

HUOM! Tämä on alkuperäisen artikkelin rinnakkaistallenne. Rinnakkaistallenne saattaa erota alkuperäisestä sivutuksestaan ja painoasultaan.

Käytä viittauksessa alkuperäistä lähdettä:

Li, Y., Wei, J., Liu, Y., Kauttonen, J. & Zhao, G. 2022. Deep Learning for Micro-Expression Recognition: A Survey. IEEE Transactions on Affective Computing, 13, 4, s. 2028–2046.  
<https://doi.org/10.1109/TAFFC.2022.3205170>.

PLEASE NOTE! This is an electronic self-archived version of the original article. This reprint may differ from the original in pagination and typographic detail.

Please cite the original version:

Li, Y., Wei, J., Liu, Y., Kauttonen, J. & Zhao, G. 2022. Deep Learning for Micro-Expression Recognition: A Survey. IEEE Transaction on Affective Computing, 13, 4, pp. 2028–2046.  
<https://doi.org/10.1109/TAFFC.2022.3205170>.



© 2022 The authors. Licensed under the terms and conditions of the Creative Commons Attribution (CC BY 4.0) license (<https://creativecommons.org/licenses/by/4.0/>).

# Deep Learning for Micro-Expression Recognition: A Survey

Yante Li<sup>1</sup>, Jinsheng Wei<sup>1</sup>, Yang Liu<sup>1</sup>, Janne Kauttonen, and Guoying Zhao<sup>1</sup>, *Fellow, IEEE*

**Abstract**—Micro-expressions (MEs) are involuntary facial movements revealing people's hidden feelings in high-stake situations and have practical importance in various fields. Early methods for Micro-expression Recognition (MER) are mainly based on traditional features. Recently, with the success of Deep Learning (DL) in various tasks, neural networks have received increasing interest in MER. Different from macro-expressions, MEs are spontaneous, subtle, and rapid facial movements, leading to difficult data collection and annotation, thus publicly available datasets are usually small-scale. Currently, various DL approaches have been proposed to solve the ME issues and improve MER performance. In this survey, we provide a comprehensive review of deep MER and define a new taxonomy for the field encompassing all aspects of MER based on DL, including datasets, each step of the deep MER pipeline, and performance comparisons of the most influential methods. The basic approaches and advanced developments are summarized and discussed for each aspect. Additionally, we conclude the remaining challenges and potential directions for the design of robust MER systems. Finally, ethical considerations in MER are discussed. To the best of our knowledge, this is the first survey of deep MER methods, and this survey can serve as a reference point for future MER research.

**Index Terms**—Micro-expression recognition, deep learning, micro-expression dataset, Survey

## 1 INTRODUCTION

Facial expression (FE) is one of the most powerful and universal means for human communication, which is highly associated with human mental states, attitudes, and intentions. Besides ordinary FEs (also known as macro-expressions) that we see daily, emotions can also be expressed in a special format of Micro-expressions (MEs) under certain conditions. MEs are FEs revealing people's hidden feelings in high-stake situations when people try to conceal their true feelings [1]. Different from macro-expressions, MEs are

spontaneous, subtle, and rapid (1/25 to 1/3 second) facial movements reacting to emotional stimulus [2], [3].

The ME phenomenon was first discovered by Haggard and Isaacs [4] in 1966. Three years later, Ekman and Friesen also declared the finding of MEs [5] during examining psychiatric patient's videos for lie detection. In the following years, Ekman et al. continued ME research and developed the Facial Action Coding System (FACS) [6] and Micro Expression Training Tool (METT) [7]. Specifically, FACS breaks down FEs into individual components of muscle movement, called Action Units (AUs) [6]. AU analysis can effectively resolve the ambiguity issue to represent individual expression and increase Facial Expression Recognition (FER) performance [8]. Fig. 1 shows the example of micro- and macro-expressions as well as activated AUs in each FE. On the other hand, METT is helpful for increasing people's emotional awareness. It can promote manual ME detection performance which provides a potential chance to build reliable ME datasets.

MER is the task of classifying ME clips into various emotion categories. In each ME clip, the frame starting facial movements is denoted as the onset frame, while the end frame is the offset frame. The frame with the largest intensity is the apex frame. Like FER, MER also classifies facial images/sequences into categories such as anger, surprise, and happiness. However, MER is more challenging as spontaneous MEs are involuntary, subtle, and fleeting. In addition, MEs can also be impacted by emotional context and cultural background [11], [12], [13]. Therefore, it is difficult to collect and annotate ME data, leading to small-scale ME datasets and existing methods are incapable of dealing with subtleness and fleetness.

MER has drawn increasing interest recently due to its practical importance in many human-computer interaction

- Yante Li, Yang Liu, and Guoying Zhao are with the Center for Machine Vision and Signal Analysis, University of Oulu, FI-90014 Oulu, Finland. E-mail: {Yante.Li, Yang.Liu, guoying.zhao}@oulu.fi.
- Jinsheng Wei is with the Center for Machine Vision and Signal Analysis, University of Oulu, FI-90014 Oulu, Finland, and also with the School of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210003, China. E-mail: 2018010217@njupt.edu.cn.
- Janne Kauttonen is with the School of Digital Business, Haaga-Helia University of Applied Sciences, FI-00520 Helsinki, Finland. E-mail: Janne.Kauttonen@haaga-helia.fi.

Manuscript received 5 November 2021; revised 23 July 2022; accepted 4 September 2022. Date of publication 10 October 2022; date of current version 15 November 2022.

This work was supported in part by the Academy of Finland for Academy Professor project EmotionAI under Grants 336116 and 345122 and in part by Ministry of Education and Culture of Finland for AI forum project and Infotech Oulu.

This work involved human subjects or animals in its research. The author(s) confirm(s) that all human/animal subject research procedures and protocols are exempt from review board approval.

(Corresponding author: Guoying Zhao.)

Recommended for acceptance by A. Dhall.

This article has supplementary downloadable material available at <https://doi.org/10.1109/TAFFC.2022.3205170>, provided by the authors.

Digital Object Identifier no. 10.1109/TAFFC.2022.3205170



Fig. 1. Examples of micro-expressions in CASME II [9] and macro-expressions in MMI [10], as well as the active AUs. The red arrow represents the muscle movement direction. AU4, AU6, AU7, AU9, AU12, AU15, and AU25 represent brow lowerer, cheek raise, lids tight, nose wrinkle, lip corner puller, lip corner depressor, and lips part, respectively.

systems. The first spontaneous MER research can be traced to Pfister et al.'s work [14] which utilized a Local Binary Pattern from Three Orthogonal Planes (LBP-TOP) [15] on the first public spontaneous ME dataset: SMIC [16]. Following the work of [15], various approaches based on appearance and geometry features [17], [18] were proposed for improving the performance of MER.

In recent years, with the advance of Deep Learning (DL) and its successful extensions on object detection [19], human tracking [20], and FER [21], researchers have started to exploit MER with DL. Although MER with DL becomes challenging because of the limited ME samples and low intensity, great progress on MER has been made through designing effective shallow networks, exploring Generative Adversarial Net (GAN) [22] and so on. Currently, DL-based MER has achieved the state-of-the-art performance.

In this survey, we review the research on MER by DL since 2016 when the DL technology was first adopted in MER. Due to the page limitation, the representative works published in well-known journals and conferences, such as IEEE TPAMI, IEEE TAC, IEEE TIP, and ACM MM are specifically discussed. The ordinary FER approaches and MER with traditional learning methods are not considered in this survey. Although a few MER surveys have discussed the historical evolution and algorithmic pipelines for MER [23], [24], [25], [26], [27], [28], they mainly focus on traditional methods and only introduce some recent DL approaches. The DL-based MER has not been discussed systematically and specifically. As far as we know, this is the first survey of the DL-based MER. Different from previous surveys, we analyze the strengths and shortcomings of dynamic network inputs which are important for MER based on DL. Furthermore, the network blocks, architectures, training strategies, and losses are discussed and summarized in detail and future research directions are identified. The goal of this survey is to provide a DL-based MER dictionary that can serve as a reference point for future MER research.

This paper is organized as follows: Section 2 introduces spontaneous ME datasets. Section 3 presents the taxonomy we defined for MER based on DL. Section 4 discusses the various inputs for deep MER. Section 5 provides a detailed review of neural networks for MER. The evaluation matrix, protocol, and the performance of representative DL-based MER are described in Section 6. Section 7 summarizes current challenges and potential study directions. Finally, Section 8 discusses the ethical considerations.

## 2 DATASETS

Different from macro-expressions which can be easily captured in our daily life, MEs are involuntary brief FEs, particularly occurring under high stake situations. Four early databases appeared continuously around 2010: Canal9 [35], York-DDT [36], Polikvsky's database [36] and USF-HD [37]. However, Canal9 and York-DDT are not aimed for ME research. Polikvsky's database and USF-HD include only posed MEs which are collected by asking participants to intentionally pose or mimic a micro movement. The posed expressions contradict with the spontaneous nature of MEs. Currently, these databases are not used anymore for MER. In the recent years, several spontaneous ME databases were created, including: SMIC [16] and its extended version SMIC-E, CASME [29], CASME II [9], CAS(ME)<sup>2</sup> [30], SAMM [31], and micro-and-macro expression warehouse (MMEW) [27]. In this survey, we focus on the spontaneous datasets.

In a general ME dataset collection procedure, participants are asked to keep a poker face while watching video clips to induce spontaneous MEs. The video clips are selected according to previous psychological studies, which can elicit strong emotions. Commonly, a high-speed camera is utilized to record facial videos. After one participant watched a video clip, he/she fills in a self-report questionnaire to report his/her true feelings about the video clip. As well, considering cultural backgrounds may have an impact on MEs [38], participants from different ethnicities could be recruited [31] for the potential study of cultural impact on MEs.

Since the MEs are subtle and rapid, annotators are usually trained with FACS and certified facial action unit coders are employed to detect the MEs in the facial videos. The FACS helps people look precisely at the facial movements to make ME detection reliable. Specifically, when the duration of the facial action unit is less than 0.5s, the clip is regarded as a ME clip. The MEs are annotated into discrete categories. In SMIC [16], the emotions are labeled as 'positive', 'negative', and 'surprise' according to the participants' self-reports. However, mixed emotions may be induced while the participants watch one video clip. Annotations based on the general emotion reported after watching the video, which usually allows one emotion, are not accurate. To this end, several datasets, such as CASME [29] and CASME II [9], consider AUs, self-reports, and the watched video clips to label the MEs. When there are ambiguities and conflicts in the emotion annotation, the emotion is annotated as 'others'. Furthermore, to alleviate annotation bias caused by an individual annotator, the ME annotations are always carried out through cross-validation by multiple annotators. The specific details of datasets are introduced as followings:

SMIC [16] is consisted of three subsets: SMIC-HS, SMIC-VIS and SMIC-NIR. SMIC-VIS and SMIC-NIR contain 71 samples recorded by normal speed cameras with 25 fps of visual (VIS) and near-infrared light range (NIR), respectively.

CASME [29] contains spontaneous 159 ME clips from 19 subjects including frames from onset to offset. The emotions were labeled partly based on AUs and also taking account of participants' self-reports and the content of the video episodes. Besides the onset and offset, the apex frames are also labeled. The shortcoming of CASME is the imbalanced sample distribution among classes.

TABLE 1  
Spontaneous Datasets for MER

Database	Resolution	Facial size	Frame rate	Samples	subjects	Expression	AU	Apex	Eth	Env
SMIC HS/NIR/VIS [16]	640 × 480	190 × 230	100/25/25	164/71/71	16/8/8	Pos (51) Neg (70) Sur (43) / Pos (28) Neg (23) Sur (20) / Pos (28) Neg (24) Sur (19)	◦	◦	3	L
CASME [29]	640 × 480 1280 × 720	150 × 90	60	195	35	Hap (5) Dis (88) Sad (6) Con (3) Fea (2) Ten (28) Sur (20) Rep (40)	*	*	1	L
CASME II [9]	640 × 480	250 × 340	200	247	35	Hap (33) Sur (25) Dis (60) Rep (27) Oth (102)	*	*	1	L
CAS(ME) <sup>2</sup> [30]	640 × 480	-	30	Macro 300 Micro 57	22	Hap (51) Neg (70) Sur (43) Oth (19)	*	*	1	L
SAMM [31]	2040 × 1088	400 × 400	200	159	32	Hap (24) Ang (20) Sur (13) Dis (8) Fea (7) Sad (3) Oth (84)	*	*	13	L
MEVIEW [32]	720 × 1280	-	25	31	16	Hap (6) Ang (2) Sur (9) Dis (1) Fea (3) Unc (13) Con(6)	*	◦	-	W
MMEW [27]	1920 × 1080	400 × 400	90	300	36	Hap (36) Ang (8) Sur (80) Dis (72) Fea (16) Sad (13) Oth (102)	*	*	1	L
Composite ME [33]	640 × 480 1280 × 720 720 × 1280	150 × 90 250 × 340 400 × 400	200	442	68	Pos (109), Neg (250), and Sur (83)	◦◦	◦◦	13	L
Compound ME [34]	640 × 480 1280 × 720 720 × 1280	150 × 90	200	1050	90	Neg (233) Pos (82) Sur (70) PS (74) N S (236) PN (197) NN (158)	◦◦	◦◦	13	L

<sup>1</sup> Eth: Ethnicity; Env: Environment.

<sup>2</sup> Pos: Positive; Neg: Negative; Sur: Surprise; Hap: Happiness; Dis: Disgust; Rep: Repression; Ang: Anger; Fea: Fear; Sad: Sadness; Con: Contempt; Unc: Unclear; Oth: Others; PS: Positively surprise; NS: Negatively surprise; PN: Positively negative; NN: Negatively negative; L: Laboratory; W: In the wild.

<sup>3</sup> ◦ represents unlabeled; \* represents labeled and - represents unknown

CASME II [9] is an improved version of the CASME dataset. Samples in CASME II are increased to 247 MEs from 26 subjects and they are recorded by high-speed camera at 200 fps with face sizes cropped to 280 × 340. Thus, it has a greater temporal and spatial resolution, compared with CASME.

CAS(ME)<sup>2</sup> [30] consists of spontaneous macro- and micro-expressions elicited from 22 subjects. CAS(ME)<sup>2</sup> has samples with longer durations which makes it suitable for ME spotting. Compared to the above datasets, the samples in CAS(ME)<sup>2</sup> were recorded with a relatively low frame rate in a relatively small number of ME samples, which makes it unsuitable for DL approaches.

SAMM [31] collects 159 ME samples from 32 participants. The samples were collected by a gray-scale camera at 200 fps in controlled lighting conditions to prevent flickering. Unlike previous datasets that lack ethnic diversity, the participants are from 13 different ethnicities.

MEVIEW [32] is in-the-wild ME dataset. The samples in MEVIEW are collected from poker games and TV interviews on the Internet. In total, 31 videos from 16 individuals were annotated in the dataset and the average length of videos is three seconds.

MMEW [27] contains 300 ME and 900 macro-expression samples acted out by the same participants with a larger resolution (1920 × 1080 pixels). MEs and macro-expressions in MMEW were annotated to the same emotion classes.

The composite dataset [33] is proposed by the 2nd Micro-Expression Grand Challenge (MEGC2019). The composite dataset merges samples from three spontaneous facial ME datasets: CASME II [9], SAMM [31], and SMIC-HS [16]. This is to facilitate the evaluation of newly developed methods. As the annotations in the three datasets vary hugely, the composite dataset unifies emotion labels in all three datasets. The emotion labels are re-annotated as *positive*, *negative*, and *surprise*.

