Weakly Supervised Learning for Facial Behavior Analysis: A Review

R. Gdana Praveen, Member, IEEE, Patrick Cardinal, Member, IEEE and Eric Granger, Member, IEEE

Abstract—Given the recent advancements in deep learning (DL), and computing capabilities, there has been significant progress in the development of systems analyzing facial behavior, evolving from images under controlled laboratory conditions, to more challenging real-world scenarios, including video-based recognition. However, DL models typically require training with large-scale datasets to provide a high level of performance. The collection and annotation of such datasets is a costly undertaking that relies on domain experts. Moreover, the annotation process is highly vulnerable to the ambiguity of expressions or Action Units (AUs) due to the bias induced by experts. This paper provides a comprehensive review of state-of-the-art weakly supervised learning (WSL) methods for facial behavior analysis based on images and videos. First, we introduce a taxonomy of relevant WSL scenarios, and then methods proposed for classification applications (using weak categorical/discrete labels), and for regression applications (using weak ordinal/dimensional labels). For both types of recognition applications (classification and regression), we provide a systematic review of state-of-the-art machine learning (ML) models for expression and AU recognition, and intensity estimation in each WSL scenario, discussing their strengths and limitations. An overview of widely used experimental methodologies (public datasets and protocols) is also provided for the performance evaluation of these state-of-the-art models. Finally, our critical analysis of the methods, along with their experimental results, provides insight into the key challenges of WSL in different scenarios, motivating future research to leverage weakly labeled data for real-world facial behavior analysis problems. Our review indicates that WSL methods may provide a cost-effective approach to train robust ML/DL models for facial behavior analysis in real-world scenarios. A website including constantly-updated survey is provided at https://github.com/praveena2j/awesome-Weakly-Supervised-Facial-Behavior-Analysis

Index Terms—Weakly Supervised Learning, Facial Expression Recognition, Intensity Estimation, Action Unit Detection, Deep Learning.

I. INTRODUCTION

FACIAL Behavior Analysis is an emerging area of interest in computer vision and affective computing, with immense potential for many applications in human-computer interaction, sociable robots, autonomous-driving, etc. It was shown that only one-third of human communication is conveyed through verbal components and two-thirds of communication occurs through non-verbal components [1]. Although emotions can be conveyed through multiple modalities, facial behavior plays a major role in conveying the mental state of a person, which can be reflected by the movements of facial muscles. Ekman and Fries conducted a cross-cultural study on facial expressions, showing that there are six basic universal facial emotions – Anger, Disgust, Fear, Happiness, Sadness, and Surprise [2] (see Figure 1). Subsequently, Contempt has been added to these basic emotions [3]. Given the simplicity of discrete representation, these seven prototypical emotions are the most widely used categorical models for the classification of facial emotions. Though the terms “expression” and “emotion” are used interchangeably in the literature, the primary difference is facial emotion conveys the mental state of a person, whereas facial expression is the indicator of the emotions being felt, i.e., facial expressions display a wide range of facial modulations but facial emotions are limited.

Facial Action Coding System (FACS) is a taxonomy of facial expressions developed by Ekman [6] that defines all observable facial movements for every emotion. It is comprised of 32 action units (AUs), and 14 additional action descriptors (ADs). AUs are described by the fundamental actions of individual muscles or a group of muscles to form a specific movement (see Figure 2), while ADs are unitary movements that account for the head pose, gaze direction, and miscellaneous actions such as jaw thrust, blow, bite, etc. The FACS has been used as a standard for manually annotating facial expressions as it defines a set of rules to express any possible facial expression in terms of specific AUs and also measure the intensity of facial expressions at five discrete levels ($A < B < C < D < E$). Continuous models over affect dimensions have also been proposed to further enhance the range of facial expressions [7]. Most of the wild datasets for the recognition of seven basic expressions [8], [9] or AUs [10] are provided as images, resulting in a limited number of samples. On the other hand, datasets for regression tasks are provided as videos [11], which can provide a large number of video frames. Therefore, the problem of limited samples is more pronounced in the case of recognizing seven basic expressions or AUs than that of continuous or ordinal regression levels.

Several techniques have been proposed for facial expression recognition (FER), often to detect the seven universal basic emotions [12], but also to estimate the level of valence and arousal [13], or intensity of affective states like fatigue [14], pain [15], and depression [16]. Most of the early approaches for FER rely on deterministic hand-crafted feature descriptors, such as the Local Binary Pattern (LBP) [17] and LBP on three orthogonal planes (LBP-TOP) [18]. Though these descriptors work well for data captured under controlled environments, they fail to handle the wide range of variations in uncontrolled real-time environments due to limited representation capabil-
ity. Recent progress in deep learning (DL) architectures and computing capability allowed the development of state-of-the-art FER models to achieve an impressive level of performance, especially by training end-to-end in a supervised fashion on large-scale fully annotated datasets [12]. However, there is typically a limited amount of relevant labeled data in the public domain, which becomes a bottleneck to accurately train data-hungry DL models. Collecting and annotating large-scale datasets for facial expressions or action units is a costly and time-consuming process. Moreover, manual annotation is a complex process that requires domain experts, which may be subjective in nature, often resulting in ambiguous annotations, especially for intensities and dimensional labels. For instance, in order to achieve minimal competency as a FACS coder, it takes over 100 hours of training, and each minute of video requires approximately one hour to annotate [19]. Annotating dimensional real-value labels, (e.g., the 2D valence and arousal space) on a continuous scale becomes even more challenging than discrete intensity levels, due to the wide range of emotions.

Given the cost of collecting and annotating data from each operational environment, DL models are commonly pre-trained with a large annotated generic dataset and then fine-tuned on the limited labeled dataset of the operational environment. For real-world applications, system accuracy can decline if there is considerable divergence or shift between the capture conditions in development and operational environments. For accurate FER, DL models should therefore be adapted to specific individuals and capture conditions (sensors, computing device, and environment), using weakly-labeled or unlabeled data from the operational environment. In order to fully leverage the potential of ML/DL models, several specialized weakly-supervised learning (WSL) methods have been proposed for training on images and videos with limited annotations. This paper focuses on state-of-the-art WSL methods for robust facial behavior analysis based on weakly annotated data.

Although several surveys have been published that focus on state-of-the-art methods for facial behavior analysis, [5], [12], [15], [20]–[22], no survey is focused on WSL methods, despite their relevance in real-world scenarios. Most surveys on facial behavior analysis provide a taxonomy of methods based on the standard algorithmic pipeline and ML paradigms [5], [20], [21]. Given the current trends in affective computing, more recent surveys focused on DL models for FER [12], or specific application areas like pain intensity estimation [15]. In this paper, we present a comprehensive review of WSL methods that are relevant to various scenarios for both image- and video-based analysis of facial behavior, primarily focusing on classification (using discrete/categorical labels) and regression (using ordinal/dimensional labels) applications. Specifically, we identify various sub-problems of WSL for facial behavior analysis and present the relevant WSL methods along with their advantages and limitations. Given the potential of AUs for interpreting expressions, and deriving high-level information, this paper reviews methods analyzing both facial expressions and AUs. Cases involving discrete/categorical labels are analyzed as classification or detection problems in expression or AU. Ordinal regression involves the estimation of discrete ordinal or intensity levels of expressions or AUs, whereas dimensional regression involves estimating the wide range of emotions on a continuous real-valued scale such as 2-D valence and arousal space. The performance of WSL methods is further compared and interpreted for different scenarios based on standard experimental protocols. Given our detailed critical analysis of WSL methods and their performance, we also discuss the limitations of the state-of-the-art methods, open challenges, and future research directions to further advance the development of WSL methods for facial behavior analysis.

