly apply the expression snippet decomposition, the Transformer, and the SOSR, to enable the effective modeling of intra- and inter-snippet expression movements for discovering more informative expression cues, thus achieving robust FER.

43-class uni-modal compound expression classification, and 43-class multi-modal compound expression classification. For 11-class single expression classification, the whole 9,172 clips from the entire single expression set were used to identify emotion categories. For the 43-class compound expression classification, which took into account both multiple and single expressions in real-world settings, 4,058 clips from the 32-class multiple expression set and the remaining 4,938 clips from the 11-class single expression set were used. Similar to the evaluation protocol of existing FER databases [20, 25], we adopt a 5-fold cross-validation protocol for these benchmarks on our MAFW database.

Preprocessing First, we extracted frame pictures for each clip using OpenCV. Then, after deleting any frames without faces, we used the face-alignment-master program [3] to collect face areas and 68 landmarks on all frames. Finally, we performed face alignment using affine transform and matrix rotation in OpenCV.

Evaluation Metrics Consistent with the previous research [20, 25], we chose four widely-used validation metrics, *i.e.*, the unweighted average recall (UAR), weighted average recall (WAR), F-score (F1), and Area under the ROC curve (AUC), to evaluate the uni-modal and multi-modal FER tasks, respectively. The UAR is the average accuracy of all expression categories, regardless of the number of samples per class. The WAR is the recognition accuracy of overall expressions, which is related to the number of samples in each category. The F1 is regarded as the weighted harmonic mean value of the accuracy and recall, and here we simply calculate the average of the F1 on all categories. AUC generically refers to the area under the receiver operating characteristic (ROC) curve, and here we calculate the average AUC for all categories. We expect the proposed model to gain improvements in UAR, WAR, F1, and AUC metrics.

Implementation Details In this paper, we employed the PyTorch framework to implement all models. We conducted experiments in the uni-modal and multi-modal FER tasks, while each task contained single and compound expression classification, respectively. The key training parameters involved in the work are presented in Table 4. All models were trained on NVIDIA GeForce

RTX 3090 and GTX1080, with an initial learning rate of 0.0001 provided by the grid search strategy. During training, the learning rate decreased at a rate of 0.2 when the loss was saturated.

Table 4: The key training parameters involved in the work.

Models	Batch size	Input size
Resnet18 [17], VIT [9]	32	224 × 224
C3D [36]	8	112 × 112
Resnet18_LSTM [16, 17, 19]	16	224 × 224
VIT_LSTM [9, 16, 19]	16	224 × 224
C3D_LSTM [16, 19, 36]	8	112 × 112
Resnet18_LSTM ^a [16, 17, 19]	8	224 × 224
C3D_LSTM ^a [16, 19, 36]	8	112 × 112
T-ESFL, T-ESFL ^a , T-ESFL ^{a+t}	8	224 × 224

^a represents multi-modal evaluation with both video and audio;
^{a+t} represents multi-modal evaluation with video, audio, and text.

5.2 Experimental Results

5.2.1 11-class Uni-modal Single Expression Classification. To evaluate uni-modal single expression classification, we compared our T-ESFL model with existing state-of-the-art FER models including three static frame-based methods (*i.e.*, Resnet18 [17], VIT [9], and EmotionClassifier [18, 23]) and four dynamic sequence-based methods (*i.e.*, C3D [36], Resnet18 [16, 17, 19], VIT_LSTM [9, 16, 19], and C3D_LSTM [16, 19, 36]). The comparison results are shown in Table 5. For these static frame-based methods, we first selected five frames from a video evenly as input and then fused the prediction probabilities of the five frames in the output layer of the models to obtain the final prediction result. For these dynamic sequence-based methods, we used all frames in a video for emotion prediction. Compared to other state-of-the-art methods, the proposed T-ESFL achieved the best WAR of 48.18%. Moreover, our approach improved the WAR by 3.43% compared to the commercial model EmotionClassifier [18, 23], and also improved the WAR by 2.62% compared to the second best sequence-based method VIT_LSTM.

Table 5: Comparison results on 11-class uni-modal single expression classification.