The compound micro-expression dataset (CMED) [34], [39] is constructed by combining MEs from the CASME, CASME II, CAS(ME)<sup>2</sup>, SMIC-HS, and SAMM datasets. Specifically, the MEs are divided into basic and compound emotional

categories, as shown in Table 1. Psychological studies demonstrate that there are usually complex expressions in daily life. Multiple emotions co-exist in one FE, termed as “compound expressions” [39]. Compound expression analysis reflects more complex mental states and more abundant human facial emotions.

The specific comparisons of the ME datasets are shown in Table 1 and example samples are shown in Fig. 2. Although MEVIEW collects MEs in the wild, the number of ME samples is too small to learn robust ME features. The state-of-the-art approaches are commonly tested on the SMIC-HS, CASME [29], CASME II [9], and SAMM databases. As some emotions are difficult to trigger, such as fear and contempt, these categories have only a few samples and are not enough for learning. In most practical experiments, only the emotion categories with more than 10 samples are considered. Recently, the composite dataset is popular, because it can verify the generalization ability of the method on datasets with different natures. For further increasing the MER performance, MMEW collected micro- and macro-expressions from the same subjects which may be helpful for further cross-modal research.

### 3 A TAXONOMY FOR MER BASED ON DL

Fig. 3 shows a taxonomy we summarize for MER based on DL, built along the important components including input and network. As the ME sequences have subtle movements and limited samples, different inputs have big impacts on MER performance. Thus the input plays an important role



Fig. 2. Examples of ME samples in ME datasets for MER.

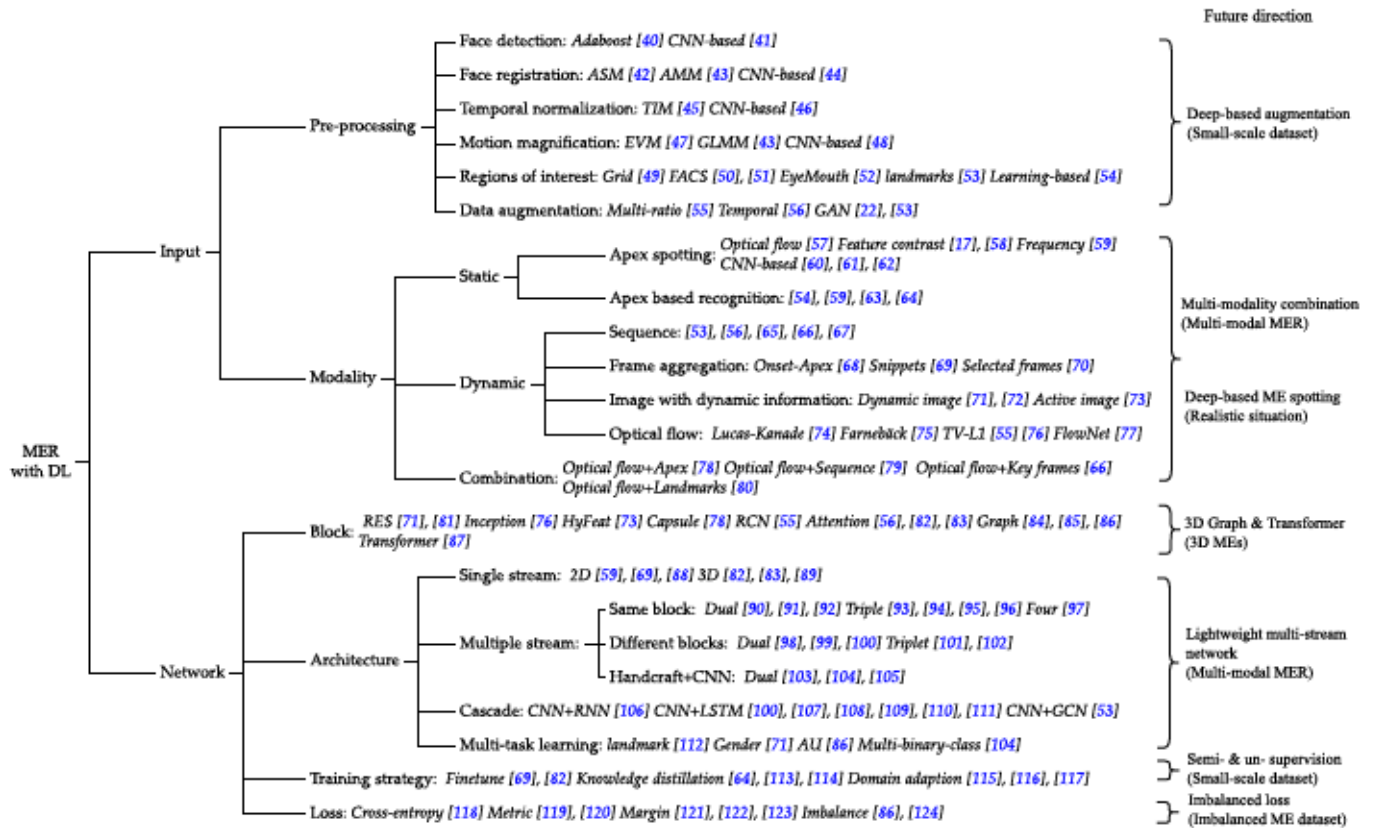


Fig. 3. Taxonomy for MER based on deep learning. The studies cited on the branches are example approaches discussed in this paper. The future directions and corresponding approaches are shown on the right side. The future directions are annotated in brackets.

in MER. First, the inputs need to be pre-processed for training a robust network. The specific pre-processing approaches and the strengths and shortcomings of various input modalities are discussed in Section 4. Then, the networks introduced in Section 5 are utilized to discriminate between MEs. A common MER network can be described from four aspects: block, architecture, training strategy, and loss. First, we introduce the special blocks designed to solve the ME challenges. Then, we describe the architecture in terms of single-stream, multi-stream, cascaded networks, and multi-task learning. Finally, the training strategies and loss functions for training networks are discussed. The future directions are annotated on the right side of Fig. 3. All the methods discussed in this survey are face-based MER with DL.

## 4 INPUTS

### 4.1 Pre-Processing

Like ordinary FEs, pre-processing involving face detection and alignment is required for robust MER. Compared with common FEs, MEs have low intensity, short duration, and small-scale datasets making MER more difficult. Therefore, besides traditional pre-processing steps, motion magnification, temporal normalization, regions-of-interest, and data augmentation have also been undertaken for better MER performance.

#### 4.1.1 Face Detection and Registration

For processing MEs, face detection which removes the background and gets the facial region is the first step. One of the most widely used algorithms for face detection is Viola-

Jones [40] based on a cascade of weak classifiers. However, this method can not deal with large pose variations and occlusions. Matsugu et al. [41] first adopted CNN network for face detection with a rule-based algorithm, which is robust to translation, scale, and pose. Recently, face detectors based on DL have been utilized in popular open source libraries, such as dlib and OpenCV.

Since spontaneous MEs involve muscle movements of low intensity, even little pose variations and movements may heavily affect MER performance. To this end, face registration is crucial for MER. It aligns the detected faces onto a reference face to handle varying head-pose issues for successful MER. Currently, one of the most used facial registration methods is the Active Shape Models (ASM) [42] encoding both geometry and intensity information. Then, the Active Appearance Models (AAM) [43] is presented for matching any face with any expression rapidly. With the fast development of DL, deep networks with cascaded regression [44] have become the state-of-the-art methods for face alignment due to their excellent performances.

#### 4.1.2 Motion Magnification

One challenge for MER is that the facial movements of MEs are too subtle to be distinguished. Therefore, motion magnification is important to enhance the ME intensity level. One of the commonly used methods is the Eulerian Video Magnification method (EVM) [47]. For MEs, the EVM is applied for facial motion magnification [17]. EVM magnifies either motion or color content across two consecutive frames in videos. However, a larger motion amplification level leads

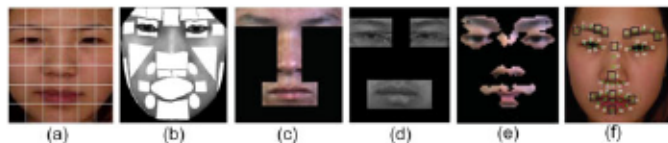


Fig. 4. Examples of regions of interest. (a) Equal block; (b) FACS-based RoIs [50]; (c) RoIs Masked eye and cheek [88]; (d) Eye and mouth [126]; (e) Difference-based ME datasets [127]; (f) landmark-based local regions [128].

to a larger scale of motion amplification, which causes bigger artifacts. Different from EVM considering local magnification, Global Lagrangian Motion Magnification (GLMM) [125] was proposed for consistently tracking and exaggerating the FEs and global displacements across a whole video. Furthermore, the learning-based motion magnification [48] was first used in ME magnification by Lei et al. [84] through extracting shape representations from the intermediate layers of networks. Compared with the traditional methods, the shape representations from the intermediate layers introduce less noise.

#### 4.1.3 Temporal Normalization (TN)

Besides the low intensity, the short and varied duration also increases the difficulty for robust MER. This problem is especially serious when the videos are filmed with relatively low frame rate. To solve this issue, the Temporal Interpolation Model [45] (TIM) was introduced to interpolate all ME sequences into the same specified length based on path graph between the frames. There are three strengths of applying TIM: 1) up-sampling ME clips with too few frames; 2) more stable features can be expected with a unified clip length; 3) extending ME clips to long sequences and sub-sampling to short clips for data augmentation. Additionally, CNN-based temporal interpolation [46] have been proposed to solve complex scenarios in reality.

#### 4.1.4 Regions of Interest (RoIs)

FEs are formulated by basic facial movements [6], [129], which correspond to specific facial muscles and relate to different facial regions. In other words, not all facial regions contribute equally to FER. Especially for MEs, the MEs only trigger specific small regions, as MEs involve subtle facial movements. Moreover, the empirical experience and quantitative analysis in [130] found that the outliers such as eyeglass have a seriously negative impact on the performance of MER. Therefore, it is important to suppress the influence of outliers.

Some studies alleviate the influence of regions without useful information by extracting features on the RoIs [88]. Several MER approaches [17], [131] divided the entire face into several equal blocks for better describing local changes (see Fig. 4a). Davison et al. [50], [51] selected RoIs from the face based on the FACS [6], shown in Fig. 4b. In addition, to eliminate the noise caused by the eye blinking and motionless regions, Le et al. [88] proposed to mask the eye and cheek regions for each image (see Fig. 4c). However, the motion of eyes has a big contribution to MER under certain situations, e.g. lid tighten refers to negative emotion. In work [126], Liong et al. utilized the eyes and mouth regions for MER, as shown in Fig. 4d. Besides, Xia et al. [127] found

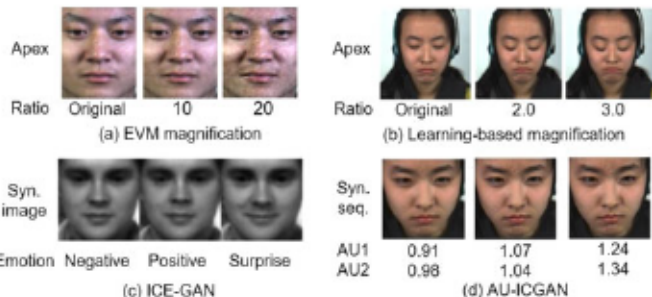


Fig. 5. Examples of magnified and synthesized MEs.

that the regions around the eyes, nose, and mouth are mostly active for MEs and can be chosen as RoIs through analyzing difference heat maps of ME datasets, as shown in Fig. 4e. Furthermore, Xie et al. [53] and Li et al. [128] proposed to extract features on small facial blocks located by facial landmarks (see Fig. 4f). In this way, the dimension of learning space can be drastically reduced and helpful for deep model learning on small ME datasets.

#### 4.1.5 Data Augmentation

The main challenge for MER with DL is the small-scale ME datasets. The current ME datasets are too limited to train a robust DL model from scratch, therefore data augmentation is necessary. The common way for data augmentation is random crop and rotation in terms of the spatial domain. Xia et al. augmented MEs through magnifying MEs with multiple ratios [55]. Figs. 5a and 5b show the examples of magnified ME apex frames with different ratios on the basis of EVM [47] and learning-based magnification [48], respectively. Additionally, Generative Adversarial Network (GAN) [132] can augment data by producing synthetic images. Xie et al. [53] introduced the AU Intensity Controllable GAN (AU-ICGAN) to synthesize subtle MEs. As Fig. 5d shows, the ME sequences with continuous AU intensity can be synthesized through [53]. Yu et al. [22] proposed a Identity-aware and Capsule-Enhanced Generative Adversarial Network (ICE-GAN) to complete the ME synthesis and recognition tasks. ICE-GAN outperformed the winner of MEGC2019 by 7%, demonstrating the effectiveness of GAN for ME augmentation and recognition. The synthesized images corresponding to different emotions are shown in Fig. 5c. Besides, Liong et al. [133] utilized conditional GAN to generate optical-flow images to improve the MER accuracy based on computed optical flow. For ME clips, sub-sampling MEs from extended ME sequences through TIM can augment ME sequences [56].

## 4.2 Input Modality

Since the MEs have low intensity, short duration, and limited data, it is challenging to recognize MEs based on DL and the MER performance varies with different inputs. In this section, we describe the various ME inputs and summarize their strengths and shortcomings, as shown in Table 2.

### 4.2.1 Static Image

For FER, a large volume of existing studies are conducted on static images without temporal information due to the availability of the massive facial images online and the

TABLE 2  
The Comparisons of Inputs for MER

Input modality		Strength	Shortcoming
Static		Efficient; Take advantage of massive facial images	Require magnification and apex detection Without temporal information
Dynamic	Sequence	Process directly	Not efficient; Information redundancy
	Frame aggregation	Efficiently leverage key temporal information	Require apex detection
	Image with dynamic information	Efficiently embed spatio-temporal information	Require dynamic information computation
	Optical flow	Remove identity to some degree; Movement considered	Optical flow computation is necessary
Combination		Explore spatial and temporal information	High computation cost

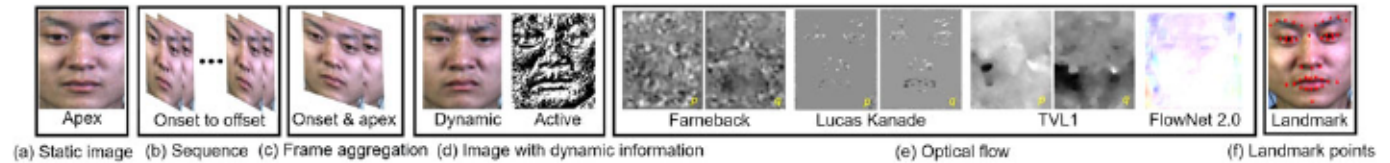


Fig. 6. Examples of various inputs.

convenience of data processing. Inspired by efficient FER with static images, some researchers [59], [63] explored the MER based on the apex frame with the largest intensity of facial movement among all frames (See Fig. 6a). Li et al. [54] studied the contribution of the apex frame and verified that DL can achieve good MER performance with the single apex frame. Furthermore, the research of Sun et al. [64] showed that the apex frame-based methods can effectively utilize the massive static images in macro-expression databases [64] and obtain better performance than onset-apex-offset sequences and the whole videos.

Apex spotting is one of the key components for building a robust MER system based on apex frames. Patel et al. [57] computed the motion amplitude of optical flow shifted over time to locate the onset, apex, and offset frames of MEs, while other works [17], [58] exploited feature differences to detect MEs in long videos. However, optical flow-based approaches required complicated feature operation and the feature contrast-based methods ignored ME dynamic information. Different from above methods estimating the facial change in the spatio-temporal domain, Li et al. [59] proposed to locate the apex frame in rapid ME clips through exploring the information in the frequency domain which clearly describes the rate of change. Furthermore, SMEConvNet [60] first adopted CNN for ME spotting and a feature matrix processing was proposed for locating the apex frame in long videos. Following SMEConvNet, various CNN-based ME spotting methods [61], [62] were proposed. In general, the performance of CNN-based spotting method is limited because of the small-scale ME datasets and mixed macro- and micro-expressions clips in long videos. Further studies on reliable spotting methods are required in the future.