The main contributions of this paper can be summarized as: (1) A taxonomy of WSL scenarios and their relevance in facial behavior analysis, along with the corresponding problem formulations for applications related to weak discrete-valued labels for classification and weak real-valued labels for regression (see Section II). (2) A comprehensive review of state-of-the-art WSL methods proposed under different
scenarios for classification (i.e., expression and AU recognition), and for regression (i.e., expression and AU intensity estimation), along with the critical analysis of their strengths and limitations (see Sections III and IV respectively). (3) An overview of experimental protocols for evaluating the WSL methods on widely used datasets, and the comparative results of these methods under different WSL scenarios (see Sections III-D and IV-C). (4) An analysis of the open problems, and research opportunities for the development of robust systems using weakly annotated data in real-world classification and regression applications (see Section V).

II. WEAKLY SUPERVISED LEARNING SCENARIOS

WSL scenarios can be classified as inexact, incomplete, and inaccurate supervision based on the availability of annotations [23]. This section introduces these three categories, and their relevance in the recognition of facial expressions and AUs, as depicted in Figures 3 and 4, respectively. This paper focuses primarily on four specific applications that are relevant in WSL for facial behavior analysis: expression detection and intensity estimation, and AU detection and intensity estimation.

A. Inexact Supervision

In this category, the labeling is provided for the data samples at a coarse level (sequence level for expressions or image level for AUs) instead of dense labeling of the data. The goal is to predict the accurate high-level or low-level labels of unknown test data using the coarsely labeled training data. MIL [24] is one of the major approaches to tackle these scenarios. The coarsely labeled data are considered a “bag”, and the samples within the bag contributing to the coarse annotation are referred to as “instances”. Several factors influence the performance of MIL algorithms such as bag composition, data distribution, and label ambiguity [25]. The expression detection task seeks to localize and predict the expressions of short video clips or frames using training data with sequence-level labels (see Figure 3b). In the context of multiple instance regression (MIR) for expression intensity estimation, the goal is to estimate the intensities of frames or sequences using training videos with sequence level labels of expression intensities, where the sequence level label is given by the maximum or average of labels of individual frames of a given sequence [26].

The task of AU detection in the context of inexact annotations is formulated as the problem of AU estimation from the expression labels of training data without AU labels, where expression labels provide weak supervision for AU labels as shown in Figure 4b. Similar to MIR for expression intensity estimation, AU intensity estimation can also be formulated in order to estimate the AU intensities of frames (instances) or sequences (bags) using training data of sequence-level AU labels.
Fig. 4. An illustration of WSL scenarios for AU recognition in images. (a) Baseline supervised learning with AU annotations. (b) Inexact WSL: MIL with image-level expression annotations. (c) Incomplete WSL: SSL with partial AU annotations. (d) Inaccurate WSL with noisy AU annotations. $y_1, y_2, \ldots, y_n$ denotes the AU labels. $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ the AU model predictions, and $\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_n$ the noisy AU labels. $Y_i$ represents the image-level expression label for image $i$. Finally, "?" refers to the case with no annotations.

intensities.

B. Incomplete Supervision

This category refers to the family of ML algorithms dealing with situations where only a small amount of labeled data is provided, despite the availability of abundant unlabeled data. Two major strategies to handle this problem is semi-supervised learning (SSL) [27] and active learning [28]. In the context of incomplete supervision for expression detection in videos (or images), annotations will be provided for a subset of videos (or images). The objective is to predict the labels of all the frames in a test sequence (or test image) using partial labels of videos (or images) of training data. For expression intensity estimation, the intensity levels will be provided only for a subset of videos (or images) as shown in Figure 3c. For AU detection, the problem can be formulated in two ways: Missing Labels and Incomplete Labels (see Figure 4c). In the first case, each sample of training data is assumed to be provided with multiple labels of Action Units but with missing labels. The task is to train the AU classifier with the training samples of missing labels to predict the complete set of labels for the test sample. On the other hand, for incomplete labels, the entire label set of multiple AUs is provided to the training data but only for a subset of images in the training data, where the rest of the training samples do not have AU labels (but may have expression labels). The problem of incomplete annotation can be extended further to AU intensity estimation, where AU intensity levels are provided only for the keyframes within a video sequence of the training data or only for a subset of the dataset of images.

C. Inaccurate Supervision

In this category, dense labels are provided for the entire dataset similar to that of supervised learning, but the labels tend to be noisy. Since inaccurate labels degrade the system performance, the goal is to overcome the challenges of noisy labels by training robust models that can provide accurate predictions on test data. One of the major strategies to deal with inaccurate labels is crowd-sourcing [29], where the labels are obtained from multiple annotators. In the case of expression detection, labeling frames of the video is a laborious task, thereby annotators are more vulnerable to mislabeling frames of the videos. For instance, the expression "sadness" may look similar to the expression "neutral". The ambiguity is even more pronounced for compound expressions, with a combination of more than one expression. The problem of inaccurate annotations is more prevalent in the case of regression, where the intensity of expressions or AUs is estimated. Since more variation is possible for dimensional regression, annotations of dimensional regression tend to be highly noisy. The framework of inaccurate annotations for expression recognition can also be extended to AU recognition, where AU labels are considered to be noisy. The framework
of inaccurate annotations for expressions and AU s are shown in Figure [3] and Figure [4] respectively.

III. METHODS FOR CLASSIFICATION

In this section, WSL methods for both expression and AU recognition are presented each WSL scenario along with the critical analysis, emphasizing the strengths and limitations. The comparison of the experimental results is also provided based on common evaluation protocols and datasets.

A. Inexact Annotations

1) Expression Recognition:

Instance Level Approaches: Expression recognition with MIL was initiated by Sikka et al. [30], where automatic pain localization was achieved using an instance-level classifier based on MILBOOST [31] and bag-level labels are predicted based on the maximum probabilities of the instances of the corresponding bag. Wu et al. [32] further enhanced this approach by incorporating a discriminative Hidden Markov Model (HMM) for instance level classifier with MIL instead of MILBOOST to efficiently capture the temporal dynamics. Chen et al. [33] explored pain classification with MIL using the relationships between AUs and pain expression, underscoring that clustering the co-occurrence of AUs provides better performance than individual AUs.

Bag Level Approaches: Unlike the aforementioned approaches that rely on a single concept assumption, Ruiz et al. [34] proposed a multi-concept MIL framework, i.e., multiple expressions in a video for estimating high-level (bag-level) semantic labels of videos. A set of k hyper-planes is modeled to discriminate k concepts (facial expressions) in the instance space and the bag level representation is obtained using the probability of bag for each concept. Similarly, Sikka et al. [35] also modeled the temporal dynamics of facial expressions in videos using discriminative templates (neutral, onset, apex, or offset). The ordering of discriminative templates in a video sequence is associated with a cost function that captures the likelihood of the occurrence of different temporal orders. Unlike conventional MIL methods, Huang et al. [36] developed a novel framework for personal affect detection with minimal annotation (PADMA) for handling user-specific differences based on the association between key facial gestures and affect labels. In particular, if an instance occurs frequently in bags of a given class, but not in others, the instance has a strong association with the label.

2) Action Unit Recognition: Since any expression can be characterized as a combination of AUs, many psychological studies have shown that there exists a strong association between expressions and AUs [37]. Due to the laborious task of obtaining AU annotations compared to expressions and the close relation between expressions and AUs (see Table 1), many researchers have explored the problem of AU detection in the framework of WSL, where expression labels are considered as weak coarse labels for AUs. One of the early works was done by Ruiz et al. [38], where each input sample is mapped to an AU, which is in turn mapped to an expression, and AU classification is considered a hidden task.

Each expression classifier is learned before training using an empirical study of the relationships between expressions and AUs [4], which is used to learn AU classifiers using gradient descent. Instead of using only the relationships between basic expressions and the corresponding AU probabilities, Wang et al. [39] leveraged expression-dependent and expression-independent AU probabilities without using extra large-scale expression-labeled facial images. First, the domain knowledge of expressions and AUs is summarized, based on which pseudo-AU labels are generated for each expression. Then a Restricted Boltzmann Machine is used to model prior joint AU distribution from the pseudo-AU labels (RBM-P). Using a similar approach, Peng et al. [40] explored adversarial training for AU recognition instead of maximizing the log-likelihood of the AU classifier with regard to the learned AU label prior. Inspired by generative adversarial networks (GAN), AU classifiers are learned by minimizing the differences between AU output distribution from AU classifiers and pseudo-AU label distribution derived from the summarized domain knowledge (RAN).