Models	Feature setting	Accuracy of each expression											Metric	
		AN	DI	FE	HA	NE	SA	SU	CO	AX	HL	DS	UAR	WAR
Resnet18 [17]	frame-based	45.02	9.25	22.51	70.69	35.94	52.25	39.04	0	6.67	0	0	25.58	36.65
VIT [9]	frame-based	46.03	18.18	27.49	76.89	50.70	68.19	45.13	1.27	18.93	1.53	1.65	32.36	45.04
EmotionClassifier [18, 23]	frame-based	13.60	4.07	0.08	81.09	75.48	47.82	53.02	-	-	-	-	39.85	44.75
C3D [36]	sequence-based	51.47	10.66	24.66	70.64	43.81	55.04	46.61	1.68	24.34	5.73	4.93	31.17	42.25
Resnet18_LSTM [16, 17, 19]	sequence-based	46.25	4.70	25.56	68.92	44.99	51.91	45.88	1.69	15.75	1.53	1.65	28.08	39.38
VIT_LSTM [9, 16, 19]	sequence-based	42.42	14.58	35.69	76.25	54.48	68.87	41.01	0	24.40	0	1.65	32.67	45.56
C3D_LSTM [16, 19, 36]	sequence-based	54.91	0.47	9	73.43	41.39	64.92	58.43	0	24.62	0	0	29.75	43.76
T-ESFL	snippet-based	62.70	2.51	29.90	83.82	61.16	67.98	48.50	0	9.52	0	0	33.28	48.18

Table 6: Comparison results on 11-class multi-modal single expression classification.

Models	Feature setting	Accuracy of each expression											Metric	
		AN	DI	FE	HA	NE	SA	SU	CO	AX	HL	DS	UAR	WAR
Resnet18_LSTM ^a [16, 17, 19, 27]	sequence-based	54.47	11.89	7.07	82.73	54.85	55.06	39.35	0	15.99	0.39	0	29.26	42.69
C3D_LSTM ^a [16, 19, 27, 36]	sequence-based	62.47	3.17	15.74	77.30	42.20	65.30	42.67	0	19.14	0	0	30.47	44.15
T-ESFL^a	snippet-based	60.73	1.26	21.4	80.31	58.24	75.31	53.23	0	14.93	0	0	33.35	48.7
T-ESFL^{a++}	snippet-based	61.89	1.1	7.69	85.90	-	71.87	62.17	0	36.00	0	0	31.00	50.29

^a represents multi-modal evaluation with both video and audio;

^{a++} represents multi-modal evaluation with video, audio, and text.

5.2.2 11-class Multi-modal Single Expression Classification. For multi-modal FER, we compared our T-ESFL model with two spatiotemporal neural network methods, *i.e.*, Resnet18_LSTM [16, 17, 19] and C3D_LSTM [16, 19, 36], as shown in Table 6. Obviously, the multiple modalities effectively improved the performance of FER. Compared to the other methods, our T-ESFL model obtained the best results in the fusion of different modalities, *e.g.*, 4.09% boost in UAR on video and audio modalities. Moreover, continuously adding the descriptive text modality obtained a relative 3.26% boost in WAR.

5.2.3 43-class Uni-modal Compound Expression Classification. Table 7 shows the comparison results of 43-class uni-modal compound expression classification. Similar to the above single expression classification, the same six models except for the EmotionClassifier were used for 43-class uni-modal compound expression recognition, with the four evaluation metrics (WAR, UAR, F1, and AUC). Compared to the other methods, the proposed T-ESFL achieved the best WAR of 34.35% and the best AUC of 75.63%.

Table 7: Comparison results on 43-class uni-modal compound expression classification.

Models	Feature setting	Metric			
		UAR	WAR	F1	AUC
Resnet18 [17]	frame-based	6.18	23.83	4.89	62.92
VIT [9]	frame-based	8.62	31.76	7.46	74.9
C3D [36]	sequence-based	9.51	28.12	6.73	74.54
Resnet18_LSTM [16, 17, 19]	sequence-based	6.93	26.6	5.56	68.86
VIT_LSTM [9, 16, 19]	sequence-based	8.72	32.24	7.59	75.33
C3D_LSTM [16, 19, 36]	sequence-based	7.34	28.19	5.67	65.65
T-ESFL	snippet-based	9.15	34.35	7.18	75.63

Table 8: Comparison results on 43-class multi-modal compound expression classification.