#### 4.2.2 Dynamic Image Sequence

As the facial movements are subtle in the spatial domain, while change fast in the temporal domain, the temporal dynamics along the video sequences are essential in improving the MER performance. In this subsection, we describe the various dynamic inputs.

*Sequence.* Most ME researches utilize consecutive frames in video clips [49], [134], [135], as shown in Fig. 6b. With the success of 3D CNN [136] and Recurrent Neural Network (RNN) [137] in video analysis [138], [139], MER based on sequence [53], [56], [65], [66], [67], [102], [140] is developed that considers the spatial and temporal information simultaneously. However, the computation cost is relatively high and the complex model tends to overfit the small-scale training data.

*Frame aggregation.* MEs are mostly collected with a high-speed camera (e.g.200 fps) to capture the rapid subtle changes. Liong et al. discovered that there is redundant information in ME clips recorded with high-speed cameras [141]. The redundancy could decrease the performance of MER. The experimental results of [141] demonstrate that the onset, apex, and offset frames can provide enough spatial and temporal information to ME classification. Liong et al. [68] extracted features on onset and apex frames for MER, as shown in Fig. 6c. Furthermore, in order to avoid apex frame spotting, Liu et al. [69] and Kumar et al. [70] designed simple strategies to select aggregated frames automatically.

*Image with dynamic information.* Image with dynamic information [142] is a standard image that holds the dynamics of an entire video sequence in a single instance. The dynamic image generated by using the rank pooling algorithm has been successfully used in MER [71], [72], [88], [143] to summarize the subtle dynamics and appearance in an image. Similar to dynamic images, active images [73] encapsulated the spatial and temporal information of a video sequence into a single instance through estimating and accumulating the change of each pixel component (See Fig. 6d).

*Optical flow.* The motion between ME frames contributes important information for ME recognition. Optical flow approximates the local image motion, which has been verified to be helpful for motion representation [144]. It specifies the magnitude and direction of pixel motion in a given sequence of images with a two-dimension vector field (horizontal and vertical optical flows). In recent years, several novel methodologies have been presented to improve optical flow techniques [74], [75], [145], [146], [147], such as Farneback's [75], Lucas-Kanade [74], TV-L1 [147], FlowNet

[77], as shown in Fig. 6e. Currently, many MER approaches utilize optical flow to represent the micro-facial movement and reduce the identity characteristic [55], [94], [148]. Researches [55], [94] indicated that optical flow-based methods always outperform appearance-based methods. To further capture the subtle facial changes, multiple works [76], [86], [101] extracted features on computed optical flows on the onset and mid-frame/apex in horizontal and vertical directions separately.

#### 4.2.3 Input Combination

Considering the strengths of apex frame and dynamic image sequences, some works [66], [78], [79], [94] analyze multiple inputs to learn features from different cues in ME videos. Specifically, in Liu et al.'s work [78], the apex frames and optical flow are utilized to extract static-spatial and temporal features, respectively. Besides the above modalities, Song et al. [94] added local facial regions of the apex frame as inputs to embed the relationship of individual facial regions for increasing the robustness of MER. In addition, Sun et al. [79] employed optical flow and sequences for fully exploring the temporal ME information. Recently, inspired by the successful application of landmarks in facial analysis (See Fig. 6f), Kumar et al. [80] proposed to fuse the landmark graph and optical flow to enhance the discriminative ability of ME repression. Currently, the approaches with multiple inputs achieve the best MER performance through leveraging as much as ME information on limited ME datasets.

### 4.3 Discussion

In summary, the input is one of the key components to guarantee robust MER. The various ME inputs have different strengths and shortcomings. The comparisons of inputs are shown in Table 2.

The input pre-processing is the first step in the MER system. Besides common face pre-processing approaches (face detection and registration), motion magnification, RoIs, and TIM also play important roles for robust MER, due to the subtle and rapid characteristics of MEs. Current motion magnification approaches always introduce noises and artifacts. More effective motion magnification approaches should be explored. Furthermore, considering the small-scale ME datasets are far from enough to train a robust deep model, data augmentation is necessary for MER. In the future, studying more robust GAN-based ME generation approaches is a promising research direction.

Regarding the static input, the apex-based MER can reduce computational complexity and take advantage of the massive FEs to resolve the small-dataset issue in some degree. But, magnification is necessary since all the temporal information is dropped in single apex-based methods and the motion intensity is still low in the apex frames. Moreover, as the apex label is absent in some ME datasets, the performance of apex-based MER severely relies on the apex detection algorithm. Currently, the apex frame detection in long videos is still challenging. The end-to-end framework for apex frame detection and MER needs to be further studied.

Compared with the static image, the dynamic input is able to leverage spatial and temporal information for robust

MER. The simplest dynamic input is ME sequence which doesn't require extra operations. However, there is redundancy in ME sequences, and the complexity of the deep model is relatively high and tends to overfit on small-scale ME datasets. To solve the problem of redundancy, frame aggregation cascading multiple key frames is utilized. Besides, the dynamic image improves the computation efficiency through embedding the temporal and spatial information to a still image. It can simultaneously consider spatial and temporal information in one image without challenging apex frame detection. Furthermore, optical flow is widely used for MER as the optical flow describes the motions and removes the identity in some degree. However, most of the current optical flow-based MER methods are based on traditional optical flow, which is not end-to-end. In the future, more DL-based optical flow extraction can be further researched.

In addition, combining various inputs is the inevitable trend to fully explore spatial and temporal information and leverage the merits of various inputs. Correspondingly, the combined inputs also inherit the shortcomings of the inputs. However, the multiple inputs could be complementary in some degree. So far, the method with various inputs has achieved the best performance. Considering the success of multiple inputs and limited ME samples, more combined modalities, such as optical flow, key frames, and landmarks can be promising research directions.

## 5 DEEP NETWORKS FOR MER

Convolutional Neural Networks (CNNs) have shown excellent performances for various computer vision tasks, such as action recognition [152] and FER [21]. In general, for image classification, CNNs employ two dimensional convolutional kernels (denoted as 2D CNN) to leverage spatial context across the height and width of the images to make predictions. Compared with 2D CNN, CNNs with three-dimensional convolutional kernels (denoted as 3D CNN) are verified more effective for exploring spatio-temporal information of videos [153]. 3D CNN can take advantage of spatio-temporal information to improve the performance but comes with a computational cost because of the increased number of parameters. Moreover, the 3D CNN only can deal with videos with the fixed length due to the pre-defined kernels. Recurrent Neural Network (RNN) [137] was proposed to process the time series data with various duration. Furthermore, Long Short-Term Memory (LSTM) was developed to settle the vanishing gradient problem that can be encountered when training RNNs.

Unlike common video-based classification problems, for the recognition of subtle, fleeting, and involuntary MEs, various DL approaches have been proposed to boost MER performance. In this section, we introduced the approaches in the view of special blocks, network architecture, training strategy, and loss.

### 5.1 Network Block

In terms of solving the two main ME challenges: overfitting on small-scale ME datasets and low intensity of MEs, various effective network blocks have been utilized and designed, such as ResNet family with residual modules [149], [154],



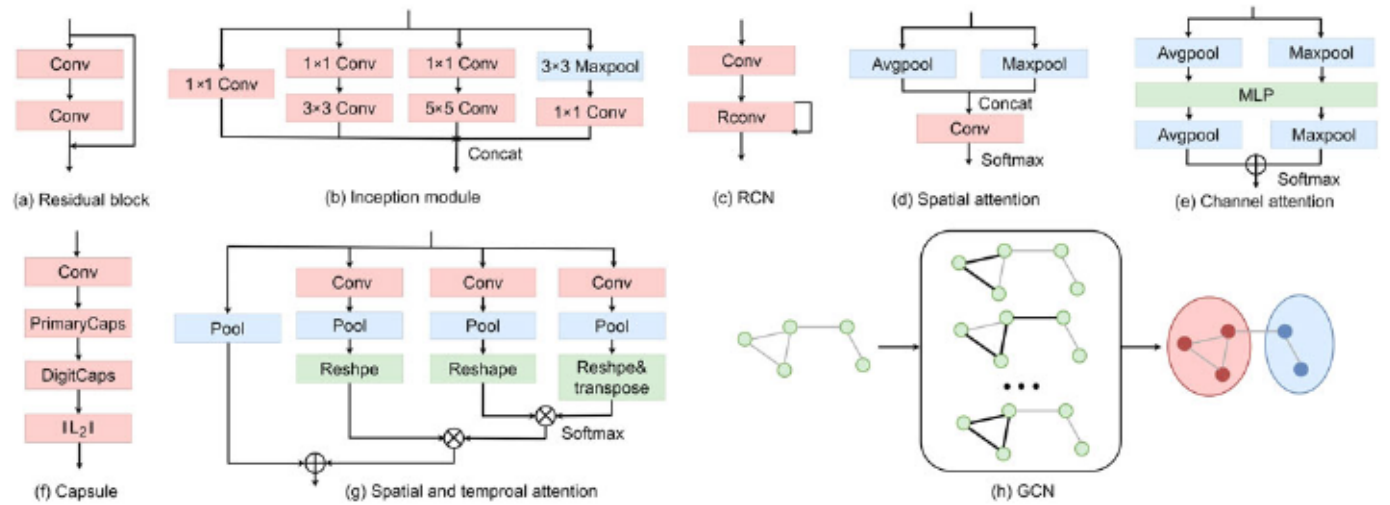


Fig. 7. Special blocks: (a) Residual block [149] (b) Inception module [150]; (c) RCN [55]; (d) Spatial attention of CBAM [82] (e) Channel attention of CBAM [82]; (f) Capsule module [151]; (g) Spatio-temporal attention [89]; (h) GCN [73].

[155], and Inception module [150]. In this subsection, we introduce the special network blocks utilized for MER improvement.

For the challenge of small-scale datasets, recent researches [149] demonstrate that residual blocks with shortcut connections (shown in Fig. 7a) achieves easy optimization and reduces the effect of the vanishing gradient problem. Multiple MER works [84], [99], [156], [157], [158] employed residual blocks for robust recognition on small-scale ME datasets. Instead of directly applying the shortcut connection, [159] further designed a convolutionable shortcut to learn the important residual information and AffectiveNet [160] introduced an MFL module learning the low- and high-level feature parallelly to increase the discriminative capability between the inter and intra-class variations.

Since the fully connected layer requires lots of parameters which makes it prone to extreme loss explosion and overfitting [161], the Inception module [162] aggregates different sizes of filters to compute multi-scale spatial information and assembles  $1 \times 1 \times 1$  convolutional filters to reduce the dimension and parameter, as shown in Fig. 7b. Multiple works [76], [86] utilized the Inception module for efficient MER. Inspired by the Inception structure, a Hybrid Feature (HyFeat) block [72], [73], [163] was proposed to preserve the domain knowledge features for expressive regions of MEs and enrich features of edge variations through using different scaled convolutional filters.

Furthermore, considering the fact that CNN with more convolutional layers has stronger representation ability, but easy to overfit on small-scale datasets, paper [55] and [164] introduced Recurrent Convolutional Network (RCN) which achieved a shallow architecture though recurrent connections, as shown in Fig. 7c.

On the other hand, MEs perform as the combination of multiple facial movements. The latent semantic information among subtle facial changes contributes important information for MER performance. Recent researches illustrate that the Graph Convolutional Network (GCN) is effective to model these semantic relationships and can be leveraged for face analysis tasks, as shown in Fig. 7h. Inspired by the successful application of GCN in FER, [53], [84], [85], [86]

developed the GCN for MER to further improve the performance by modeling the relationship between the local facial movements. Lei et al. [84], [87] built graphs on the RoIs along facial landmarks contributing information to subtle MEs. The TCN residual blocks [84], [165] and transformer [87], [166] were applied for reasoning the relationships of RoIs. On the other hand, as the FE analysis can be benefited from the knowledge of AUs and FACS, the works [53], [85], [86] built graph on AU-level representations to boost the MER performance by inferring the AU relationship.

Besides graph, Capsule Neural Network (CapsNet) [151] was employed to explore part-whole relationships on face to promote MER performance through better model hierarchical relationships by routing procedure [22], [63], [78], as shown in Fig. 7f.

In addition, since MEs have specific muscular activations on the face, MEs are related with local regional changes [167]. Therefore, it is crucial to highlight the representation on RoIs [8], [108]. Several approaches [98], [168], [169], [170], [171], [172] have shown the benefit of enhancing spatial encoding with attention module.

Except for spatial information, the temporal change also plays an important role for MER. As MEs have rapid changes, the frames have unequal contribution to MER. Wang et al. [89] explored a global spatial and temporal attention module (GAM) based on the non-local network [173] to encode wider spatial and temporal information to capture local high-level semantic information, as shown in Fig. 7g.

Moreover, Yao et al. [174] learned the weights of each feature channel adaptively through adding squeeze-and-excitation blocks. Additionally, recent works [56], [82], [83], [175] encoded the spatio-temporal and channel attention simultaneously to further boost the representational power of MEs. Specifically, CBAMNet [82] presented a convolutional block attention module (CBAM) cascading the spatial attention module (see Fig. 7d) and channel attention module (see Fig. 7e).

In summary, due to the special characteristics of MEs, many DL-based methods designed special blocks to extract discriminative ME representations from the latent semantic information. Recent MER researches indicate that attention

and graph blocks are effective to model the semantic relationships. Current GCN-based MER are always based on the local facial regions and AU labels. In the future, more compact and concise representation, such as landmark location, can be further developed for efficient MER. Moreover, the transformer [166] has been verified effectively on modeling the relationship. For future MER research, transformers can be further applied to model the relationships between facial landmarks, AUs, RoIs and frames to enhance ME representation. On the other hand, other special blocks [55] targeted at learning discriminative ME features with less parameters to avoid overfitting. In the future, more efficient blocks should be studied to dig subtle ME movements on limited ME datasets.

## 5.2 Network Architecture

Besides designing special blocks for discriminative ME representation, the way of combining the blocks is also very important. The current network architecture of MER methods can be classified to five categories: single-stream, multi-stream, cascaded, multi-task learning and transfer learning. In this section, we will discuss the details of the five network architectures.

### 5.2.1 Single-Stream Networks

Typical deep MER methods adopt single CNN with individual input [176]. The apex frame, optical flow images and dynamic images are common inputs for single-stream 2D CNNs, while single-stream 3D CNNs extract the spatial and temporal features from ME sequences directly. Considering the limited ME samples are far from enough to train a robust deep network, multiple works designed single-stream shallow CNNs for MER [135], [177], [178]. Belaiche et al. [156] achieved a shallow network through deleting multiple convolutional layers of the deep network Resnet. Zhao et al. [39] proposed a 6-layer CNN in which the input is followed by an  $1 \times 1$  convolutional layer to increase the non-linear representation.

Besides designing shallow networks, many studies [59], [69], [88] fine-tuned deep networks pre-trained on large face datasets to avoid the overfitting problem. Li et al. [59] first adopted the 16-layer VGG-FACE model pre-trained on VGG-FACE dataset [179] for MER. Following [59], the MER with Resnet50, SEnet50 and VGG19 pre-trained on Imagenet was explored in [88]. The results illustrate that VGG surpasses other architectures regarding the MER topic and is good at distinguishing the complex hidden information in data.

All of above works are based on 2D CNN with image input, while several works employed single 3D CNN to directly extract the spatial and temporal features from ME sequences. GAM [89], MERANet [83] and CBAMNet [82] combined attention modules to 3D CNN to enhance the representation in spatial and temporal dimensions.