TABLE I

| Expression | AUs |
|------------|-----|
| Anger      | 4, 5, 7, 10, 17, 22-26 |
| Disgust    | 9, 10, 16, 17, 25, 26 |
| Fear       | 1, 2, 4, 5, 20, 25, 26, 27 |
| Happiness  | 6, 12, 25 |
| Sadness    | 1, 4, 6, 11, 15, 17 |
| Surprise   | 1, 2, 5, 26, 27 |
| Pain       | 4, 6, 7, 9, 10, 12, 20, 25, 26, 27, 43 |

Unlike the prior approaches, Wang et al. [41] modeled the relation between expressions and AU probabilities as inequalities instead of exact probabilities, i.e., higher probabilities of occurrence have higher rankings than those with lower probabilities. Similarly, Zhang et al. [42] comprehensively summarized the domain knowledge and exploited both expression-dependent and expression-independent AU probabilities to model the relationships among AU probabilities (LPSM). Inspired by the idea of dual learning, Wang et al. [43] integrated the task of face synthesis along with AU recognition (WSDL), where the latter is considered as the main task and the former as an auxiliary task. Specifically, AU labels are predicted using AU classifiers learned from the domain knowledge, and a synthetic face is generated using predicted AU labels.

3) Discussion: In the case of instance-level approaches, Wu et al. [32] showed that effectively capturing the temporal dynamics of expressions in videos plays a pivotal role for better performance. Though the relationships between expressions and AUs has been well-explored for AU classification [39], [40], they are not much explored for expression classification. Chen et al. [33] showed that leveraging the relationships between AUs and expressions can improve the performance of instance-level expression classification. Though initial approaches [30], [32], [33] using MIL are based on single-concept assumption, multi-concept approaches are
more relevant for real-world scenarios. Effective modeling of the temporal dynamics of multiple concepts (expressions) in the videos plays a crucial role for bag-level classification. Ruiz et al. [34] explored probabilistic modeling of the multiple expressions in the videos, whereas [35] captured the temporal dynamics of expressions based on statistics (frequency) of expressions in videos. Unlike these two approaches, Sikka et al. [30] showed that modeling the temporal ordering of expressions across the frames of the video seems to be quite promising to effectively capture the temporal dynamics of expressions.

Among AU classification approaches based on expression labels, various aspects of the relationships between expressions and AUs are explored. Ruiz et al. [38] explored the basic relationships between AUs and expressions. Wang et al. [39] and Peng et al. [40] improved the performance by analyzing the expression-dependent and expression-independent AUs. Compared to [38], [40] demonstrated that adversarial training using GANs can help in learning the hidden AU classifiers better than RBMs. Unlike these approaches, [41] and [42] explored the relationships in terms of relative probabilities using inequality constraints and showed that they can perform better than that of approaches relying on exact probabilities between expressions and AUs. In addition to the learning hidden AU classifiers from expression labels, [43] explored a novel direction of dual learning framework where the task of face synthesis is also deployed, which implicitly guides in learning better AU classifiers, achieving better performance than prior approaches. Approaches for AU detection with weak expression labels have also been extended to the problem of incomplete AU annotations by deploying additional loss components for the partial AU annotations [38–43].

B. Incomplete Annotations

1) Expression Recognition:

Pseudo-Labeling: Pseudo-labeling seeks to predict the labels of unlabeled data, where the predicted pseudo-labels of higher confidence are in turn used to train the unlabeled data in a supervised setting. Happy et al. [44] explored expression classification even with low intensities. Initially, they train a CNN model with limited labeled data until adequate performance is achieved. Subsequently, model parameters are further updated by fine-tuning using a portion of unlabeled data with high-confidence predictions, obtained by the current model in every epoch. Li et al. [45] proposed an entropy minimization method based on adaptive confidence margin (Ada-CM) to obtain more reliable pseudo labels, where they used high-confidence unlabeled samples to obtain pseudo labels, while exploiting the samples with low confidence for contrastive learning to improve the feature representations.

Consistency Regularization: It is based on the assumption that realistic perturbations of the same input generate consistent predictions. Jiang et al. [46] explored two pairs of teacher-student models, where the outputs of teacher model is forced to be consistent with that of student model in a cross-guidance mechanism. The teacher enforces stronger learning ability and guides the student model, gradually achieving similar learning ability (Progressive Teacher).

Hybrid Methods: Some of the approaches have explored both pseudo-labeling and consistency regularization in a hybrid framework. Florea et al. [47] (margin-mix) improved the idea of center loss [48] by maximizing the distance between the centroids of the different classes in the loss function. Pseudo labels are estimated based on the distances to centroids of different classes and used along with mix-up augmentation [49] to avoid over-fitting. Fang et al. [50] proposed a novel framework of pseudo-labeling strategy (Rethink PL) by addressing the problem of class distribution mismatch between the labeled and unlabeled datasets using clustering-based approach.

Unlike the above-mentioned approaches, Kurup et al. [51] explored Deep Belief Networks (DBN) to train the selected features of unlabeled data, which is further fine-tuned on labeled data.

2) Action Unit Recognition:

Missing Labels: Song et al. [52] developed a Bayesian graphical framework (BGCS) to encode sparsity and co-occurrence using compressed sensing and group-wise sparsity inducing priors based on two key observations: only very few AUs are active at any moment (sparsity), and overlapping of AUs in multiple groups (co-occurrence). Wu et al. [53] proposed a multi-label learning framework with missing labels (MLML) by enforcing the constraints of consistency between predicted labels and provided labels (label consistency) as well as with label smoothness, i.e., labels of similar features should be close to each other along with modeling the co-occurrence relationships among AUs. However, Li et al. [54] found that the constraint of label smoothness with shared feature space among AUs is violated for the task of AU recognition due to the diverse nature of the occurrence of AUs. That is, different AUs occur in different face regions, thereby features selected for one AU classifier may not be discriminative for other AU classifiers. Discriminative features are therefore learned for each AU class before deploying the constraint of label smoothness. Li et al. [55] further extended the idea of [54] by addressing the problem of class imbalance in two aspects – the number of positive AUs being much smaller than the negative AUs in each sample (image) and the rate of positive samples of different AUs being significantly different.

Incomplete Labels: Wang et al. [56] dealt with incomplete AU labels but complete expression labels by modeling the dependencies among AUs and the relationships between expressions and AUs with Bayesian network (BN) using maximum likelihood estimation. Peng et al. [57] explored an adversarial GAN-based approach with dual learning by leveraging domain knowledge of expressions and AUs along with facial image synthesis from predicted AUs. Specifically, the probabilistic duality between tasks and the dependencies among facial features, AUs, and expressions are explored in an adversarial learning framework.

Unlike the above two approaches, Wu et al. [58] used only incomplete AU annotations without expression labels and modeled the prior relationships among AUs using the Restricted Boltzmann Machine (RBM). Multiple SVMs are used to learn AU classifiers using deep features while simultaneously maximizing the log-likelihood of the AU label distribution model to be consistent with learned AU label
distributions. Inspired by the idea of co-training, Niu et al. \cite{59} further improved the performance using a novel approach of multi-label co-regularization for semi-supervised AU recognition without expression labels. Specifically, a multi-view loss is designed to ensure the features generated from the two views are conditionally independent by orthogonalizing weights of AU classifiers of two views.