Models	Feature setting	Metric			
		UAR	WAR	F1	AUC
Resnet18_LSTM ^a [16, 17, 19, 27]	sequence-based	7.85	31.03	5.95	71.08
C3D_LSTM ^a [16, 19, 27, 36]	sequence-based	7.45	29.88	5.76	68.13
T-ESFL^a	snippet-based	9.93	34.67	8.44	74.13
T-ESFL^{a++}	snippet-based	9.68	35.02	8.65	74.35

^a represents multi-modal evaluation with both video and audio;

^{a++} represents multi-modal evaluation with video, audio, and text.

5.2.4 43-class Multi-modal Compound Expression Classification. For 43-class multi-modal compound expression classification, we also compared our T-ESFL with Resnet18_LSTM and C3D_LSTM, as shown in Table 8. Compared to the two methods on the multi-modal task, the proposed T-ESFL on video and audio modalities achieved the best UAR of 9.93% and WAR of 34.67%, respectively. Moreover, the results of T-ESFL kept achieving improvements after adding the descriptive text modality, *i.e.*, with a relative increase of 1% in WAR, 2.5% in F1, and 0.3% in AUC.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we propose a large-scale, multi-label, multi-modal affective database called MAFW in the wild, which contains 10,045 video-audio clips. Each clip is annotated with a high-reliability compound emotional category and a couple of sentences that describe the subjects' affective behaviors in the clip. Therefore, MAFW is the first affective database that provides three types of emotion annotations, *i.e.*, single expression labels (11 class), multiple expression labels (32 class), and bilingual emotion captions. Moreover, we also propose a novel Transformer-based expression snippet feature

learning method to obtain movement-sensitive emotion representation, thus achieving state-of-the-art performance on both uni-modal and multi-modal FER in the wild. In the future, we will continue to maintain the MAFW and hope that the release of this database can encourage more research on dynamic FER under unconstrained conditions, e.g., multi-modal emotion recognition, self-supervision FER, video emotion caption, zero-shot AU detection, etc.