### 5.2.2 Multi-Stream Network

Single stream is a basic model structure and only extracts features from the single view of MEs. However, MEs have subtle movements and limited samples, the single view is not able to provide sufficient information. As we discussed in Section 4.2, the various inputs from different views is

able to effectively explore spatial and temporal information. Thus, the multi-stream network is adopted in MER to learn features from multiple inputs. The multi-stream structure allows the network extracting multi-view features through multi-path networks, as shown in Fig. 8g. In general, multi-stream networks can be classified to networks with the same blocks, different blocks and handcrafted features.

*Multi-Stream Networks With the Same Blocks.* The Optical Flow Features from Apex frame Network (OFF-ApexNet) [90] and Dual-stream shallow network (DSSN) [91] built the dual-stream CNN for MER based on optical flow extracted from onset and apex. Furthermore, Liong et al. [133] extended OFF-ApexNet to multiple streams with various optical flow components as input data. The multi-stream CNN with optical flow [81] and Three-Stream CNN (TSCNN) [93], [94] designed three-stream CNN models for MER with three kinds of inputs (See Fig. 8c). Specifically, the former one utilized apex frame, optical flow and the apex frame masked by the optical flow threshold, while the latter approach employed the apex frames, optical flow between onset, apex, and offset frames to investigate the information of the static spatial, dynamic temporal and local information. In addition, She et al. [97] proposed a four-stream model considering three RoIs and global regions as each stream to explore the local and global information. Besides multi-stream 2D CNNs, 3DFCNN [95], SETFNet [174] and [92] applied 3D flow-based CNNs for video-based MER consisting of multiple sub-streams to extract features from frame sequences and optical flow, or RoIs.

*Multi-stream networks with different blocks.* For enhancing the ME feature representation, some works [97], [98], [101], [102], [160] investigated the combination of different convolutions. Liong et al. designed a Shallow Triple Stream Three-dimensional CNN (STSTNet) [101] adopting multiple 2D CNN with different kernels. Instead of utilizing different kernels, AffectiveNet [160] constructed a four-path network with four different receptive fields (RF) to obtain multi-scale features for better describing subtle MEs. On the other hand, Landmark Relations with Graph Attention Convolutional Network (LR-GACNN) [70] and MER-GCN [85] built two-stream graph networks to explore relationships between landmark points and the local patches, and AUs and sequence, respectively. Furthermore, [98] and [102] integrated 2D CNN and 3D CNN to extract spatio-temporal information.

*Multi-stream networks with handcrafted features.* Since the subtle facial movements of MEs are highly related to face textures, the handcrafted features for low-level representation also plays an important role in MER. Multiple works [103], [104], [105] combined deep features and handcrafted features to leverage the low-level and high-level information for robust MER. Specifically, in the works [103] and [105], the CNN features on apex frame and LBP-TOP were concatenated to represent MEs.

### 5.2.3 Cascaded Network

Cascaded network combines various modules for different tasks sequentially to construct an effective network, as shown in Fig. 8g. Recent FE studies [21] demonstrate that learning a hierarchy of features gradually filters out the information unrelated to expressions.

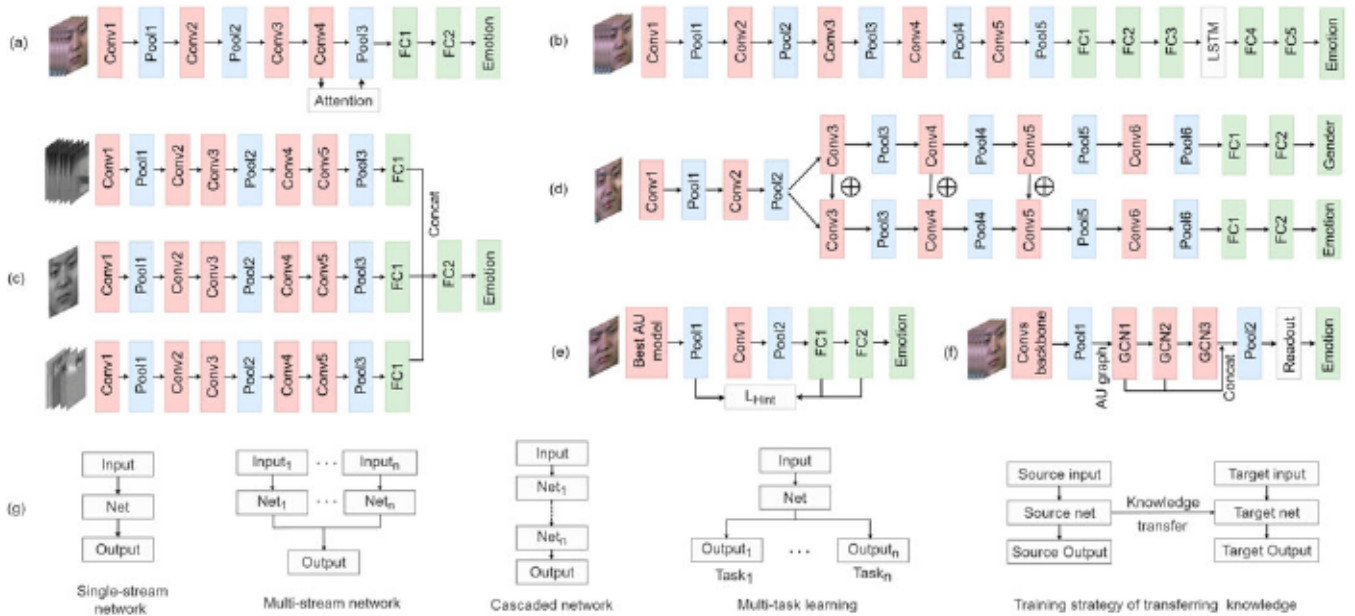


Fig. 8. (a) GAM based on single stream [89]; (b) CNN cascaded with LSTM [109]; (c) TSCNN [94] based on three-stream network; (d) A dual-stream multi-task network incorporating gender detection designed by GEME [71]; (e) CNN cascaded with GCNs on the basis of AU-feature graph [53]; (f) MER based on knowledge distillation [64]; and (g) The general concept of single-stream, multi-stream, cascaded networks, multi-task learning, and the training strategy of transferring knowledge.

Inspired by the FE studies [21], for further exploring the temporal information of MEs, Nistor et al. [106] cascaded CNN and RNN to extract features from individual frames of the sequence and capture the facial evolution during the sequence, respectively. Furthermore, Bai et al. [109] and Zhi et al. [111] combined CNN with LSTMs in series to deal with ME samples with various duration directly, as shown in Fig. 8b. Besides, in order to explore the AU semantics in MEs, Xie et al. proposed an AU-assisted Graph Attention Convolutional Network (AU-GACN) [53] cascading 3D CNN and GCN to infer MEs based on AU features (see Fig. 8f).

In addition, multiple MER works combined multi-stream and cascaded structure to further explore the multi-view series information. VGGFace2+LSTM [109], Temporal Facial Micro-Variation Network (TFMVN) [108] and MER with Ternary Attentions (MERTA) [96] developed three stream VGGNets followed by LSTMs to extract multi-view spatio-temporal features. Different from above works, Khor et al. [107] proposed an Enriched Long-term Recurrent Convolutional Network (ELRCN) adding one VGG+LSTM path with channel-wise stacking inputs for spatial enrichment. Besides, AT-Net [99] and SHCFNet [100] extracted spatial and temporal features by CNN and LSTM from the apex frame and optical-flow in parallel and concatenated them together to represent MEs.

#### 5.2.4 Multi-Task Network

Most existing works for MER focus on learning features that are sensitive to expressions. However, MEs in the real world are intertwined with various factors, such as subject identity and AUs. The approaches aiming at a single MER task are incapable of making full use of the information on face. To address this issue, several multi-task learning-based MER approaches have been subsequently developed for better MER [71], [112]. First, Li et al. [112] developed a multi-task

network combining facial landmarks detection and optical flow extraction to refine the optical flow features for MER with SVM. Following [112], several end-to-end deep multi-task networks leveraging different side tasks were proposed. Gender-based ME recognition (GEME) [71] designed a dual-stream multi-task network incorporating gender detection task with MER (see Fig 8d), while feature refinement [180] and MER-auGCN [86] simultaneously detected AUs and MEs and further aggregated AU representation into ME representation. On the other hand, considering that a common feature representation can be learned from multiple tasks, Hu et al. [104] formulated MER as a multi-task classification problem in which each category classification can be regarded as one-against-all pairwise classification problem.

In summary, the network architecture can be roughly divided into single-stream, multi-stream, cascaded networks, and multi-task learning, as shown in Fig. 8g. Single stream is the simple basic model architecture. However, single-stream networks only consider the single view of MEs. To further leverage the ME information, the multi-stream network is proposed to learn features from multiple views for robust MER. Moreover, since learning a hierarchy of features can gradually filter out the information unrelated to expressions, the network cascades various modules, such as LSTMs and GCNs, sequentially to construct an effective MER network. In the future, more effective modules should be combined in multi-stream and cascaded ways to further boost the MER performance.

In terms of the tasks, multiple task learning [181] can share knowledge among tasks, introducing extra information and a low risk of overfitting in each task. Currently, most ME research only studied the contribution of landmarks detection, gender classification, and AU detection. Other tasks, such as face recognition and eye gaze tracking may also introduce useful knowledge for MER. Exploring

and taking advantage of more face related-tasks is a practical way to further improve MER performance.

### 5.3 Training Strategy

As we discussed before, DL-based MER suffers from a lack of adequate data. It is almost impossible to train a reliable deep model from scratch. Currently, there are large-scale FE datasets with labels. Leveraging the FE datasets by special training strategy, such as fine-tuning [94], knowledge distillation [64], and domain adaptation [117], is a reasonable way to solve the problem of a small amount of data. The knowledge of a pre-trained model for a related task can be transferred to MER to boost performance. The training strategy of transferring knowledge is shown in Fig 8g.

Fine-tuning ME datasets on pre-trained models is widely used in MER [54], [69], [82], [94]. Patel et al. [182] provided two models pre-trained on ImageNet dataset and FE datasets, respectively. The feature selection method was also adopted to improve the model's performance. It was found that features captured from the FE datasets performed better in terms of accuracy, as it is more similar to the ME datasets than object/face datasets.

Besides fine-tuning, another effective transfer learning strategy is knowledge distillation. Knowledge distillation achieves small and fast networks through leveraging information from pre-trained high-capacity networks. Sun et al. [64] utilized Fitnets [183] to guide the shallow network learning for MER by mimicking the intermediate features of the deep network pre-trained for macro-expression recognition and AU detection, as shown in Fig 8e. However, the appearances of MEs and macro-expressions are different due to the different intensity of facial movements. Thus, mimicking the macro-expression representation directly is not reasonable. Instead, SAAT [116] transferred attention on the style aggregated MEs generated by CycleGAN [184].

In addition, domain adaptation methods can obtain domain invariant representations by embedding domain adaptation in the pipeline of deep learning. In [115], [117], and [185], the gap between the MEs and macro-expressions was narrowed down by domain adaption based on adversarial learning strategy.

In general, fine-tuning is most widely used in MER. To further effectively transfer meaningful information from massive FEs, knowledge distillation and domain adaptation are also applied to MER by distilling knowledge and extracting domain invariant representations, respectively. However, the domain adaptation with adversarial learning increases the learning complexity. There are significant differences both spatially and temporally between macro-expressions and MEs, therefore, directly transferring the knowledge is not able to fully leverage the macro-expression information. Considering that the facial muscle movements are consistent between MEs and macro-expressions, the attention and AUs can be further studied for transfer learning in future ME research. Moreover, semi-supervised and unsupervised learning could also be further developed to take advantage of unlabeled facial images.

### 5.4 Loss Functions

Different from traditional methods, where the feature extraction and classification are independent, deep networks can

perform end-to-end classification through loss functions by penalizing the deviation between the predicted and true labels during training. Most MER works directly applied the commonly used softmax cross-entropy loss [118]. The softmax loss is typically good at correctly classifying known categories. However, in practical classification tasks, the unknown samples need to be classified. Therefore, in order to obtain better-generalized ability, the inter-class difference and intra-class variation should be further optimized and reduced, respectively, especially for subtle and limited MEs. The metric learning techniques, such as contrastive loss [119] and triplet loss [120], was developed to ensure intra-class compactness and inter-class separability through measuring the relative distances between inputs. Xia et al. [117] adopted an adversarial learning approach and triplet loss with inequality regularization to converge the output of MicroNet efficiently. However, metric learning loss usually requires effective sample mining strategies for robust recognition performance. Metric learning alone is not enough for learning a discriminative metric space for MEs. Intensive experiments demonstrate that importing a large margin on softmax loss can increase the inter-class difference. Lalitha et al. [186] and Li et al. [54] combined softmax cross-entropy loss and center loss [187] to increase the compactness of intra-class variations and separable inter-class differences through penalizing the distance between deep features and their corresponding class centers.

Some special MEs are difficult to trigger, thus leading to data imbalance. Multiple MER works [55], [71], [86], [158] utilized the Focal loss to overcome the imbalance challenge by adding a factor to put more focus on misclassified and hard samples which are difficult to recognize. Moreover, MER-auGCN [86] designed an adaptive factor with the Focal loss to balance the proportion of the negative and positive samples in a given training batch.

In summary, MER suffers from high intra-class variation, low inter-class differences, and imbalanced distribution because of the low intensity and spontaneous characteristics of MEs. Currently, most MER approaches are based on the basic softmax cross-entropy loss, but others utilized the triplet loss, center loss, or focal loss to encourage inter-class separability, intra-class compactness, and balanced learning. In the future, exploring more effective loss functions to learn discriminative representation for MEs can be a promising research direction. Considering the low intensity of facial movements leading to low inter-class differences, better metric space and larger margin loss for MER should be further studied. Recently, various methods [188] have been proposed for the classification of imbalanced long-tail distribution data. ME research can leverage the ideas for long-tail data to improve the MER performance.

### 5.5 Discussion

MEs are involuntary, subtle, and brief facial movements. How to extract high-level discriminative representations on limited subtle ME samples is the main challenge for robust MER with DL. In order to extract discriminative ME representation, various blocks have been designed based on exploring the special characteristics of MEs with less parameters, such as the attention module and capsule module. In the future, more effective blocks, such as attention, GCN

and transformer, should be further developed for MER performance improvement. On the other hand, considering the limited ME samples, more efficient blocks should be studied to learn discriminative ME features with less parameters for avoiding overfitting on small-scale ME datasets.

In terms of the network architecture, compared with basic single stream networks, multi-stream networks can extract features from multi-view inputs to provide more information for MER. On the other hand, the cascaded network combines various modules for different tasks sequentially to construct an effective network and gradually filter out the information unrelated to MEs. Considering the strengths of multi-stream and cascaded networks, multi-stream cascaded networks have been developed to boost the MER performance further. In the future, exploring multi-stream cascaded networks combined with various efficient blocks is a promising research direction for MER. In addition, the multi-task learning framework achieves robust MER through leveraging information from related tasks. Multi-task learning is able to make use of more available information on the face. Current MER explored gender classification, landmark detection, and AU detection to take advantage of existing information as much as possible. In the future, more relevant tasks, such as identity classification and age estimation, could be studied.

Fine-tuning is widely used in MER. Recent research [64] illustrated that borrowing information from large FE datasets through knowledge distillation and domain adaptation can achieve promising performance. For future ME research, how to effectively leverage massive face images will be a focus. Besides, the semi-supervised learning [189] and unsupervised learning [190] could be promising research directions.