3) Discussion: For expression classification, approaches based on pseudo-labeling \cite{44} have shown promising performance, however, incorrect pseudo-labels may degrade the performance. Therefore, most of the prior approaches of pseudo-labeling rely only on high-confidence samples, ignoring the low-confidence samples. However, \cite{45} showed that low-confidence samples can also be exploited to improve the feature representations along with high-confidence samples. It has been shown that exploiting the large-scale data without labels or with noisy labels seems to be promising line of research to deal with data-hungry DL models \cite{44}–\cite{46}. Recently, hybrid methods \cite{47}, \cite{50} have leveraged both strategies of consistency regularization \cite{46} and pseudo-labeling \cite{44}, \cite{45}, thereby achieving better performance. \cite{47} explored center-loss for expression classification, which seems to be an interesting idea for estimating pseudo-labels, while still leveraging the mix-up augmentation to deal with over-fitting issues. In most of these approaches, the class distribution mismatch between the reliable labeled data and large-scale unlabeled data is often overlooked, which has been addressed by \cite{50}. Majority of these methods explore Resnet-18 \cite{46}, WideResnet-28-2 \cite{47} or both \cite{45}, \cite{50}.

For AU detection, two research directions have been explored: missing and incomplete labels. \cite{52}–\cite{55} addressed the problem of missing labels, whereas \cite{56}–\cite{59} focused on handling incomplete labels. The core idea of dealing with missing labels is to exploit the co-occurrence structure of AUs to estimate the missing labels. In addition to the co-occurrence structure, \cite{52} leveraged the sparse nature of AUs whereas \cite{53}–\cite{55} exploited the constraints of label-consistency and label-smoothness. Compared to \cite{53} and \cite{54}, \cite{55} further showed improvement by addressing the problem of class imbalance among AUs along with these constraints. For incomplete AU labels, Wang et al. \cite{56} and Peng et al. \cite{57} leveraged the relationships between the expression labels and AUs along with incomplete AU labels, while Wu et al. \cite{58} and Niu et al. \cite{59} depend only on incomplete AU labels. \cite{57} explored adversarial training for better modeling of the relationships between expressions and AUs similar to their previous work of AU recognition from expressions \cite{40}, whereas \cite{58} used Bayesian networks. Along with adversarial training, \cite{57} also leveraged dual learning to improve the modeling of relationships between expressions and AUs similar to that of \cite{43}. The idea of leveraging dual learning seems to be promising by implicitly enforcing better learning of the hidden AU classifiers. \cite{58} focused on estimating the AUs of unlabeled samples using prior relationships among AUs (co-occurrence), which is modeled using RBMs whereas \cite{59} showed better improvement using co-regularization based on the idea of co-training.

C. Inaccurate Annotations

Since annotating expressions or AUs is a complex process, they are highly vulnerable to noise and uncertainty.

1) Expression Recognition: Though expression recognition with noisy annotations has also been addressed from the perspective of pose and occlusion challenges, we confine ourselves to the works that explicitly address the problem of noisy annotations.

Relabeling: The idea of relabeling (or sample selection) is to learn more from clean samples and then relabel the noisy ones. Wang et al. \cite{60} proposed a self-cure network by estimating the noisy or uncertain samples based on importance weighting using ranking regularization, which is further relabeled based on maximum predicted probability. Zhang et al. \cite{61} proposed a relative uncertainty module to estimate uncertainty based on the relative difficulty of samples from different classes, where hard samples corresponding to large uncertainty values are relabeled from mixed features.

Label Distribution Learning: She et al. \cite{62} proposed a latent distribution mining approach based on multiple auxiliary classifiers and an uncertainty estimation module. The former is used to refine the latent distribution in label space while retaining similarity-preserving semantic features and the latter estimates the uncertainty or noisy samples using cosine similarity. Lukov et al. \cite{63} explored label smoothing regularization to obtain soft labels, which is further deployed into the mean-teacher framework to estimate the uncertainty using the student network, supervised by the soft logits of the teacher network. Shao et al. \cite{64} leveraged a self-paced learning paradigm \cite{65} based on label distributions obtained from label distribution generator to learn and suppress label uncertainties.

Label Ensembling: Barsoum et al. \cite{66} analyzed four different strategies for effective label ensembling: majority-voting, multi-label learning, probabilistic label drawing, and cross-entropy loss, and showed that the latter two approaches that leverage label distribution outperform the former ones. Zeng et al. \cite{67} proposed a novel framework of Inconsistent Pseudo Annotations to Latent Truth (IPA2LT) to discover the latent true labels of noisy data with multiple inconsistent annotations. First, predictive models are trained for individually labeled datasets. Next, multiple pseudo-annotations are generated from the trained predictive models for each image, which is used to discover latent true labels based on log-likelihood. Zhang et al. \cite{68} explored the problem of ambiguous and noisy annotations in a decoupled framework using co-training to divide into clean, ambiguous, and noisy samples based on the consistency of the two networks and labels. They further leverage separate regularization strategies for these samples.

Unlike the above-mentioned approaches, Zhang et al. \cite{69} explored a new feature learning perspective to deal with noisy annotations by focusing on the part of features pertinent to noisy annotations. They explored attention consistency by dynamically erasing the input images to prevent the model from over-fitting the noisy samples. Li et al. \cite{8} proposed a novel architecture of the Deep Locality-preserving CNN (DLP-CNN) method to obtain more discriminative deep fea-
tures by preserving the locality closeness while maximizing the inter-class scatters.

2) Action Unit Recognition: Zhao et al. [70] explored weakly supervised clustering on large-scale images from the Web to derive a weakly supervised spectral algorithm that learns an embedding space to couple image appearance and semantics. Next, the noisy annotations are refined using rank-order clustering by identifying groups of visually and semantically similar images. Fabian et al. [71] proposed a global-local loss function by combining global and local loss components in a unified framework. The local loss component emphasizes accurate detection by focusing on salient regions. However, it requires very accurate labels for better convergence, which is circumvented by combining a global loss component that captures the global structure of images yielding consistent results for AU recognition.

3) Discussion: For expression classification, most of the approaches explored deep networks due to the availability of large-scale data with noisy annotations [66], [67], [72]. Relabeling methods [60], [61] depend on the small-loss assumption [73], which may fail to discriminate hard (difficult to classify) samples and noisy (mislabeled) samples as both of them have high loss values during the training process. To discriminate the clean samples from the noisy samples, [60] explored ranking regularization whereas [61] showed that modeling the relative uncertainty to different classes is a promising direction as the uncertainty of noisy samples vary with different classes. On the other hand, label ensembling methods [60], [67] provide different views of the same sample using different networks, similar to crowd-sourcing in real FER applications. To estimate the latent true labels of the noisy samples, [67] explored probabilistic modeling of hidden true labels whereas [68] explored co-training based approach to discriminate noisy samples from hard samples. Unlike these two methods, [69] explored a novel direction of refining the noisy samples in the feature space based on the observation that FER models learn noisy samples only on a part of the features instead of whole features. However, label-ensembling methods are computationally expensive, making them less desirable in real-world applications. Label distribution learning is another paradigm [62], [63] allowing us to deal with noisy annotations label distribution of soft labels instead of hard labels. [62] explored multiple auxiliary classifiers to refine the noisy labels in the latent distributions space, whereas [63] showed that label smoothing regularization using soft labels can help in effectively refining the noisy samples. Although they offer flexibility in capturing a wide range of emotions, they can lead to spurious distribution depending on the noisy samples.

For AU recognition, Zhao et al. [70] explored a clustering approach in the embedding space, while Fabian et al. [71] leveraged the local semantics of AUs that retains the global facial structure for better convergence.

D. Experimental Evaluations

1) Datasets: In this section, we provide some of the widely used datasets for evaluating the WSL approaches for facial behavior analysis.

UNBC-McMaster [74]: This database contains 200 video sequences of 48398 frames captured from 25 participants, who self-identified with shoulder pain. Each frame of the video sequence is labeled with 5 discrete intensity levels of AUs pertinent to pain (A < B < C < D < E) obtained by three certified FACS coders. Only the AUs related to pain are considered: AU4, AU6, AU7, AU9, AU10, AU12, AU20, AU25, AU26, AU27 and AU43. However, AU43 is assigned only to binary labels. In addition to the annotations based on FACS, they have also provided labels of discrete pain intensities both at the sequence and frame levels. Prkachin and Solomon Pain Intensity Scale (PSPI) of pain intensities are labeled at frame level with 16 discrete levels from 0-15 and Observer Pain Intensity (OPI) ratings are provided at sequence level on a scale of 0 - 5.