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REFERENCES

- [1] Samuel Albanie, Arsha Nagrani, Andrea Vedaldi, and Andrew Zisserman. 2018. Emotion Recognition in Speech Using Cross-Modal Transfer in the Wild. In *Proceedings of the 26th ACM International Conference on Multimedia*. ACM, 292–301. <https://doi.org/10.1145/3240508.3240578>
- [2] AmirAli Bagher Zadeh, Paul Pu Liang, Soujanya Poria, Erik Cambria, and Louis-Philippe Morency. 2018. Multimodal Language Analysis in the Wild: CMU-MOSEI Dataset and Interpretable Dynamic Fusion Graph. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. ACL, 2236–2246. <https://doi.org/10.18653/v1/P18-1208>
- [3] Adrian Bulat and Georgios Tzimiropoulos. 2017. How Far are We from Solving the 2D & 3D Face Alignment Problem? (and a Dataset of 230,000 3D Facial Landmarks). In *2017 IEEE International Conference on Computer Vision (ICCV)*. 1021–1030. <https://doi.org/10.1109/ICCV.2017.116>
- [4] Zheng Chen, Meiyu Liang, Wanying Yu, Yongkang Huang, and Xiaoxiao Wang. 2021. Intelligent Teaching Evaluation System Integrating Facial Expression and Behavior Recognition in Teaching Video. In *2021 IEEE International Conference on Big Data and Smart Computing (BigComp)*. 52–59. <https://doi.org/10.1109/BigComp51126.2021.00019>
- [5] Xiang Chu and Qiuyan Zhong. 2016. Crowdsourcing quality control model protecting location privacy of workers. *Systems Engineering - Theory & Practice* 36, 8 (2016), 2047–2055. [https://doi.org/10.12011/1000-6788\(2016\)08-2047-09](https://doi.org/10.12011/1000-6788(2016)08-2047-09)
- [6] Lee J. Cronbach. 1951. Coefficient alpha and the internal structure of tests. *Psychometrika* 16, 3 (Sept. 1951), 297–334. <https://doi.org/10.1007/BF02310555>
- [7] Abhinav Dhall, Roland Goecke, Shreya Ghosh, Jyoti Joshi, Jesse Hoey, and Tom Gedeon. 2017. From Individual to Group-Level Emotion Recognition: EmotiW 5.0. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction*. ACM, 524–528. <https://doi.org/10.1145/3136755.3143004>
- [8] Kollias Dimitrios and Zafeiriou Stefanos. 2019. Expression, Affect, Action Unit Recognition: Aff-Wild2, Multi-Task Learning and ArcFace. In *30th British Machine Vision Conference (BMVC)*.
- [9] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In *9th International Conference on Learning Representations (ICLR)*. <https://openreview.net/forum?id=YicbFdNTTy>
- [10] Shichuan Du, Yong Tao, and Aleix M. Martinez. 2014. Compound facial expressions of emotion. *Proceedings of the National Academy of Sciences* 111, 15 (2014), 1454–1462. <https://doi.org/10.1073/pnas.1322355111>
- [11] Joy O. Egede, Siyang Song, Temitayo A. Olugbade, Chongyang Wang, Amanda C. De C. Williams, Hongying Meng, Min Aung, Nicholas D. Lane, Michel Valstar, and Nadia Bianchi-Berthouze. 2020. EMOPAIN Challenge 2020: Multimodal Pain Evaluation from Facial and Bodily Expressions. In *15th IEEE International Conference on Automatic Face and Gesture Recognition (FG)*. 849–856. <https://doi.org/10.1109/FG47880.2020.00078>
- [12] Paul Ekman. 1984. Expression and the nature of emotion. *Approaches to Emotion* (1984).
- [13] Paul Ekman. 1993. Facial expression and emotion. *American Psychologist* 48, 4 (1993), 384–392. <https://doi.org/10.1037/0003-066X.48.4.384>
- [14] Panagiotis Paraskevas Filntisis, Niki Efthymiou, Petros Koutras, Gerasimos Potamianos, and Petros Maragos. 2019. Fusing Body Posture With Facial Expressions for Joint Recognition of Affect in Child–Robot Interaction. *IEEE Robotics and Automation Letters* 4, 4 (2019), 4011–4018. <https://doi.org/10.1109/LRA.2019.2930434>
- [15] Tobias Gehrig and Hazım Kemal Ekenel. 2013. Why is Facial Expression Analysis in the Wild Challenging?. In *Proceedings of the 2013 on Emotion Recognition in the Wild Challenge and Workshop*. ACM, 9–16. <https://doi.org/10.1145/2531923.2531924>
- [16] F.A. Gers, J. Schmidhuber, and F. Cummins. 1999. Learning to forget: continual prediction with LSTM. In *9th International Conference on Artificial Neural Networks (ICANN)*, Vol. 2. 850–855. <https://doi.org/10.1049/cp:19991218>
- [17] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep Residual Learning for Image Recognition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 770–778. <https://doi.org/10.1109/CVPR.2016.90>
- [18] Zhenliang He, Meina Kan, Jie Zhang, Xilin Chen, and Shiguang Shan. 2017. A fully end-to-end cascaded cnn for facial landmark detection. In *12th IEEE International Conference on Automatic Face Gesture Recognition (FG)*. 200–207. <https://doi.org/10.1109/FG.2017.33>
- [19] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long Short-Term Memory. *Neural Computation* 9, 8 (Nov. 1997), 1735–1780. <https://doi.org/10.1162/neco.1997.9.8.1735>