For the losses, most DL-based MER employs the basic softmax cross-entropy loss. Several works utilized the metric learning loss and margin loss to increase the compactness of intra-class variations and separable inter-class differences. Furthermore, since the ME datasets are imbalanced, multiple works aimed to boost MER performance through Focal loss. However, current MER methods just employed the losses designed for common tasks, such as image classification and face recognition. MER is a special task due to the ME characteristics (low intensity and imbalanced small-scale ME datasets), effective losses aimed for MER should be explored in the future.

## 6 EXPERIMENTS

### 6.1 Evaluation Matrix

The common evaluation metrics for MER are accuracy and F1-score. In general, the accuracy metric measures the ratio of correct predictions over the total evaluated samples. However, the accuracy is susceptible to bias data. F1-score solves the bias problem by considering the total True Positives (TP), False Positives (FP) and False Negatives (FN) to reveal the true classification performance.

For the composited dataset which combines multiple datasets leading to severe data imbalance, Unweighted F1-score (UF1) and Unweighted Average Recall (UAR) are utilized to measure the performance of various methods. UF1 is also known as macro-averaged F1-score which is determined

by averaging the per-class F1-scores. UF1 provides equal emphasis on rare classes in imbalanced multi-class settings. UAR is defined as the average accuracy of each class divided by the number of classes without consideration of samples per class. UAR can reduce the bias caused by class imbalance and is known as balanced accuracy.

### 6.2 Model Evaluation Protocols

Cross-validation is the widely utilized protocol for evaluating the MER performance. In cross-validation, the dataset is splitted into multiple folds and the training and testing were evaluated on different folds. It regards a fair verification and prevents overfitting on the small-scale ME datasets. In the MER field, cross-validation includes leave-one-subject-out (LOSO), leave-one-video-out (LOVO), and K-Fold cross-validations.

In LOSO, every subject is taken as a test set in turn and the other subjects as the training data. This kind of subject-independent protocol can avoid subject bias and evaluate the generalization performance of various algorithms. LOSO is the most popular cross-validation in MER.

The LOVO takes each sample as the validation unit which enables more training data and alleviates the overfitting to some degree. However, it is not subject-independent, thus it can not well evaluate the generalization capability. Another problem is that the test number of LOVO is the sample size which may lead to huge time cost, not suitable for deep learning.

For K-fold cross-validation, the original samples are randomly partitioned into  $k$  equal-sized parts. Each part is taken as a test set in turn and the rest are the training data. Thus, the number of cross-validation tests is  $K$ . In practice, the evaluation time can be greatly reduced by setting an appropriate  $K$ . The typical  $K$  values are 5 or 10.

Since the MEs have small-scale datasets, the experiments on MER do not have reliable validation datasets. According to the released codes, some works [115] utilized the test datasets as the validation datasets directly and reserved the best epoch results on each fold as the final results. As the data is limited, even only two samples for some subjects, the final MER results will be greatly improved by regarding the test data as the validation data. According to [164], compared to the experiments based on the same epoch on all of the folds, the results can be increased by more than 10% by testing on the test datasets. But, in practice, the test data is unknown and it is not reasonable to reserve the best epoch results on each fold of the test data as the final results.

Tables 3 and 4 list the reported performance of representative recent work of DL-based MER on popular ME datasets. As we discussed before, the evaluation protocol is varying and the practical training rule of each paper is ambiguous, we can not directly make a conclusion that which method performs best for MER. But, from the experimental results, the general trends of MER can be found.

For the input, in general, the combined inputs can provide promising results on all of the datasets [70], [94], [175]. This is because the different input modalities can contribute information from different views. On the basis of various input modalities, we can explore useful information on limited ME samples to the greatest extent. Since the combined inputs is a good choice for robust MER, the multi-stream

TABLE 3  
MER on SMIC, CASME, CASME II, SMM, and CMED Datasets

Dataset	Method	Year	Pre-p.	Input	Network architecture	Block	Pre-train	Protocol	Cate.	F1	ACC (%)
SMIC	TSCNN [94]	2019	E, R	OF+Apex	3S-CNN	-	FER2013 [191]	LOSO	3	0.7236	72.74
	DIKD [64]	2020	-	Apex	CNN+KD+SVM	-	-	LOSO	3	0.71	76.06
	MTMNet [117]	2020	-	Onset-Apex	2S-CNN+DA+GAN	RES	CK+ [192],MMI [10], Oulu-CASIA [193]	LOSO	3	0.744	76.0
	MiMaNet [185]	2021	T	Apex+sequence	2S-CNN+DA	RES	CK+ [192],MMI [10]	LOSO	3	0.778	78.6
	DSTAN [175]	2021	T	OF+sequence	2S-CNN+LSTM+SVM	Attention	-	LOSO	3	0.78	77
	AMAN [172]	2022	E,T	sequence	CNN	Attention	FER2013 [191]	LOSO	3	0.77	79.87
CASME	TSCNN [94]	2019	E,R	OF+Apex	3S-CNN	-	FER2013 [191]	LOSO	4	0.7270	73.88
	DIKD [64]	2020	-	Apex	CNN+KD+SVM	RES	-	LOSO	4	0.77	81.80
	AffectiveNet [160]	2020	E	DI	4S-CNN	MFL	-	LOSO	4	-	72.64
	DSTAN [175]	2021	T	OF+sequence	2S-CNN+LSTM+SVM	Attention	-	LOSO	4	0.75	78
CASME II	OFF-ApexNet [90]	2019	-	OF	2S-CNN	-	-	LOSO	3	0.8697	88.28
	TSCNN [94]	2019	E, R	OF+Apex	3S-CNN	-	FER2013 [191]	LOSO	5	0.807	80.97
	STSTNet [101]	2019	E	OF	3S-3DCNN	-	-	LOSO	3	0.8382	86.86
	Graph-TCN [84]	2020	L, R	Apex	TCN+GCN	Graph	-	LOSO	5	0.7246	73.98
	SMA-STN [69]	2020	-	Snippet	CNN	Attention	WIDER FACE [194]	LOSO	5	0.7946	82.59
	GEME [71]	2021	-	DI	2S-CNN+ML	RES	-	LOSO	5	0.7354	75.20
	MiMaNet [185]	2021	T	Apex+sequence	2S-CNN+DA	RES	CK+ [192],MMI [10]	LOSO	5	0.759	79.9
	LR-GACNN [70]	2021	E	OF+Landmark	2S-GACNN	Graph	-	LOSO	5	0.7090	81.30
	DSTAN [175]	2021	T	OF+sequence	2S-CNN+LSTM+SVM	Attention	-	LOSO	5	0.73	75
AMAN [172]	2022	E,T	sequence	CNN	Attention	FER2013 [191]	LOSO	5	0.71	75.40	
SMM	DIKD [64]	2020	-	Apex	CNN+KD+SVM	-	-	LOSO	4	0.83	86.74
	SMA-STN [69]	2020	-	Snippet	CNN	-	WIDER FACE [194]	LOSO	5	0.7033	77.20
	MTMNet [117]	2020	-	Onset-Apex	2S-CNN+GAN+DA	RES	CK+ [192],MMI [10], Oulu-CASIA [193]	LOSO	5	0.736	74.1
	MiMaNet [185]	2021	T	Apex+sequence	2S-CNN+DA	RES	CK+ [192],MMI [10]	LOSO	5	0.764	76.7
	LR-GACNN [70]	2021	E	OF+Landmark	2S-GACNN	-	-	LOSO	5	0.8279	88.24
	GRAPH-AU [87]	2021	L	Apex	2S-CNN+GCN	Graph, Transformer	-	LOSO	5	0.7045	74.26
	AMAN [172]	2022	E,T	sequence	CNN	Attention	FER2013 [191]	LOSO	5	0.67	68.85
CMED	Shallow CNN [39]	2020	E	OF	CNN	-	-	LOSO	7	0.6353	66.06

<sup>1</sup> Pre-p.: Pre-processing; E:EVM; R:RoI; T: Temporal normalization; L: Learning-based magnification.

<sup>2</sup> OF: Optical flow; DI: Dynamic image.

<sup>3</sup> nS-CNN: n-stream CNN; ML: Multi-task learning; DA: Domain adaption; KD: Knowledge distillation.

<sup>4</sup> Cate: Category; F1: F1-score; ACC: Accuracy; RES: Residual block.

TABLE 4  
MER on the Composite Dataset (MECG2019)

Method	Year	Pre-p.	Input	Network architecture	Block	Pre-train	Protocol	Cate.	UFI	UAR
NMER [115]	2019	E, R	OF	CNN+DA	-	-	LOSO	3	0.7885	0.7824
Dual-Inception [76]	2019	-	OF	2S-CNN	Inception	-	LOSO	3	0.7322	0.7278
ICE-GAN [22]	2020	GAN	Apex	CNN+GAN	Capsule	ImageNet	LOSO	3	0.845	0.841
MTMNet [117]	2020	-	Onset-Apex	2S-CNN+GAN+DA	RES	CK+ [192],MMI [10], Oulu-CASIA [193]	LOSO	3	0.864	0.857
FR [180]	2021	-	OF	2S-CNN+ML	Inception	-	LOSO	3	0.7838	0.7832
MiMaNet [185]	2021	T	Apex+sequence	2S-CNN+DA	RES	CK+ [192],MMI [10]	LOSO	3	0.883	0.876
GRAPH-AU [87]	2021	L	Apex	2S-CNN+GCN	Graph, Transformer	-	LOSO	3	0.7914	0.7933
BDCNN [131]	2022	L	OF	4S-CNN	-	-	LOSO	3	0.8509	0.8500

<sup>1</sup> Pre-p.: Pre-processing; E: EVM; R: RoI; T: Temporal normalization; L: Learning-based magnification.

<sup>2</sup> OF: Optical flow; DI: Dynamic image.

<sup>3</sup> nS-CNN: n-stream CNN; ML: Multi-task learning; DA: Domain adaption; KD: Knowledge distillation.

<sup>4</sup> Cate: Category; RES: Residual block.

network is recommended to learn effective representations from various inputs [70], [94], [175]. In contrast to the combined inputs, the sole sequence performs worse [172], due to the limited information and redundancy.

Besides, from Tables 3 and 4, it can be seen that the learning strategy including fine-tuning [69], domain adaptation [117], [185] and knowledge distillation [64] can achieve state-of-the-art results on both the individual datasets and the composite dataset. This could be explained that the limited ME sample is the main challenge for MER and leveraging other related data sources is a reasonable and effective

solution. In the future, domain adaption and knowledge distillation should be further researched to boost MER performance.

In some latest works [70], [84], [87], the GCN becomes a mainstream choice for MER and shows promising performance. Currently, the spatio-temporal graph representation combined with GCNs obtains more attention in MER studies. The possible reason is that the landmark and AU information are helpful and effective for locating and representing the facial muscle movements. However, the small-sample ME datasets limit the ability of graph representation. The

combination of transfer learning and graph should be a promising direction for future ME studies.

## 7 CHALLENGES AND FUTURE DIRECTIONS

MER has a wide range of potential applications in various fields, such as psychological disorders, education, business negotiation, and security control. More specific descriptions about applications of MER are introduced in Appendix A. Although MER could facilitate society in various fields, there are many challenges. In this section, we discuss the challenges and future directions of MER.

### 7.1 Dealing With Small-Scale Dataset

Deep learning is a data-driven method, and successful training requires various large-scale data. Recent studies indicated that annotation bias, emotional contexts, and cultural backgrounds could affect the ME perception [195]. They may mislead the model training and finally cause misclassification. Unfortunately, existing ME datasets are far from enough for training a robust model. To this end, more diverse ME datasets should be collected. Besides, effective deep-based data augmentation approaches should be further developed for ME analysis to avoid over-fitting. Semi-supervised and unsupervised learning could also be potential solutions.

In addition, some emotions, such as fear, are challenging to be evoked and collected. The data imbalance causes the network to be biased towards classes in the majority. Therefore, effective imbalanced losses are needed.

### 7.2 3D ME Sequence

Currently, the main focus of MER is based on the 2D domain because of the data prevalence in the relevant modalities including images and videos. Although significant progress has been made for MER in recent years, most existing MER algorithms based on 2D facial images and sequences can not solve the challenging problems of illumination and pose variations in real-world applications. Recent research about FE analysis illustrates that the above issues can be addressed through 3D facial data [196]. Inherent characteristics of 3D face make facial recognition robust to lighting and pose variations. Moreover, 3D geometry information may include important features for FER and provide more data for better training. Thanks to the benefits of 3D faces and the technological development of 3D scanning, MER based on 3D sequence could be a promising research direction. Special 3D blocks, such as 3D Graph and Transformer, should be studied in 3D MER.

### 7.3 AU Analysis in MEs

MEs reveal people's hidden emotions in high-stake situations [3], [197] and have various applications such as clinic diagnosis and national security. However, ME interpretation suffers ambiguities [50], e.g., the inner brow raiser may refer to surprise or sad. The FACS [6] has been verified to be effective for resolving the ambiguity issue. In FACS, action units (AUs) are defined as the basic facial movements, working as the building blocks to formulate multiple FEs [6]. Furthermore, the criteria for AU and FE correspondence is defined in FACS manual. Encoding AUs has been verified to benefit the MER [53], [64], [198] through embedding AU

features. In the future, the relationship between AUs and MEs can be further explored to improve MER.

### 7.4 Multi-Modal MER

One of the MER challenges is that the low-intensity and small-scale ME datasets provide very limited information for robust MER. Recent research demonstrated that utilizing multiple modalities can provide complementary information and enhance classification robustness. Different emotional expressions can produce different changes in autonomic activity, e.g. fear leads to increased heart rate and decreased skin temperature. Thus, the physiological signal can be utilized to incorporate complementary information for further improving MER. Besides, in recent years, new micro-gesture datasets [199] had been proposed. The micro-gesture is body movements that are elicited when hidden expressions are triggered in unconstrained situations. The hidden emotional states can be reflected through micro-gestures. How to combine multiple modalities to enhance MER performance is an important future direction. Lightweight multi-stream networks should be developed to learn multi-view ME information effectively and efficiently.

### 7.5 The Explainability of MER Based on DL

The neural network is a brain-inspired model developed by neurobiologists and psychologists to test the computational analog of neurons [200]. Naturally, it could be a tool to verify the theory in other disciplines, such as psychology, to enhance psychological and human communication study. In addition, the current DL is a "black box" algorithm [200] and focuses on learning features and recognizing patterns by updating the weights of networks. The interpretation and understanding of the inside DL process can get experts from cross disciplines involved in the internal state analysis and therefore facilitate building interpretable and reliable deep models.

### 7.6 MEs in Realistic Situations

Currently, most existing MER researches focus on classifying the basic MEs collected in controlled environments from the frontal view without any head movements, illumination variations or occlusion. However, it is almost impossible to reproduce such strict conditions in real-world applications. The approaches based on the constrained settings usually do not generalize well to videos recorded in-the-wild environment. Practical and robust algorithms for recognizing MEs in realistic situations with pose changes and illumination variations should be developed in the future.

Moreover, most ME researches assume that there are just MEs in a video clip. However, in real life, MEs can appear with macro-expressions. Future studies should explore deep-based ME spotting methods to detect and distinguish the micro- and macro-expressions when they occur at the same time. Analyzing the macro and micro-expressions simultaneously would be helpful to understand people's intentions and feelings in reality more accurately.

## 8 ETHICAL CONSIDERATIONS

As discussed above, MEs can help reveal people's hidden feelings in high-stake situations and have practical applications in various fields, such as medical treatment and interrogations.

MER, like many other computer vision and machine learning tasks, could be misused, especially when used in surveillance with predatory data collection practices [201], [202], [203], [204]. Therefore, ethical issues should be considered.