CK+ [75]: This database consists of 593 video sequences captured in controlled laboratory conditions, where the emotions are spontaneously performed by 123 participants. All the video sequences are considered to vary from neutral face to peak formation of the facial expressions and the duration of the sequences varies from 10 to 60 frames. Since the initial labels of these sequences are unreliable, they are further refined based on FACS with seven basic expression labels (including Contempt), and each emotion is defined by a prototypical combination of specific AUs. Out of 593 sequences, it was found that only 327 sequences satisfy the refined labeling strategy, where each video sequence is labeled with the corresponding emotion label. Since the emotion labels are provided at the video level, static approaches assign the emotion label of the video sequence to the last one to three frames that exhibit the peak formation of the expression, and the first frame is considered a neutral frame.

MMI [10], [76]: The database contains 326 video sequences spontaneously captured in laboratory-controlled conditions from 32 subjects, and it includes challenging variations such as large interpersonal variations, pose, etc. compared to CK+ database. The sequences are captured as onset-apex-offset i.e., the sequence starts with neutral expression (onset), reaches the peak (apex), and returns again to neutral expression (offset). As per the standard of FACS, 213 sequences are labeled with six basic facial expressions (excluding Contempt) at the video level, of which 205 sequences are captured in frontal view. They have also provided frame-level annotations for some of the sequences. For approaches based on static images, only the first frame (neutral expression) and peak frames (apex of expressions) are considered.

DISFA [77]: The dataset is created using 9 short video clips from YouTube, where the participants of 27 adults are allowed to watch the short video clips pertaining to various emotions. The facial expressions of each of the participants are captured with a high-resolution video of 1024x768 pixels with a frame rate of 20fps resulting in 1,30,754 frames in total. Each of these frames is annotated with AUs along with the discrete intensity levels by FACS expert raters. The AUs related to the expressions in the database are AU1, AU2, AU4, AU5, AU6, AU9, AU12, AU15, AU17, AU20, AU25, and AU26, whose intensities are provided on a six-point ordinal scale (neutral <
Fig. 5. Accuracy of expression classification methods with incomplete annotations on RAF-DB (top) and FER+ (bottom) datasets. Dotted and dashed lines denote performance using Resnet-18 and WideResnet-28-2, respectively.

RAF-DB [8]: This is a large-scale in-the-wild dataset, which consists of extremely diverse facial images downloaded from the Internet. The obtained images were labeled by 315 annotators, and each image was ensured to be labeled by 40 independent labelers. The final annotations were obtained using crowd-sourcing techniques for seven basic emotions (including neutral expression). The dataset is partitioned into 12,271 training samples and 3,068 test samples. Some of the images are also labeled with compound expressions of 11 classes.

AffectNet [9]: This is the largest dataset captured in the wild, consisting of 0.4 million images, downloaded from the Internet using three search engines based on expression-related keywords. Its images are labeled with seven basic expressions (excluding neutral), resulting in 2,80,000 samples as training samples and 3,500 images as validation sets.

FER+ [66]: The dataset is an extension of the FER2013 dataset [78]. The FER2013 dataset [78] is labeled automatically by the Google image search engine. All the images in FER2013 have been registered and resized to 48x48 pixels. The dataset is partitioned into 28,709 training images, 3,589 validation images, and 3,589 test images with seven basic expression labels. The images are further relabeled by 10 individuals, thereby obtaining more reliable annotations.

2) Experimental Protocol: To compare methods, the annotations of datasets are further modified to match the corresponding task. For the classification task, the performance of

Fig. 6. F1 Score of AU detection methods with incomplete annotations on CK+, MMI, UNBC and DISFA datasets.
### TABLE II
Performance of state-of-the-art facial expression classification approaches under various WSL settings on most widely evaluated datasets. 'Conventional' refers to the training and testing partitions provided by the dataset organizers. † denotes that the model is trained on both RAF-DB and AffectNet training sets.

| WSL Setting | Dataset       | Method       | Task                  | Features | Learning Model | Validation | Accuracy |
|-------------|---------------|--------------|-----------------------|----------|----------------|------------|----------|
| Inexact     | UNBC - McMaster | Sikka et al. [10] (FG 2013) | Pain [2 classes] | BoW      | MILBOOST       | LOSO       | 83.70    |
|             |               | Wu et al. [32] (FG 2015) | Pain [2 classes] | geometric | HMM            | LOSO       | 85.23    |
|             |               | Chen et al. (2019) [33] | Pain [2 classes] | AU-based  | MILBOOST       | 10-fold   | 85.60    |
|             |               | Adria et al. [34] (BMVC 2014) | Pain [2 classes] | 3D-SIFT  | RMC-MIL        | LOSO       | 85.70    |
|             |               | Sikka et al. [35] (CVPR 2016) | Pain [2 classes] | SIFT     | LOMo           | LOSO       | 87.00    |
|             |               | Huang et al. [36] (TAC 2016) | Pain [2 classes] | geometric | A-MIL          | LOSO       | 84.40    |
| Inaccurate  | RAF-DB        | Li et al. [8] (CVPR 2017) | Expression [7 classes] | Decaf    | DLP-CNN        | Conventional | 80.89    |
|             |               | Zeng et al. [67] (ECCV 2018) | Expression [7 classes] | ResNet   | IPA2LT         | Conventional | 86.77    |
|             |               | Wang et al. [60] (CVPR 2020) | Expression [7 classes] | ResNet-18 | SCN            | Conventional | 87.03    |
|             |               | She et al. [62] (CVPR 2021) | Expression [7 classes] | ResNet-18 | DMUE           | Conventional | 88.76    |
|             |               | Zhang et al. [63] (NIPS 2021) | Expression [7 classes] | ResNet-18 | RUL            | Conventional | 88.98    |
|             |               | Lukov et al. [63] (ECCV 2022) | Expression [7 classes] | ResNet-18 | SOFT           | Conventional | 90.42    |
|             |               | Zhang et al. [69] (ECCV 2022) | Expression [7 classes] | ResNet-18 | EAC            | Conventional | 89.99    |
|             |               | Shao et al. [64] (ACM MM 2022) | Expression [7 classes] | ResNet-18 | SPLDL          | Conventional | 88.59    |
|             |               | Zhang et al. [68] (PRL 2022) | Expression [7 classes] | ResNet-18 | MAN            | Conventional | 90.25    |
| Inexact     | AffectNet     | Li et al. [8] (CVPR 2017) | Expression [7 classes] | Decaf    | DLP-CNN        | Conventional | 54.47    |
|             |               | Zeng et al. [67] (ECCV 2018) | Expression [8 classes] | ResNet   | IPA2LT         | Conventional | 55.71    |
|             |               | Wang et al. [60] (CVPR 2020) | Expression [8 classes] | ResNet-18 | SCN            | Conventional | 60.23    |
|             |               | Shao et al. [64] (ACM MM 2022) | Expression [7 classes] | ResNet-18 | SPLDL          | Conventional | 59.76    |
|             |               | She et al. [62] (CVPR 2021) | Expression [8 classes] | ResNet-18 | DMUE           | Conventional | 62.84    |
|             |               | Zhang et al. [66] (NIPS 2021) | Expression [8 classes] | ResNet-18 | RUL            | Conventional | 61.43    |
|             |               | Lukov et al. [63] (ECCV 2022) | Expression [8 classes] | ResNet-18 | SOFT           | Conventional | 62.69    |
|             |               | Zhang et al. [69] (ECCV 2022) | Expression [7 classes] | ResNet-18 | EAC            | Conventional | 65.32    |
|             |               | Zhang et al. [68] (PRL 2022) | Expression [8 classes] | ResNet-18 | MAN            | Conventional | 62.47    |
| Inexact     | FER+          | Wang et al. [60] (CVPR 2020) | Expression [8 classes] | ResNet-18 | SCN            | Conventional | 89.35    |
|             |               | She et al. [62] (CVPR 2021) | Expression [8 classes] | ResNet-18 | DMUE           | Conventional | 88.64    |
|             |               | Barsoum et al. [66] (ICMI 2016) | Expression [8 classes] | Decaf    | DLP-CNN        | Conventional | 85.10    |
|             |               | Zhang et al. [66] (NIPS 2021) | Expression [8 classes] | ResNet-18 | RUL            | Conventional | 88.75    |
|             |               | Zhang et al. [69] (ECCV 2022) | Expression [8 classes] | ResNet-18 | EAC            | Conventional | 89.64    |
|             |               | Lukov et al. [63] (ECCV 2022) | Expression [8 classes] | ResNet-18 | SOFT           | Conventional | 88.60    |
|             |               | Zhang et al. [68] (PRL 2022) | Expression [8 classes] | ResNet-18 | MAN            | Conventional | 89.86    |