- [20] Xingxun Jiang, Yuan Zong, Wenming Zheng, Chuangao Tang, Wanchuang Xia, Cheng Lu, and Jiateng Liu. 2020. DFEW: A Large-Scale Database for Recognizing Dynamic Facial Expressions in the Wild. In *Proceedings of the 28th ACM International Conference on Multimedia*. ACM, 2881–2889. <https://doi.org/10.1145/3394171.3413620>
- [21] Rie Johnson and Tong Zhang. 2017. Deep Pyramid Convolutional Neural Networks for Text Categorization. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, Vol. 1. ACL, 562–570. <https://doi.org/10.18653/v1/P17-1052>
- [22] Jiyoung Lee, Seungryong Kim, Sunok Kim, Jungin Park, and Kwanghoon Sohn. 2019. Context-Aware Emotion Recognition Networks. In *IEEE/CVF International Conference on Computer Vision (ICCV)*. 10142–10151. <https://doi.org/10.1109/ICCV.2019.01024>
- [23] Haoxiang Li, Zhe Lin, Xiaohui Shen, Jonathan Brandt, and Gang Hua. 2015. A convolutional neural network cascade for face detection. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 5325–5334. <https://doi.org/10.1109/CVPR.2015.7299170>
- [24] Shan Li and Weihong Deng. 2020. Deep Facial Expression Recognition: A Survey. *IEEE Transactions on Affective Computing* 01 (mar 2020), 1–1. <https://doi.org/10.1109/TAFFC.2020.2981446>
- [25] Shan Li, Weihong Deng, and JunPing Du. 2017. Reliable Crowdsourcing and Deep Locality-Preserving Learning for Expression Recognition in the Wild. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2584–2593. <https://doi.org/10.1109/CVPR.2017.277>
- [26] Ziwei Liu, Ping Luo, Xiaoang Wang, and Xiaoou Tang. 2015. Deep Learning Face Attributes in the Wild. In *IEEE International Conference on Computer Vision (ICCV)*. 3730–3738. <https://doi.org/10.1109/ICCV.2015.425>
- [27] Beth Logan. 2000. Mel Frequency Cepstral Coefficients for Music Modeling. In *1st International Symposium on Music Information Retrieval (ISMIR)*.
- [28] Patrick Lucey, Jeffrey F. Cohn, Takeo Kanade, Jason Saragih, Zara Ambadar, and Iain Matthews. 2010. The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*. 94–101. <https://doi.org/10.1109/CVPRW.2010.5543262>
- [29] Debin Meng, Xiaojiang Peng, Kai Wang, and Yu Qiao. 2019. Frame Attention Networks for Facial Expression Recognition in Videos. In *IEEE International Conference on Image Processing (ICIP)*. 3866–3870. <https://doi.org/10.1109/ICIP.2019.8803603>
- [30] Mehdi Noroozi and Paolo Favaro. 2016. Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles. In *European Conference on Computer Vision (ECCV)*. 69–84.
- [31] M. Pantic, M. Valstar, R. Rademaker, and L. Maat. 2005. Web-based database for facial expression analysis. In *IEEE International Conference on Multimedia and Expo (ICME)*. 317–320. <https://doi.org/10.1109/ICME.2005.1521424>
- [32] R. Plutchik. 2000. A general psychoevolutionary theory of emotion. *Emotion Theory Research & Experience* 21, 4-5 (2000), 529–553.
- [33] Maryam Pourebadi and Laurel D. Riek. 2022. Facial Expression Modeling and Synthesis for Patient Simulator Systems: Past, Present, and Future. *ACM Trans. Comput. Healthcare* 3, 2, Article 23 (mar 2022), 32 pages. <https://doi.org/10.1145/3483598>
- [34] A. P. Dawida. M. Skene. 1979. Maximum Likelihood Estimation of Observer Error-Rates Using the EM Algorithm. *Journal of the Royal Statistical Society* 28, 1 (1979), 20–28.
- [35] Nummenmaa Tapio. 1988. The recognition of pure and blended facial expressions of emotion from still photographs. *Scandinavian Journal of Psychology* 29, 1 (1988), 33–47. <https://doi.org/10.1111/j.1467-9450.1988.tb00773.x>
- [36] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. 2015. Learning Spatiotemporal Features with 3D Convolutional Networks. In *IEEE International Conference on Computer Vision (ICCV)*. 4489–4497. <https://doi.org/10.1109/ICCV.2015.510>
- [37] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is All You Need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS)*. Curran Associates Inc., 6000–6010.

- [38] Hang Yu, Yufei Xu, Jing Zhang, Wei Zhao, Ziyu Guan, and Dacheng Tao. 2021. AP-10K: A Benchmark for Animal Pose Estimation in the Wild. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*.
- [39] Xing Zhang, Lijun Yin, Jeffrey F. Cohn, Shaun Canavan, Michael Reale, Andy Horowitz, Peng Liu, and Jeffrey M. Girard. 2014. BP4D-Spontaneous: a high-resolution spontaneous 3D dynamic facial expression database. *Image and Vision Computing* 32, 10 (2014), 692–706. <https://doi.org/10.1016/j.imavis.2014.06.002>
- [40] Ying Zhou, Hui Xue, and Xin Geng. 2015. Emotion Distribution Recognition from Facial Expressions. In *Proceedings of the 23rd ACM International Conference on Multimedia*. ACM, 1247–1250. <https://doi.org/10.1145/2733373.2806328>