Privacy and data protection is the primarily and frequently discussed ethical issue in machine learning. For MER, the critical privacy concern is the privacy of personal data. Currently, data protection laws are well established to regulate data privacy, for example, the EU General Data Protection Regulation (GDPR) [205]. The legislation defined rules for the protection of personal data, including international data protection agreements, privacy shields, transfer of participant names, record data, etc. In the research community, consent forms concerning data collection, processing, and sharing need to be signed when collecting ME data. In practical applications, consent forms should also be considered to regulate the usage, as people's faces are present in the recorded images/videos with sensitive and biometric information that may be misused beyond the intended purpose. Pilot studies aim to remove sensitive information like identity while preserving facial properties [206], which could be further explored in MER.

Moreover, questions of reliability in MER systems are further pointed out together with privacy and data protection [207]. Results of a deep learning-based MER system usually depend on the quality of training data, which are difficult to ascertain because of possible data biases. Transparency of data and models should be aware and well-studied.

## REFERENCES

- [1] P. Ekman, "Darwin, deception, and facial expression," *Ann. New York Acad. Sci.*, vol. 1000, no. 1, pp. 205–221, 2003.
- [2] P. Ekman and W. Friesen, "Constants across cultures in the face and emotion," *Pers. Social Psychol.*, vol. 17, no. 2, pp. 124–129, 1971.
- [3] P. Ekman, "Lie catching and microexpressions," *The Philosophy of Deception*, London, U.K.: Oxford Univ. Press, 2009, pp. 118–133.
- [4] E. A. Haggard and K. S. Isaacs, "Micromomentary facial expressions as indicators of ego mechanisms in psychotherapy," in *Methods of Research in Psychotherapy*, Berlin, Germany: Springer, 1966, pp. 154–165.
- [5] P. Ekman and W. V. Friesen, "Nonverbal leakage and clues to deception," *Psychiatry*, vol. 32, no. 1, pp. 88–106, 1969.
- [6] W. V. Friesen and P. Ekman, "Facial action coding system: A technique for the measurement of facial movement," *Palo Alto*, vol. 3, 1978, Art. no. 5.
- [7] P. Ekman, "Microexpression training tool (METT)," 2002, [Online]. Available: <https://www.paulekman.com/micro-expressions-training-tools/>
- [8] X. Niu, H. Han, S. Yang, Y. Huang, and S. Shan, "Local relationship learning with person-specific shape regularization for facial action unit detection," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2019, pp. 11 917–11 926.
- [9] W. J. Yan et al., "CASME II: An improved spontaneous micro-expression database and the baseline evaluation," *Plos One*, vol. 9, no. 1, 2014, Art. no. e86041.
- [10] M. Pantic, M. Valstar, R. Rademaker, and L. Maat, "Web-based database for facial expression analysis," in *Proc. IEEE Int. Conf. Multimedia Expo*, 2005, Art. no. 5.
- [11] W. Merghani, A. K. Davison, and M. H. Yap, "A review on facial micro-expressions analysis: Datasets, features and metrics," 2018, *arXiv:1805.02397*.
- [12] C. Crivelli and A. J. Fridlund, "Inside-out: From basic emotions theory to the behavioral ecology view," *J. Nonverbal Behav.*, vol. 43, no. 2, pp. 161–194, Jan. 2019.
- [13] P. M. Niedenthal, M. Rychlowska, F. Zhao, and A. Wood, "Historical migration patterns shape contemporary cultures of emotion," *Perspectives Psychol. Sci.*, vol. 14, no. 4, pp. 560–573, 2019.
- [14] T. Pfister, X. Li, G. Zhao, and M. Pietikäinen, "Differentiating spontaneous from posed facial expressions within a generic facial expression recognition framework," in *Proc. Int. Conf. Comput. Vis.*, 2011, pp. 1449–1456.
- [15] X. Li, T. Pfister, X. Huang, G. Zhao, and M. Pietikäinen, "A spontaneous micro-expression database: Inducement, collection and baseline," in *Proc. IEEE Conf. Workshops Autom. Face Gesture Recognit.*, 2013, pp. 1–6.
- [16] X. Li, T. Pfister, X. Huang, G. Zhao, and M. Pietikäinen, "A spontaneous micro-expression database: Inducement, collection and baseline," in *Proc. IEEE 10th Int. Conf. Workshops Autom. Face Gesture Recognit.*, 2013, pp. 1–6.
- [17] X. Li et al., "Towards reading hidden emotions: A comparative study of spontaneous micro-expression spotting and recognition methods," *IEEE Trans. Affect. Comput.*, vol. 9, no. 4, pp. 563–577, Oct.–Dec. 2018.
- [18] J. Wei, G. Lu, and J. Yan, "A comparative study on movement feature in different directions for micro-expression recognition," *Neurocomputing*, vol. 449, pp. 159–171, 2021.
- [19] L. Liu et al., "Deep learning for generic object detection: A survey," *Int. J. Comput. Vis.*, vol. 128, no. 2, pp. 261–318, 2020.
- [20] A. Brunetti, D. Buongiorno, G. F. Trotta, and V. Bevilacqua, "Computer vision and deep learning techniques for pedestrian detection and tracking: A survey," *Neurocomputing*, vol. 300, pp. 17–33, 2018.
- [21] S. Li and W. Deng, "Deep facial expression recognition: A survey," *IEEE Trans. Affect. Comput.*, vol. 13, no. 3, pp. 1195–1215, Jul.–Sep. 2020.
- [22] J. Yu, C. Zhang, Y. Song, and W. Cai, "ICE-GAN: Identity-aware and capsule-enhanced GAN for micro-expression recognition and synthesis," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, 2021.
- [23] H.-X. Xie, L. Lo, H.-H. Shuai, and W.-H. Cheng, "An overview of facial micro-expression analysis: Data, methodology and challenge," *IEEE Trans. Affect. Comput.*, p. 1, 2022.
- [24] K. M. Goh, C. H. Ng, L. L. Lim, and U. U. Sheikh, "Micro-expression recognition: An updated review of current trends, challenges and solutions," *Vis. Comput.*, vol. 36, no. 3, pp. 445–468, 2020.
- [25] M. Takalkar, M. Xu, Q. Wu, and Z. Chaczko, "A survey: Facial micro-expression recognition," *Multimedia Tools Appl.*, vol. 77, no. 15, pp. 19 301–19 325, 2018.
- [26] Y.-H. Oh, J. See, A. C. Le Ngo, R. C.-W. Phan, and V. M. Bakaran, "A survey of automatic facial micro-expression analysis: Databases, methods, and challenges," *Front. Psychol.*, vol. 9, 2018, Art. no. 1128.
- [27] X. Ben et al., "Video-based facial micro-expression analysis: A survey of datasets, features and algorithms," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, no. 9, pp. 5826–5846, 2021.
- [28] L. Zhou, X. Shao, and Q. Mao, "A survey of micro-expression recognition," *Image Vis. Comput.*, vol. 105, 2021, Art. no. 104043.
- [29] W. Yan, Q. Wu, Y. Liu, S. Wang, and X. Fu, "CASME database: A dataset of spontaneous micro-expressions collected from neutralized faces," in *Proc. IEEE Conf. Autom. Face Gesture Recognit.*, 2013, pp. 1–7.
- [30] F. Qu, S.-J. Wang, W.-J. Yan, H. Li, S. Wu, and X. Fu, "CAS (ME)<sup>2</sup>: A database for spontaneous macro-expression and micro-expression spotting and recognition," *IEEE Trans. Affect. Comput.*, vol. 9, no. 4, pp. 424–436, Oct.–Dec. 2017.
- [31] A. K. Davison, C. Lansley, N. Costen, K. Tan, and M. H. Yap, "SAMM: A spontaneous micro-facial movement dataset," *IEEE Trans. Affect. Comput.*, vol. 9, no. 1, pp. 116–129, Jan.–Mar. 2018.
- [32] P. Husák, J. Cech, and J. Matas, "Spotting facial micro-expressions "in the wild"," in *Proc. 22nd Comput. Vis. Winter Workshop*, 2017, pp. 1–9.
- [33] J. See, Y. Hoon, J. Li, X. Hong, and S. Wang, "MEGC 2019—the second facial micro-expressions grand challenge," in *Proc. IEEE 14th Int. Conf. Autom. Face Gesture Recognit.*, 2019, pp. 1–5.
- [34] Y. Zhao and J. Xu, "A convolutional neural network for compound micro-expression recognition," *Sensors*, vol. 19, no. 24, 2019, Art. no. 5553.
- [35] A. Vinciarelli, A. Dielmann, S. Favre, and H. Salamin, "Canal9: A database of political debates for analysis of social interactions," in *Proc. IEEE 3rd Int. Conf. Affect. Comput. Intell. Interact. Workshops*, 2009, pp. 1–4.
- [36] S. Polikovskiy, Y. Kameda, and Y. Ohta, "Facial micro-expressions recognition using high speed camera and 3D-gradient descriptor," in *Proc. IEEE Third Int. Conf. Crime Detection Prevention*, 2009, pp. 1–6.

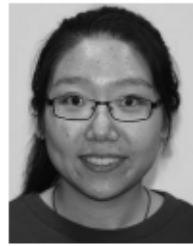


- [37] M. Shreve, S. Godavarthy, D. Goldgof, and S. Sarkar, "Macro- and micro-expression spotting in long videos using spatio-temporal strain," in *Proc. IEEE Conf. Workshops Autom. Face Gesture Recognit.*, 2011, pp. 51–56.
- [38] M. Zhang, Q. Fu, Y.-H. Chen, and X. Fu, "Emotional context modulates micro-expression processing as reflected in event-related potentials," *PsyCh J.*, vol. 7, no. 1, pp. 13–24, 2018.
- [39] Y. Zhao and J. Xu, "Compound micro-expression recognition system," in *Proc. IEEE Int. Conf. Intell. Transp. Big Data Smart City*, 2020, pp. 728–733.
- [40] P. Viola et al., "Robust real-time object detection," *Int. J. Comput. Vis.*, vol. 4, no. 34–47, 2001, Art. no. 4.
- [41] M. Matsugu, K. Mori, Y. Mitari, and Y. Kaneda, "Subject independent facial expression recognition with robust face detection using a convolutional neural network," *Neural Netw.*, vol. 16, no. 5/6, pp. 555–559, 2003.
- [42] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models—their training and application," *Comput. Vis. Image Understanding*, vol. 61, no. 1, pp. 38–59, 1995.
- [43] T. F. Cootes, G. J. Edwards, and C. J. Taylor, "Active appearance models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 6, pp. 681–685, Jun. 2001.
- [44] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint face detection and alignment using multitask cascaded convolutional networks," *IEEE Signal Process. Lett.*, vol. 23, no. 10, pp. 1499–1503, Oct. 2016.
- [45] Z. Zhou, G. Zhao, and M. Pietikäinen, "Towards a practical lip-reading system," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2011, pp. 137–144.
- [46] S. Niklaus and F. Liu, "Context-aware synthesis for video frame interpolation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 1701–1710.
- [47] H. Wu, E. Shih, E. Shih, J. Guttag, and W. Freeman, "Eulerian video magnification for revealing subtle changes in the world," *ACM Trans. Graph.*, vol. 31, no. 4, pp. 1–8, 2012.
- [48] T.-H. Oh et al., "Learning-based video motion magnification," in *Proc. Eur. Conf. Comput. Vis.*, 2018, pp. 633–648.
- [49] G. Zhao and M. Pietikäinen, "Dynamic texture recognition using local binary patterns with an application to facial expressions," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 6, pp. 915–928, Jun. 2007.
- [50] A. Davison, W. Merghani, C. Lansley, C.-C. Ng, and M. H. Yap, "Objective micro-facial movement detection using face-based regions and baseline evaluation," in *Proc. 13th IEEE Int. Conf. Autom. Face Gesture Recognit.*, 2018, pp. 642–649.
- [51] W. Merghani and M. H. Yap, "Adaptive mask for region-based facial micro-expression recognition," in *Proc. 15th IEEE Int. Conf. Autom. Face Gesture Recognit.*, 2020, pp. 428–433.
- [52] M. Shreve, J. Brizzi, S. Fefilyatov, T. Laguev, D. Goldgof, and S. Sarkar, "Automatic expression spotting in videos," *Image Vis. Comput.*, vol. 32, no. 8, pp. 476–486, 2014.
- [53] H.-X. Xie, L. Lo, H.-H. Shuai, and W.-H. Cheng, "AU-assisted graph attention convolutional network for micro-expression recognition," in *Proc. 28th ACM Int. Conf. Multimedia*, 2020, pp. 2871–2880.
- [54] Y. Li, X. Huang, and G. Zhao, "Joint local and global information learning with single apex frame detection for micro-expression recognition," *IEEE Trans. Image Process.*, vol. 30, pp. 249–263, Nov. 2020.
- [55] Z. Xia, X. Hong, X. Gao, X. Feng, and G. Zhao, "Spatiotemporal recurrent convolutional networks for recognizing spontaneous micro-expressions," *IEEE Trans. Multimedia*, vol. 22, no. 3, pp. 626–640, Mar. 2020.
- [56] Y. Li, X. Huang, and G. Zhao, "Micro-expression action unit detection with spatial and channel attention," *Neurocomputing*, vol. 436, pp. 221–231, 2021.
- [57] D. Patel, G. Zhao, and M. Pietikäinen, "Spatiotemporal integration of optical flow vectors for micro-expression detection," in *Proc. Int. Conf. Adv. Concepts Intell. Vis. Syst.*, 2015, pp. 369–380.
- [58] Y. Han, B. Li, Y.-K. Lai, and Y.-J. Liu, "CFD: A collaborative feature difference method for spontaneous micro-expression spotting," in *Proc. IEEE 25th Int. Conf. Image Process.*, 2018, pp. 1942–1946.
- [59] Y. Li, X. Huang, and G. Zhao, "Can micro-expression be recognized based on single apex frame?," in *Proc. IEEE Int. Conf. Image Process.*, 2018, pp. 3094–3098.
- [60] Z. Zhang, T. Chen, H. Meng, G. Liu, and X. Fu, "SMEconvNet: A convolutional neural network for spotting spontaneous facial micro-expression from long videos," *IEEE Access*, vol. 6, pp. 71143–71151, 2018.
- [61] T.-K. Tran, Q.-N. Vo, X. Hong, X. Li, and G. Zhao, "Micro-expression spotting: A new benchmark," *Neurocomputing*, vol. 443, pp. 356–368, 2021.
- [62] H. Pan, L. Xie, and Z. Wang, "Local bilinear convolutional neural network for spotting macro- and micro-expression intervals in long video sequences," in *Proc. IEEE 15th Int. Conf. Autom. Face Gesture Recognit.*, 2020, pp. 343–347.
- [63] N. V. Quang, J. Chun, and T. Tokuyama, "CapsuleNet for micro-expression recognition," in *Proc. IEEE 14th Int. Conf. Autom. Face Gesture Recognit.*, 2019, pp. 1–7.
- [64] B. Sun, S. Cao, D. Li, J. He, and L. Yu, "Dynamic micro-expression recognition using knowledge distillation," *IEEE Trans. Affect. Comput.*, vol. 13, no. 2, pp. 1037–1043, second quarter 2020.
- [65] R. Zhi, H. Xu, M. Wan, and T. Li, "Combining 3D convolutional neural networks with transfer learning by supervised pre-training for facial micro-expression recognition," *IEICE Trans. Inform. Syst.*, vol. 102, no. 5, pp. 1054–1064, 2019.
- [66] D. Kim, W. J. Baddar, and Y. M. Ro, "Micro-expression recognition with expression-state constrained spatio-temporal feature representations," in *Proc. 24th ACM Int. Conf. Multimedia*, 2016, pp. 382–386.
- [67] J. Li, Y. Wang, J. See, and W. Liu, "Micro-expression recognition based on 3D flow convolutional neural network," *Pattern Anal. Appl.*, vol. 33, pp. 1331–1339, 2019.
- [68] S.-T. Liong and K. Wong, "Micro-expression recognition using apex frame with phase information," in *Proc. IEEE Asia-Pacific Signal Inform. Process. Assoc. Annu. Summit Conf.*, 2017, pp. 534–537.
- [69] J. Liu, W. Zheng, and Y. Zong, "SMA-STN: Segmented movement-attending spatiotemporal network for micro-expression recognition," 2020, *arXiv:2010.09342*.
- [70] A. J. R. Kumar and B. Bhanu, "Micro-expression classification based on landmark relations with graph attention convolutional network," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops*, 2021, pp. 1511–1520.
- [71] X. Nie, M. A. Takalkar, M. Duan, H. Zhang, and M. Xu, "GEME: Dual-stream multi-task gender-based micro-expression recognition," *Neurocomputing*, vol. 427, pp. 13–28, 2021.
- [72] M. Verma, S. K. Vipparthi, G. Singh, and S. Murala, "LEARNet: Dynamic imaging network for micro expression recognition," *IEEE Trans. Image Process.*, vol. 29, pp. 1618–1627, Sep. 2019.
- [73] M. Verma, S. K. Vipparthi, and G. Singh, "Non-linearities improve originet based on active imaging for micro expression recognition," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, 2020, pp. 1–8.
- [74] B. D. Lucas, "Generalized image matching by the method of differences," *Carnegie Mellon Univ.*, 1985.
- [75] G. Farneback, "Two-frame motion estimation based on polynomial expansion," in *Proc. Scand. Conf. Image Anal.*, 2003, pp. 363–370.
- [76] L. Zhou, Q. Mao, and L. Xue, "Dual-inception network for cross-database micro-expression recognition," in *Proc. 14th IEEE Int. Conf. Autom. Face Gesture Recognit.*, 2019, pp. 1–5.
- [77] D. Alexey et al., "FlowNet: Learning optical flow with convolutional networks," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2015, pp. 2758–2766.
- [78] N. Liu, X. Liu, Z. Zhang, X. Xu, and T. Chen, "Offset or onset frame: A multi-stream convolutional neural network with capsuleNet module for micro-expression recognition," in *Proc. 5th Int. Conf. Intell. Inform. Biomed. Sci.*, 2020, pp. 236–240.
- [79] B. Sun, S. Cao, J. He, and L. Yu, "Two-stream attention-aware network for spontaneous micro-expression movement spotting," in *Proc. IEEE 10th Int. Conf. Softw. Eng. Serv. Sci.*, 2019, pp. 702–705.
- [80] A. J. R. Kumar and B. Bhanu, "Micro-expression classification based on landmark relations with graph attention convolutional network," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2021, pp. 1511–1520.
- [81] J. Liu, K. Li, B. Song, and L. Zhao, "A multi-stream convolutional neural network for micro-expression recognition using optical flow and EVM," 2020, *arXiv:2011.03756*.
- [82] B. Chen, Z. Zhang, N. Liu, Y. Tan, X. Liu, and T. Chen, "Spatiotemporal convolutional neural network with convolutional block attention module for micro-expression recognition," *Information*, vol. 11, no. 8, 2020, Art. no. 380.
- [83] V. R. Gajjala, S. P. T. Reddy, S. Mukherjee, and S. R. Dubey, "MERANet: Facial micro-expression recognition using 3D residual attention network," in *Proc. Twelfth Indian Conf. Comput. Vis., Graph. Image Process.*, 2021, pp. 1–10.
- [84] L. Lei, J. Li, T. Chen, and S. Li, "A novel Graph-TCN with a graph structured representation for micro-expression recognition," in *Proc. 28th ACM Int. Conf. Multimedia*, 2020, pp. 2237–2245.