### TABLE III
Performance of state-of-the-art AU classification approaches under WSL settings on most widely evaluated datasets.

| WSL Setting | Dataset       | Method       | Task                  | Features | Learning Model | Validation | F1-Score |
|-------------|---------------|--------------|-----------------------|----------|----------------|------------|----------|
| Inexact     | UNBC - McMaster | Ruiz et al. [38] (ICCV 2015) | AU [6 AUs] | SIFT      | HTL            | 5-fold     | 0.235    |
|             |               | Wang et al. [39] (TAC 2020) | AU [6 AUs] | geometric | RBM-P          | 5-fold     | 0.351    |
|             |               | Wang et al. [43] (TMM 2019) | AU [6 AUs] | geometric | WSDL          | 5-fold     | 0.400    |
|             |               | Peng et al. [40] (CVPR 2018) | AU [6 AUs] | geometric | RAN            | 5-fold     | 0.376    |
| Inexact     | CK+           | Ruiz et al. [38] (ICCV 2015) | AU [12 AUs] | SIFT      | HTL            | 5-fold     | 0.469    |
|             |               | Wang et al. [39] (TAC 2020) | AU [12 AUs] | geometric | RBM-P          | 5-fold     | 0.705    |
|             |               | Wang et al. [43] (TMM 2019) | AU [12 AUs] | geometric | WSDL          | 5-fold     | 0.740    |
|             |               | Peng et al. [40] (CVPR 2018) | AU [12 AUs] | geometric | RAN            | 5-fold     | 0.715    |
|             |               | Zhang et al. [42] (CVPR 2018) | AU [8 AUs] | LBP       | LP-SM          | 5-fold     | 0.732    |
| Inexact     | MMI            | Ruiz et al. [38] (ICCV 2015) | AU [14 AUs] | SIFT      | HTL            | 5-fold     | 0.431    |
|             |               | Wang et al. [39] (TAC 2020) | AU [13 AUs] | geometric | RBM-P          | 5-fold     | 0.516    |
|             |               | Wang et al. [43] (TMM 2019) | AU [13 AUs] | geometric | WSDL          | 5-fold     | 0.530    |
|             |               | Peng et al. [40] (CVPR 2018) | AU [13 AUs] | geometric | RAN            | 5-fold     | 0.520    |
|             |               | Zhang et al. [42] (CVPR 2018) | AU [8 AUs] | LBP       | LP-SM          | 5-fold     | 0.481    |
| Inexact     | DISFA          | Ruiz et al. [38] (ICCV 2015) | AU [12 AUs] | SIFT      | HTL            | 5-fold     | 0.371    |
|             |               | Wang et al. [39] (TAC 2020) | AU [12 AUs] | geometric | RBM-P          | 5-fold     | 0.424    |
expressions and AUs are expressed in terms of accuracy and F1-score respectively. For a fair comparison, Tables II and III present the methods that follow the same experimental protocol for expressions and AUs, respectively. Unless specified, all the results are shown in a within-database setting.

**Inexact Annotations:** Although the UNBC-McMaster dataset is annotated with pain intensity levels, it has been explored for classification by converting its ordinal labels (OPI ratings) to binary labels based on a threshold i.e., $\text{OPI} \geq 3$ is treated as pain and $\text{OPI} = 0$ as no pain, which results in a total of 149 sequences with 57 positive bags and 92 negative bags. For AU classification, 7319 frames are chosen from 30 video sequences of 17 subjects that exhibit the expression of pain with PSPI $\geq 5$. Six AU labels are associated with the chosen frames i.e., AU4, AU6, AU7, AU9, AU10, and AU43, which are related to pain expressions. In all these methods, 5-fold cross-validation is used. For CK+, MMI, and DISFA datasets, AUs, which are available for more than 10% of all frames are chosen. Based on this criterion, 309 sequences of 106 subjects are chosen from 593 sequences of 123 subjects, resulting in 12 AUs for the CK+ dataset. For the MMI dataset, AUs are available for more than 10% of all samples, resulting in 171 sequences from 27 subjects with 15 labels. For the DISFA dataset, 482 apex frames are chosen based on AU intensity levels, for which expression labels are obtained by FACS. Similar to CK+ and MMI, 9 AUs are considered. 5-fold cross-validation is deployed, where 20% of the whole database is used as validation set according to subjects. All the experiments are conducted in a subject-independent protocol.

**Incomplete Annotations:** RAF-DB and FER+ are the widely used datasets for expression classification with semi-supervised learning. The labeled images are randomly chosen at growing levels of supervision at 400, 1000, and 4000, where the remaining images are considered to be unlabeled. Since most approaches use both Resnet-18 [80] and WideResNet-28-2-81 as backbones CNNs pre-trained on MS-Celeb-1M [82], we have compared the methods on both backbones as shown in Figure 5. For AU detection, UNBC-McMaster, CK+, MMI, and DISFA datasets are used, where training data is obtained by randomly missing the AU labels at growing rates (from 0.1 to 0.9). All the experiments are carried out in a 5-fold cross-validation setting. The experimental strategy of [38], [56], [52] and [53] differ from that of [39], [43] and [40]. Authors in [39] have re-conducted the experiments of [38], [56], [52] and [53] with the setup of [39] in order to have fair comparison.

**Inaccurate Annotations:** RAF-DB, FER+, and AffectNet have been widely used to deal with noisy annotations for expression recognition. For the AffectNet dataset, 33,803 facial images are considered clean data, and 1,71,005 facial images as noisy data for training. 3500 facial images are further used for validation with 500 images per expression. In the case of RAF-DB, 12271 training samples are used for training, and the results are reported on the test set of 3068 samples. For the FER+ dataset, 28,709 images are used for training, 3,589 for validation, and 3,589 for testing. With all these datasets, the results are shown based on the training and testing partition provided by the dataset organizers.

**E. Critical Analysis and Results**

Facial expressions and AUs evolve over time, therefore facial video may capture significant temporal information about facial behavior. However, temporal information is less explored in the WSL literature, having only been investigated in a few works [39], [53]. Most of the works on expression detection in the context of incomplete and inaccurate annotations are based on images. Videos have been explored mostly in the context of inexact annotations. Current works on expression detection with inexact annotations used max-pooling or displacement of facial landmarks to extract relevant dynamic information from video sequences. Displacement of facial landmarks was found to capture the temporal dynamics better than max-pooling [32], [35] is the only work that focused on leveraging the temporal dynamics, showing significant performance improvements over state-of-the-art methods as shown in Table III. Most of these methods for inexact supervision do not leverage the potential of DL models due to limited training data. Few works [39], [43] explored RBMs to capture domain knowledge of expressions and AUs for AU recognition. Most of the works leveraged the domain knowledge of dependencies among AUs and between basic expressions and AUs for AU recognition, achieving comparable performance with each other. In contrast, [43] explored dual learning of AU recognition as the main task and face synthesis as an auxiliary task, showing a significant improvement on several datasets as shown in Table III.

Recently, DL models have been explored for incomplete and inaccurate annotations by leveraging large-scale unlabeled and noisy data sets captured in the wild, respectively. Deep networks have shown robustness in handling a wide range of variations such as illumination, pose, identity, etc., over shallow networks when a large amount of training data is made available [83]. Although pseudo-labeling-based methods [44], [45] and consistency regularization methods [46] have individually shown better performance, effectively leveraging the benefits of both pseudo-labeling and data augmentation was found to be promising, achieving significant improvement over state-of-the-art methods [50] as seen in Figure 5. For AU detection, leveraging expression labels with incomplete AU labels significantly helped to achieve better performance as seen in Figure 6. Specifically, exploring auxiliary tasks seems to be a promising research direction as [43] achieved state-of-the-art performance.

WSL with inaccurate annotations is less explored with AU recognition than with expression classification. Most approaches rely on modeling the uncertainty either based on label distribution [62], [63], sample selection [60], [61], or label ensembling [67]. Among these approaches, methods based on label distribution [62], [63] were found to be most promising. In particular, [63] has shown a significant improvement in performance by modeling labels based on instance-aware distributions that are independent of the class. Among relabeling methods, leveraging the relative uncertainty of ambiguous samples is a promising approach to effectively deal with ambiguous samples [61]. Another promising approach consists of exploring an attention mechanism (e.g., in [69]) to focus on...
the features relevant to noisy samples, which have been found to outperform state-of-the-art methods.

IV. METHODS FOR REGRESSION

In this section, we present the WSL methods in each scenario along with experimental results and critical analysis for both expressions and AUs similar to that of classification.

A. Inexact Annotations

In the case of regression with inexact annotations, the intensity levels of expressions or AUs are provided at the global sequence level. The goal is to estimate the intensity level of individual frames or sub-sequences.

1) Expression Intensity Estimation: Ruiz et al. [84] proposed multi-instance dynamic ordinal random fields (MIDORF) to estimate ordinal intensity levels of frames, where the ordinal variables are modeled as normal distribution and the relationships between the given observation (frame) and latent ordinal value is obtained by projecting the given observation (frame) onto the ordinal line, which is divided by the consecutive overlapping cut-off points of the normal distributions. Praveen et al. [85] further improved performance using the 3D CNN model (I3D in [86]) by integrating MIL into adversarial deep domain adaptation framework [87] for estimating pain intensity, where the source domain is assumed to have fully annotated videos and target domain have period-ically annotated weak labels. They have further extended their approach by leveraging the ordinal nature of pain intensity levels and adaptive pooling of instances in the MIL framework [14].

2) AU Intensity Estimation: Ruiz et al. [88] extended the idea of [84] for AU intensity estimation by modeling the relationships between the weak sequence-level label and instance label using two strategies: the maximum or relative values of the instance labels. Unlike the conventional framework of MIL, Zhang et al. [89] explored domain knowledge of relevance using labels of peak and valley frames. Specifically, they have considered three major factors: ordinal relevance, intensity smoothness, and relevance smoothness based on the gradually evolving process of facial behavior.

3) Discussion: For expression intensity estimation, Ruiz et al. [84] used features based on facial landmarks and ordinal random fields to model the semantic relationships between the bag label and the latent key instance, as well as temporal dynamics, which has also been extended to AU intensity estimation. Praveen et al. [14], [85] explored deep models with weakly supervised domain adaptation for pain intensity estimation, where the source domain is exploited to deal with limited representative data.

For AU intensity estimation, both [88] and [89] used facial landmark-based features and focused on modeling the ordinal relevance of labels along with the temporal smoothness of images in the sequence. However, [88] leverages only the labels of peak frames, whereas [89] uses the labels of both peak and valley frames. Exploiting both peak and valley frames seems to be efficient in relatively modeling the AU intensity levels instead of relying only on peak frames. The problem of expression and AU intensity estimation with inexact annotations is still at rudimentary level, though it has been well explored in fully supervised setting [83], [90].

B. Incomplete Annotations

In this case, the intensities of frames are only provided for a subset of the training data. This task seeks to train a robust model for predicting intensity values of test data at the frame level using partially labeled data.

1) Expression Intensity Estimation: To the best of our knowledge, only one work has addressed this problem. Rui et al. [91] proposed a max-margin based ordinal support vector regression (OSVR) using ordinal relationship, which is flexible and generic in handling the varying levels of annotations and a linear model is learned by solving the optimization problem using the alternating direction method of multipliers to predict the frame-level intensity of test images.

2) AU Intensity Estimation: Zhang et al. [92] designed a CNN using annotations of only peak and valley frames, where the parameters of the CNN are learned by exploiting domain knowledge of facial symmetry, temporal intensity ordering, relative appearance similarity, and contrastive appearance difference of unlabeled frames. In addition to the domain knowledge of unlabeled frames, [93] explored joint learning of feature representations and estimator of AUs, where facial landmark based features are transformed to a latent space, which is learnt along with the AU estimators. Motivated by different learning dynamics of multiple AUs, Zhang et al. [94] proposed a context-aware feature and label-fusion modules using an augmented attention mechanism, where feature fusion exploits the spatial relevance of different AUs and label-fusion leverages the partially annotated labels to capture the temporal dynamics of AUs.

Unlike other approaches, Zhang et al. [95] do not rely on keyframes, and extended [92] to joint estimation of the intensities of multiple AUs by introducing a task index to update the corresponding parameters of the fully connected layer. Wang et al. [96] also extended the idea of [88] for AU intensity estimation, where RBM is used to model the relationships among AUs, which is explored for AU intensity estimation with partial labels. Sanchez et al. [97] explored self-supervised learning to learn the spatiotemporal representation of large-scale unlabeled videos based on contrastive learning, which is further adapted to partially (randomly) labeled datasets without prior information of key-frames.

3) Discussion: Expression intensity estimation with partial or incomplete annotations is an under-researched problem in the literature. For AU intensity estimation, [92], [95] and [93] explored knowledge-based information such as facial symmetry, temporal intensity ordering, and relative label smoothness. However, [92], [95] used deep features with labels of only peak and valley frames (1% labeled frames), whereas [93] used facial landmark-based features with additional randomly selected labeled frames (total 6% labeled frames). Unlike these two approaches, [94] showed that different AUs has different learning dynamics, and explored context-aware feature fusion for learning feature representations of AUs. [96] explored
TABLE IV
Performance of state-of-art methods for regression of expressions and AUs under various modes of WSL setting on the most widely evaluated datasets.