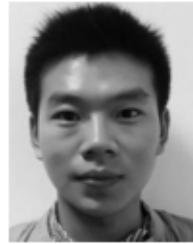
- [85] L. Lo, H.-X. Xie, H.-H. Shuai, and W.-H. Cheng, "MER-GCN: Micro-expression recognition based on relation modeling with graph convolutional networks," in *Proc. IEEE Conf. Multimedia Informat. Process. Retrieval*, 2020, pp. 79–84.
- [86] L. Zhou, Q. Mao, and M. Dong, "Objective class-based micro-expression recognition through simultaneous action unit detection and feature aggregation," 2020, *arXiv:2012.13148*.
- [87] L. Lei, T. Chen, S. Li, and J. Li, "Micro-expression recognition based on facial graph representation learning and facial action unit fusion," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops*, 2021, pp. 1571–1580.
- [88] T. T. Q. Le, T.-K. Tran, and M. Rege, "Dynamic image for micro-expression recognition on region-based framework," in *IEEE 21st Int. Conf. Informat. Reuse Integration Data Sci.*, 2020, pp. 75–81.
- [89] Y. Wang, H. Ma, X. Xing, and Z. Pan, "Eulerian motion based 3DCNN architecture for facial micro-expression recognition," in *Proc. Int. Conf. Multimedia Model.*, 2020, pp. 266–277.
- [90] Y. Gan, S. Liong, W. Yau, Y. Huang, and L. Tan, "Off-apexnet on micro-expression recognition system," *Signal Process.: Image Commun.*, vol. 74, pp. 129–139, 2019.
- [91] H.-Q. Khor, J. See, S.-T. Liong, R. C. Phan, and W. Lin, "Dual-stream shallow networks for facial micro-expression recognition," in *Proc. IEEE Int. Conf. Image Process.*, 2019, pp. 36–40.
- [92] H. Yan and L. Li, "Micro-expression recognition using enriched two stream 3D convolutional network," in *Proc. 4th Int. Conf. Comput. Sci. Appl. Eng.*, 2020, pp. 1–5.
- [93] K. Li et al., "Three-stream convolutional neural network for micro-expression recognition," *Aust. J. Intell. Informat. Process. Syst.*, vol. 15, no. 3, pp. 41–48, 2019.
- [94] B. Song et al., "Recognizing spontaneous micro-expression using a three-stream convolutional neural network," *IEEE Access*, vol. 7, pp. 184 537–184 551, 2019.
- [95] J. Li, Y. Wang, J. See, and W. Liu, "Micro-expression recognition based on 3D flow convolutional neural network," *Pattern Anal. Appl.*, vol. 22, no. 4, pp. 1331–1339, 2019.
- [96] B. Yang, J. Cheng, Y. Yang, B. Zhang, and J. Li, "MERTA: Micro-expression recognition with ternary attentions," *Multimedia Tools Appl.*, vol. 80, no. 11, pp. 1–16, 2021.
- [97] W. She et al., "Micro-expression recognition based on multiple aggregation networks," in *Proc. Asia-Pacific Signal Informat. Process. Assoc. Annu. Summit Conf.*, 2020, pp. 1043–1047.
- [98] L. Wang, J. Jia, and N. Mao, "Micro-expression recognition based on 2D-3DCNN," in *Proc. 39th Chin. Control Conf.*, 2020, pp. 3152–3157.
- [99] M. Peng, C. Wang, T. Bi, Y. Shi, X. Zhou, and T. Chen, "A novel apex-time network for cross-dataset micro-expression recognition," in *Proc. 8th Int. Conf. Affect. Comput. Intell. Interact.*, 2019, pp. 1–6.
- [100] J. Huang, X. Zhao, and L. Zheng, "Shcfnnet on micro-expression recognition system," in *Proc. IEEE 13th Int. Congr. Image Signal Process. BioMed. Eng. Inform.*, 2020, pp. 163–168.
- [101] S. Liong, Y. Gan, J. See, H. Khor, and Y. Huang, "Shallow triple stream three-dimensional CNN (STSTNet) for micro-expression recognition," in *Proc. IEEE 14th Int. Conf. Autom. Face Gesture Recognit.*, 2019, pp. 1–5.
- [102] C. Wu and F. Guo, "TSNN: Three-stream combining 2D and 3D convolutional neural network for micro-expression recognition," *IEEE Trans. Elect. Electron. Eng.*, vol. 16, no. 1, pp. 98–107, 2021.
- [103] M. A. Takalkar, M. Xu, and Z. Chaczko, "Manifold feature integration for micro-expression recognition," *Multimedia Syst.*, vol. 26, no. 5, pp. 535–551, 2020.
- [104] C. Hu, D. Jiang, H. Zou, X. Zuo, and Y. Shu, "Multi-task micro-expression recognition combining deep and handcrafted features," in *Proc. 24th Int. Conf. Pattern Recognit.*, 2018, pp. 946–951.
- [105] H. Pan, L. Xie, Z. Lv, J. Li, and Z. Wang, "Hierarchical support vector machine for facial micro-expression recognition," *Multimedia Tools Appl.*, vol. 79, no. 41, pp. 31 451–31 465, 2020.
- [106] S. C. Nistor, "Multi-staged training of deep neural networks for micro-expression recognition," in *Proc. IEEE 14th Int. Symp. Appl. Comput. Intell. Inform.*, 2020, pp. 000 029–000 034.
- [107] H.-Q. Khor, J. See, R. C. W. Phan, and W. Lin, "Enriched long-term recurrent convolutional network for facial micro-expression recognition," in *Proc. IEEE 13th Int. Conf. Autom. Face Gesture Recognit.*, 2018, pp. 667–674.
- [108] M. Zhang, Z. Huan, and L. Shang, "Micro-expression recognition using micro-variation boosted heat areas," in *Proc. Chin. Conf. Pattern Recognit. Comput. Vis.*, 2020, pp. 531–543.
- [109] M. Bai and R. Goecke, "Investigating LSTM for micro-expression recognition," in *Proc. Companion Pub. Int. Conf. Multimodal Interact.*, 2020, pp. 7–11.
- [110] D. Y. Choi and B. C. Song, "Facial micro-expression recognition using two-dimensional landmark feature maps," *IEEE Access*, vol. 8, pp. 121 549–121 563, 2020.
- [111] R. Zhi, M. Liu, H. Xu, and M. Wan, "Facial micro-expression recognition using enhanced temporal feature-wise model," in *Cyber-space Data and Intelligence, and Cyber-Living, Syndrome, and Health*, Berlin, Germany: Springer, 2019, pp. 301–311.
- [112] Q. Li, S. Zhan, L. Xu, and C. Wu, "Facial micro-expression recognition based on the fusion of deep learning and enhanced optical flow," *Multimedia Tools Appl.*, vol. 78, no. 20, pp. 29 307–29 322, 2019.
- [113] G. Hinton, O. Vinyals, and J. Dean, "Distilling the knowledge in a neural network," *Statistics*, vol. 1050, pp. 1–9, 2015.
- [114] N. Komodakis and S. Zagoruyko, "Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer," in *Proc. Int. Conf. Learn. Representations*, 2017, pp. 1–13.
- [115] Y. Liu, H. Du, L. Zheng, and T. Gedeon, "A neural micro-expression recognizer," in *Proc. 14th IEEE Int. Conf. Autom. Face Gesture Recognit.*, 2019, pp. 1–4.
- [116] L. Zhou, Q. Mao, and L. Xue, "Cross-database micro-expression recognition: A style aggregated and attention transfer approach," in *Proc. IEEE Int. Conf. Multimedia Expo Workshops*, 2019, pp. 102–107.
- [117] B. Xia, W. Wang, S. Wang, and E. Chen, "Learning from macro-expression: A micro-expression recognition framework," in *Proc. 28th ACM Int. Conf. Multimedia*, 2020, pp. 2936–2944.
- [118] D. M. Kline and V. L. Berardi, "Revisiting squared-error and cross-entropy functions for training neural network classifiers," *Neural Comput. Appl.*, vol. 14, no. 4, pp. 310–318, 2005.
- [119] R. Hadsell, S. Chopra, and Y. LeCun, "Dimensionality reduction by learning an invariant mapping," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, 2006, pp. 1735–1742.
- [120] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2015, pp. 815–823.
- [121] W. Liu, Y. Wen, Z. Yu, and M. Yang, "Large-margin softmax loss for convolutional neural networks," in *Proc. Int. Conf. Mach. Learn.*, 2016, Art. no. 7.
- [122] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "Arcface: Additive angular margin loss for deep face recognition," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2019, pp. 4690–4699.
- [123] H. Wang et al., "CosFace: Large margin cosine loss for deep face recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 5265–5274.
- [124] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, "Focal loss for dense object detection," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2017, pp. 2980–2988.
- [125] A. C. Le Ngo, A. Johnston, R. C.-W. Phan, and J. See, "Micro-expression motion magnification: Global lagrangian versus local eulerian approaches," in *Proc. IEEE 13th Int. Conf. Autom. Face Gesture Recognit.*, 2018, pp. 650–656.
- [126] S.-T. Liong, J. See, R. C.-W. Phan, K. Wong, and S.-W. Tan, "Hybrid facial regions extraction for micro-expression recognition system," *J. Signal Process. Syst.*, vol. 90, no. 4, pp. 601–617, 2018.
- [127] Z. Xia, X. Hong, X. Gao, X. Feng, and G. Zhao, "Spatiotemporal recurrent convolutional networks for recognizing spontaneous micro-expressions," *IEEE Trans. Multimedia*, vol. 22, no. 3, pp. 626–640, Mar. 2020.
- [128] J. Li, C. Soladie, and R. Segquier, "LTP-ML: Micro-expression detection by recognition of local temporal pattern of facial movements," in *Proc. IEEE 13th Int. Conf. Autom. Face Gesture Recognit.*, 2018, pp. 634–641.
- [129] E. L. Rosenberg and P. Ekman, *What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS)*, London, U.K.: Oxford Univ. Press, 2020.
- [130] X. Huang, G. Zhao, W. Zheng, and M. Pietikainen, "Towards a dynamic expression recognition system under facial occlusion," *Pattern Recognit. Lett.*, vol. 33, no. 16, pp. 2181–2191, 2012.
- [131] B. Chen, K.-H. Liu, Y. Xu, Q.-Q. Wu, and J.-F. Yao, "Block division convolutional network with implicit deep features augmentation for micro-expression recognition," *IEEE Trans. Multimedia*, to be published, doi: 10.1109/TMM.2022.3141616.

- [132] F. Zhang, T. Zhang, Q. Mao, and C. Xu, "Joint pose and expression modeling for facial expression recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 3359–3368.
- [133] S.-T. Liong et al., "Evaluation of the spatio-temporal features and GAN for micro-expression recognition system," *J. Signal Process. Syst.*, vol. 92, pp. 705–725, 2020.
- [134] S.-J. Wang et al., "Micro-expression recognition using color spaces," *IEEE Trans. Image Process.*, vol. 24, no. 12, pp. 6034–6047, Dec. 2015.
- [135] V. Mayya, R. M. Pai, and M. M. Pai, "Combining temporal interpolation and DCNN for faster recognition of micro-expressions in video sequences," in *Proc. IEEE Int. Conf. Adv. Comput., Commun. Inform.*, 2016, pp. 699–703.
- [136] S. Ji, W. Xu, M. Yang, and K. Yu, "3D convolutional neural networks for human action recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 1, pp. 221–231, Jan. 2013.
- [137] L. R. Medsker and L. Jain, "Recurrent neural networks," *Des. Appl.*, vol. 5, pp. 64–67, 2001.
- [138] A. Ullah, J. Ahmad, K. Muhammad, M. Sajjad, and S. W. Baik, "Action recognition in video sequences using deep bi-directional LSTM with CNN features," *IEEE Access*, vol. 6, pp. 1155–1166, 2017.
- [139] H. Yang et al., "Asymmetric 3D convolutional neural networks for action recognition," *Pattern Recognit.*, vol. 85, pp. 1–12, 2019.
- [140] M. Peng et al., "Recognizing micro-expression in video clip with adaptive key-frame mining," 2020, *arXiv:2009.09179*.
- [141] S. Liong, J. See, K. S. Wong, and R. C. W. Phan, "Less is more: Micro-expression recognition from video using apex frame," *Signal Process. Image Commun.*, vol. 62, pp. 82–92, 2018.
- [142] H. Bilen, B. Fernando, E. Gavves, A. Vedaldi, and S. Gould, "Dynamic image networks for action recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 3034–3042.
- [143] H. Bilen, B. Fernando, E. Gavves, and A. Vedaldi, "Action recognition with dynamic image networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 12, pp. 2799–2813, Dec. 2017.
- [144] J. L. Barron, D. J. Fleet, and S. S. Beauchemin, "Performance of optical flow techniques," *Int. J. Comput. Vis.*, vol. 12, no. 1, pp. 43–77, 1994.
- [145] B. K. Horn and B. G. Schunck, "Determining optical flow," *Artif. Intell.*, vol. 17, no. 1/3, pp. 185–203, 1981.
- [146] T. Senst, V. Eiselein, and T. Sikora, "Robust local optical flow for feature tracking," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 22, no. 9, pp. 1377–1387, Sep. 2012.
- [147] A. Wedel, T. Pock, C. Zach, H. Bischof, and D. Cremers, "An improved algorithm for TV-L1 optical flow," in *Statistical and Geometrical Approaches to Visual Motion Analysis*, Berlin, Germany: Springer, 2009, pp. 23–45.
- [148] B. Allaert, I. R. Ward, I. M. Bilasco, C. Djeraba, and M. Bannamoun, "Optical flow techniques for facial expression analysis: Performance evaluation and improvements," 2019, *arXiv:1904.11592*.
- [149] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 770–778.
- [150] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, "Inception-V4, inception-ResNet and the impact of residual connections on learning," in *Proc. AAAI Conf. Artif. Intell.*, 2017, pp. 4278–4284.
- [151] S. Sabour, N. Frosst, and G. E. Hinton, "Dynamic routing between capsules," *Adv. Neural Inf. Process. Syst.*, vol. 30, pp. 1–11, 2017.
- [152] P. Pareek and A. Thakkar, "A survey on video-based human action recognition: Recent updates, datasets, challenges, and applications," *Artif. Intell. Rev.*, vol. 54, no. 3, pp. 2259–2322, 2021.
- [153] K. Hara, H. Kataoka, and Y. Satoh, "Can spatiotemporal 3D cnns retrace the history of 2D cnns and imagenet?," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 6546–6555.
- [154] S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He, "Aggregated residual transformations for deep neural networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 1492–1500.
- [155] Z. Wu, C. Shen, and A. Van Den Hengel, "Wider or deeper: Revisiting the resnet model for visual recognition," *Pattern Recognit.*, vol. 90, pp. 119–133, 2019.
- [156] R. Belaiche, Y. Liu, C. Migniot, D. Ginjac, and F. Yang, "Cost-effective CNNs for real-time micro-expression recognition," *Appl. Sci.*, vol. 10, no. 14, 2020, Art. no. 4959.
- [157] J. Wen, W. Yang, L. Wang, W. Wei, S. Tan, and Y. Wu, "Cross-database micro expression recognition based on apex frame optical flow and multi-head self-attention," in *Proc. Inf. Symp. Parallel Architectures Algorithms Program.*, 2020, pp. 128–139.
- [158] Z. Lai, R. Chen, J. Jia, and Y. Qian, "Real-time micro-expression recognition based on resnet and atrous convolutions," *J. Ambient Intell. Humanized Comput.*, pp. 1–12, Mar. 2020.
- [159] G. Chinnappa and M. K. Rajagopal, "Residual attention network for deep face recognition using micro-expression image analysis," *J. Ambient Intell. Humanized Comput.*, pp. 1–14, Mar. 2021.
- [160] M. Verma, S. K. Vipparthi, and G. Singh, "Affectivenet: Affective-motion feature learning for micro expression recognition," *IEEE MultiMedia*, vol. 28, no. 1, pp. 17–27, Jan.–Mar., 2020.
- [161] W. Li, F. Abtahi, and Z. Zhu, "Action unit detection with region adaptation, multi-labeling learning and optimal temporal fusing," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 1841–1850.
- [162] C. Szegedy et al., "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2015, pp. 1–9.
- [163] M. Verma, S. K. Vipparthi, and G. Singh, "HiNet: Hybrid inherited feature learning network for facial expression recognition," *IEEE Lett. Comput. Soc.*, vol. 2, no. 4, pp. 36–39, Dec. 2019.
- [164] Z. Xia, W. Peng, H.-Q. Khor, X. Feng, and G. Zhao, "Revealing the invisible with model and data shrinking for composite-database micro-expression recognition," *IEEE Trans. Image Process.*, vol. 29, pp. 8590–8605, Aug. 2020.
- [165] S. Bai, J. Z. Kolter, and V. Koltun, "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling," 2018, *arXiv:1803.01271*.
- [166] N. Parmar et al., "Image transformer," in *Proc. Int. Conf. Mach. Learn.*, 2018, pp. 4055–4064.
- [167] D. Acharya, Z. Huang, D. Pani Paudel, and L. Van Gool, "Covariance pooling for facial expression recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops*, 2018, pp. 367–374.
- [168] M. A. Takalkar, S. Thuseethan, S. Rajasegarar, Z. Chaczko, M. Xu, and J. Yearwood, "LGAttNet: Automatic micro-expression detection using dual-stream local and global attentions," *Knowl.-Based Syst.*, vol. 212, 2021, Art. no. 106566.
- [169] M. Bai, "Detection of micro-expression recognition based on spatio-temporal modelling and spatial attention," in *Proc. Int. Conf. Multimodal Interact.*, 2020, pp. 703–707.
- [170] M. F. Hashmi et al., "LARNet: Real-time detection of facial micro expression using lossless attention residual network," *Sensors*, vol. 21, no. 4, 2021, Art. no. 1098.
- [171] Y. Su, J. Zhang, J. Liu, and G. Zhai, "Key facial components guided micro-expression recognition based on first and second-order motion," in *Proc. IEEE Int. Conf. Multimedia Expo.*, 2021, pp. 1–6.
- [172] M. Wei, W. Zheng, Y. Zong, X. Jiang, C. Lu, and J. Liu, "A novel micro-expression recognition approach using attention-based magnification-adaptive networks," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, 2022, pp. 2420–2424.
- [173] X. Wang, R. Girshick, A. Gupta, and K. He, "Non-local neural networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 7794–7803.
- [174] L. Yao, X. Xiao, R. Cao, F. Chen, and T. Chen, "Three stream 3D CNN with se block for micro-expression recognition," in *Proc. Int. Conf. Comput. Eng. Appl.*, 2020, pp. 439–443.
- [175] Y. Wang et al., "Micro expression recognition via dual-stream spatiotemporal attention network," *J. Healthcare Eng.*, vol. 2021, pp. 1–10, 2021.
- [176] X. Li, G. Wei, J. Wang, and Y. Zhou, "Multi-scale joint feature network for micro-expression recognition," *Comput. Vis. Media*, vol. 7, pp. 407–417, 2021.
- [177] Y. Gan and S.-T. Liong, "Bi-directional vectors from apex in CNN for micro-expression recognition," in *Proc. IEEE 3rd Int. Conf. Image Vis. Comput.*, 2018, pp. 168–172.
- [178] P. Gupta, "MERASTC: Micro-expression recognition using effective feature encodings and 2D convolutional neural network," *IEEE Trans. Affective Comput.*, to be published, doi: 10.1109/TAFFC.2021.3061967.
- [179] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," in *Proc. Brit. Mach. Vis. Conf.*, 2015, pp. 1–12.
- [180] L. Zhou, Q. Mao, X. Huang, F. Zhang, and Z. Zhang, "Feature refinement: An expression-specific feature learning and fusion method for micro-expression recognition," 2021, *arXiv:2101.04838*.
- [181] Y. Zhang and Q. Yang, "A survey on multi-task learning," *IEEE Trans. Knowl. Data Eng.*, to be published, doi: 10.1109/TKDE.2021.3070203.
- [182] D. Patel, X. Hong, and G. Zhao, "Selective deep features for micro-expression recognition," in *Proc. IEEE Int. Conf. Pattern Recognit.*, 2017, pp. 2258–2263.
- [183] A. Romero, N. Ballas, E. K. Samira, A. Chassang, C. Gatta, and B. Yoshua, "FitNets: Hints for thin deep nets," *Proc. Int. Conf. Learn. Representations*, 2015, pp. 1–13.

- [184] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2017, pp. 2223–2232.
- [185] B. Xia and S. Wang, "Micro-expression recognition enhanced by macro-expression from spatial-temporal domain," in *Proc. 13th Int. Joint Conf. Artif. Intell.*, 2021, pp. 1186–1193.
- [186] S. Lalitha and K. Thyagarajan, "Micro-facial expression recognition based on deep-rooted learning algorithm," *Statistics*, vol. 12, pp. 903–913, 2019.
- [187] Y. Wen, K. Zhang, Z. Li, and Y. Qiao, "A discriminative feature learning approach for deep face recognition," in *Proc. Eur. Conf. Comput. Vis.*, 2016, pp. 499–515.
- [188] Y. Li et al., "Overcoming classifier imbalance for long-tail object detection with balanced group softmax," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2020, pp. 10 991–11 000.
- [189] J. E. Van Engelen and H. H. Hoos, "A survey on semi-supervised learning," *Mach. Learn.*, vol. 109, no. 2, pp. 373–440, 2020.
- [190] X. Wang, X. Wang, and Y. Ni, "Unsupervised domain adaptation for facial expression recognition using generative adversarial networks," *Comput. Intell. Neurosci.*, vol. 2018, pp. 1–11, 2018.
- [191] I. J. Goodfellow et al., "Challenges in representation learning: A report on three machine learning contests," in *Proc. Int. Conf. Neural Informat. Process.*, 2013, pp. 117–124.
- [192] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, "The extended cohn-kanade dataset (CK+): A complete dataset for action unit and emotion-specified expression," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Workshops*, 2010, pp. 94–101.
- [193] G. Zhao, X. Huang, M. Taini, S. Z. Li, and M. Pietikäinen, "Facial expression recognition from near-infrared videos," *Image Vis. Comput.*, vol. 29, no. 9, pp. 607–619, 2011.
- [194] S. Yang, P. Luo, C.-C. Loy, and X. Tang, "WIDER FACE: A face detection benchmark," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 5525–5533.
- [195] J. Li et al., "CAS (ME) 3: A third generation facial spontaneous micro-expression database with depth information and high ecological validity," *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published, doi: 10.1109/TPAMI.2022.3174895.
- [196] G. Sandbach, S. Zafeiriou, M. Pantic, and L. Yin, "Static and dynamic 3D facial expression recognition: A comprehensive survey," *Image Vis. Comput.*, vol. 30, no. 10, pp. 683–697, 2012.
- [197] P. Ekman and W. Friesen, "Nonverbal leakage and clues to deception," *Study Interpers.*, vol. 32, pp. 88–106, 1969.
- [198] Y. Chen and J. Joo, "Understanding and mitigating annotation bias in facial expression recognition," in *Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2021, pp. 14 980–14 991.
- [199] H. Chen, X. Liu, X. Li, H. Shi, and G. Zhao, "Analyze spontaneous gestures for emotional stress state recognition: A micro-gesture dataset and analysis with deep learning," in *Proc. IEEE 14th Int. Conf. Autom. Face Gesture Recognit.*, 2019, pp. 1–8.
- [200] A. B. Arrieta et al., "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Informat. Fusion*, vol. 58, pp. 82–115, 2020.
- [201] M. Kosinski, "Facial recognition technology can expose political orientation from naturalistic facial images," *Sci. Rep.*, vol. 11, no. 1, pp. 1–7, 2021.
- [202] S. Zuboff, *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power: Barack Obama's Books of 2019*, London, UK: Profile books, 2019.
- [203] I. D. Raji, T. Gebru, M. Mitchell, J. Buolamwini, J. Lee, and E. Denton, "Saving face: Investigating the ethical concerns of facial recognition auditing," in *Proc. AAAI/ACM Conf. AI*, 2020, pp. 145–151.
- [204] S. Oviatt, "Technology as infrastructure for dehumanization: Three hundred million people with the same face," in *Proc. Int. Conf. Multimodal Interact.*, 2021, pp. 278–287.
- [205] P. Voigt and A. Von dem Bussche, "The eu general data protection regulation (GDPR)," *A Practical Guide*, vol. 10, no. 3152676, pp. 10–5555, 2017.
- [206] H. Proença, "The UU-Net: Reversible face de-identification for visual surveillance video footage," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 32, no. 2, pp. 496–509, Feb. 2022.
- [207] B. C. Stahl, "Ethical issues of AI," in *Artificial Intelligence for a Better Future*, Berlin, Germany: Springer, 2021, pp. 35–53.
- [208] M. A. Takalkar and M. Xu, "Image based facial micro-expression recognition using deep learning on small datasets," in *Proc. IEEE Int. Conf. Digit. Image Comput.: Techn. Appl.*, 2017, pp. 1–7.



**Yante Li** received the PhD degree in computer science from the University of Oulu, Oulu, Finland, in 2022. She is currently a postdoc in the Center for Machine Vision and Signal Analysis of University of Oulu. Her current research interests include affective computing, micro-expression analysis and facial action unit detection.



**Jinsheng Wei** received the graduate degree in successive master-doctor program from the Nanjing University of Posts and Telecommunications (NUPT), Nanjing, China. He is a visiting scholar with the Center for Machine Vision and Signal Analysis, University of Oulu, Finland. His research interests include micro-expression recognition, image processing, pattern recognition, computer vision, and machine learning.



**Yang Liu** received the PhD degree in computer science and technology from the South China University of Technology, in 2021. He is currently a postdoctoral researcher with the Center for Machine Vision and Signal Analysis, University of Oulu, Finland. His current research interests include facial expression recognition, affective computing, and deep learning.



**Janne Kauttonen** received the MSc and PhD degrees in physics from the University of Jyväskylä, Finland, in 2005 and 2012, respectively. His postdoc research in the Aalto University (Finland) and Carnegie Mellon University (USA) included neuroimaging experiments, development of computational methods, data and statistical analyses. Since 2019 he has worked as a researcher with Haaga-Helia University of Applied Sciences (Finland) in fields of data science, applied machine learning, cognitive sciences and human-computer interaction."



**Guoying Zhao** (Fellow, IEEE) received the PhD degree in computer science from the Chinese Academy of Sciences, Beijing, China, in 2005. She is currently an academy professor and full professor (tenured, in 2017) with University of Oulu. She is also a visiting professor with Aalto University. She is a member of Finnish Academy of Sciences and Letters, IAPR Fellow and AAIA Fellow. She has authored or co-authored more than 280 papers in journals and conferences with 20100+ citations in Google Scholar and h-index 66. She is panel chair for FG 2023, was co-program chair for ACM International Conference on Multimodal Interaction (ICMI 2021), co-publicity chair for FG2018, and has served as area chairs for several conferences and was/is associate editor for *IEEE Transactions on Multimedia*, *Pattern Recognition*, *IEEE Transactions on Circuits and Systems for Video Technology*, and *Image and Vision Computing Journals*. Her current research interests include image and video descriptors, facial-expression and micro-expression recognition, emotional gesture analysis, affective computing, and biometrics. Her research has been reported by Finnish TV programs, newspapers and MIT Technology Review.

▷ For more information on this or any other computing topic, please visit our Digital Library at [www.computer.org/csdl](http://www.computer.org/csdl).