| WSL Setting | Dataset       | Method  | Task       | Features | Learning Model | Validation | MAE  | PCC  | ICC  |
|-------------|---------------|---------|------------|----------|----------------|------------|------|------|------|
| Inexact     | UNBC-McMaster | Ruiz et al. (TIP 2018) | Pain [6 levels] | geometric | DORF | LOSO | 0.710 | 0.360 | 0.340 |
|             | Praveen et al. (FG 2020) | Pain [6 levels] | IJD | WSDA | LOSO | 0.714 | 0.630 | 0.567 |
|             | Praveen et al. (IVU 2020) | Pain [6 levels] | IJD | WSDA-OR | LOSO | 0.530 | 0.705 | 0.696 |
|             | Zhang et al. (CVPR 2018) | Pain [6 levels] | geometric | BORMIR | LOSO | 0.821 | 0.605 | 0.531 |
|             | Ruiz et al. (TIP 2018) | 12 AUs [6 levels] | geometric | DORF | 5-fold | 1.130 | 0.400 | 0.260 |
|             | Zhao et al. (CVPR 2016) | 12 AUs [6 levels] | LBP | OSVR | 5-fold | 1.380 | 0.350 | 0.150 |
|             | Zhang et al. (CVPR 2018) | 12 AUs [6 levels] | geometric | BORMIR | 5-fold | 0.789 | 0.353 | 0.283 |
| FERA 2015   | Zhang et al. (CVPR 2018) | 5 AUs [6 levels] | geometric | BORMIR | Valster et al. [98] | 0.852 | 0.635 | 0.620 |
|             | Ruiz et al. (TIP 2018) | Pain [6 levels] | geometric | DORF | LOSO | 0.510 | 0.460 | 0.460 |
|             | Zhao et al. (CVPR 2016) | Pain [6 levels] | LBP | OSVR | LOSO | 0.951 | 0.544 | 0.495 |
|             | Ruiz et al. (TIP 2018) | 12 AUs [6 levels] | geometric | DORF | 5-fold | 0.480 | 0.420 | 0.380 |
|             | Zhao et al. (CVPR 2016) | 12 AUs [6 levels] | LBP | OSVR | 5-fold | 0.800 | 0.370 | 0.290 |
|             | Zhang et al. (CVPR 2018) | 12 AUs [6 levels] | CNN | KBSS | 3-fold | 0.330 | 0.360 |
|             | Zhang et al. (IEEE Access) | 12 AUs [6 levels] | CNN | KBSS-Joint | 3-fold | 0.330 | 0.350 |
|             | Wang et al. (TAC 2019) | 12 AUs [6 levels] | RBM | RBM-P | 3-fold | 0.431 | 0.592 | 0.549 |
|             | Zhang et al. (CVPR 2019) | 12 AUs [6 levels] | geometric | KJRE | 5-fold | 0.910 | 0.370 | 0.350 |
|             | Zhang et al. (ICCV 2019) | 12 AUs [6 levels] | Resnet-18 | CFLF | 3-fold | 0.329 | 0.408 |
|             | Sanchez et al. (ACCV 2020) | 12 AUs [6 levels] | Resnet-18 | Self-SL | 3-fold | 0.376 | 0.413 |
|             | Wang et al. (TAC 2019) | 5 AUs [6 levels] | RBM | RBM-P | Valster et al. [98] | 0.728 | 0.605 | 0.585 |
|             | Zhao et al. (CVPR 2016) | 5 AUs [6 levels] | LBP | OSVR | Valster et al. [98] | 1.077 | 0.545 | 0.344 |
|             | Zhang et al. (IEEE Access) | 5 AUs [6 levels] | CNN | KBSS-Joint | Valster et al. [98] | 0.640 | 0.670 |
|             | Zhang et al. (CVPR 2018) | 5 AUs [6 levels] | CNN | KBSS | Valster et al. [98] | 0.660 | 0.670 |
|             | Zhang et al. (CVPR 2019) | 5 AUs [6 levels] | geometric | KJRE | Valster et al. [98] | 0.870 | 0.620 | 0.600 |
|             | Sanchez et al. (ACCV 2020) | 12 AUs [6 levels] | Resnet-18 | Self-SL | 3-fold | 0.798 | 0.680 |
|             | Zhang et al. (ICCV 2019) | 5 AUs [6 levels] | Resnet-18 | CFLF | Valster et al. [98] | 0.741 | 0.661 |

C. Experimental Evaluations

1) Datasets: To cover the wide range of facial expressions, several databases have been developed with intensity levels of expressions such as pain and AUs. In this section, we describe a dataset for regression that does not appear in Section III-D1.

FERA 2015 Challenge [98]: The dataset is drawn from BP4D [99] and SEMAINE [100] databases for the task of AU occurrence and intensity estimation, where only five AUs from BP4D i.e., AU6, AU10, AU12, AU14, and AU17 are considered for AU intensity estimation and 14 AUs from both SEMAINE and BP4D for occurrence detection i.e., AU1, AU2, AU4, AU6, AU7, AU10, AU12, AU14, AU15, AU17, AU23, AU25, AU28, and AU45. The original dataset of BP4D is used as the training set, where training data is drawn from 21 subjects, development set from 20 subjects, and the dataset is further extended for test-set captured from 20 subjects, resulting in 75,586 images in the training partition, 71,261 images in development partition and 75,726 in the testing partition. Similarly for the SEMAINE dataset, 48,000 images are used for training, 45,000 for development, and 37,695 for testing. The entire dataset is annotated frame-wise for AU occurrence and intensity level for the corresponding subset of AUs. For the BP4D-extended set, the onset and offsets are treated as B-level of intensity. In both datasets, most facially expressive segments are coded for AUs and AU intensities. The intensity levels of AUs are coded on an ordinal scale of 0-5.

2) Experimental Protocol: The intensities of pain and AUs are evaluated in terms of Mean Absolute Error (MAE), Pearson Correlation Coefficient (PCC), and Intra-class Correlation Coefficient (ICC). The comparison of performances of state-of-the-art methods, that follow the same experimental protocol for each category of WSL for regression is shown in Table IV.

Inexact Annotations: In case of regression on the UNBC-
McMaster dataset, PSPI labels of the frames are converted to 6 ordinal levels: 0(0), 1(1), 2(2), 3(3), 4-5(4), 6-15(5). The bag label of each pain sequence is considered the maximum of frame labels. Out of 25 subjects, 15 are used for training, 9 for validation, and 1 for testing. LOSO cross-validation is followed. For the DISFA and FERA datasets, bags are considered sequences with monotonically increasing or decreasing offset and onset frames. Similar to UNBC, the bag label is considered the maximum of the frame labels of AU intensities. 5-fold cross-validation is deployed for DISFA and official training/validation split for FERA. In order to compare the work of [88] with the conventional approach of pain detection [30], MILBOOST is deployed and the output probabilities of pain detection are normalized between 0 and 5 to have a fair comparison with that of [88].

**Incomplete Annotations:** For the UNBC-McMaster dataset, only 10% of annotations are considered in each sequence for the task of pain regression. For the task of AU regression in DISFA datasets, only 10% of annotated frames are considered in [88], [96], and [91] in order to incorporate the setting of incomplete annotations, whereas [97]–[95] and [92] considered only the annotations of peak and valley frames, [97] uses only 2% of randomly annotated frames. In the case of the FERA 2015 dataset, official training and development sets provided by the FERA 2015 challenge [98] are deployed. Similar to UNBC-McMaster and DISFA, [96], [56] considers only 10% of annotated frames while [91], [89], [92] considers annotations of peak and valley.

### D. Critical Analysis and Results

The intensity estimation of facial expressions or AUs is more challenging than the task of classification due to the complexity of capturing subtle variations in facial appearance. Therefore, it remains an under-researched problem compared to the task of classification. To the best of our knowledge, there are no works on inaccurate annotations with intensity estimation despite the high level of uncertainty in intensity labels. Since temporal dynamics plays a crucial role in conveying significant information for the task of estimating the intensity level, [89] and [88] modeled the relevant ordinal relationships across temporal frames by incorporating intensity and relevance smoothness into the objective function. However, both of these approaches rely on classical ML models. They have been outperformed by [14], [85] that leverage 3D-CNN models as shown in Table [14].

The task of estimating intensity is less explored in the context of inexact annotations when compared to incomplete annotations.

For incomplete annotations, [92], [95] and [93] explored temporal, feature, and label smoothness in addition to the temporal relevance, where the former shows better performance by leveraging more constraints. [94] explored attention mechanisms at both the feature and label levels, showing an improvement over prior approaches [92], [93], [95], [97] and [96] further improved performance by leveraging large-scale pre-trained models based on self-supervised learning and RBMs to model AU relationships, where the latter has shown better performance. Compared to classical ML models [88], [89], DL models [96], [97] have shown significant improvements for both inexact and incomplete annotations. However, a challenge in using DL models for estimating the intensity of facial expressions or AUs is the requirement of a large number of representative samples with intensity annotations, which is costly and requires domain expertise. Estimation of intensity levels using DL models is therefore explored in the context of incomplete annotations by leveraging large-scale pre-trained models [97] or large-scale unlabeled data [25]. Similar to that of classification, DL models with inexact annotations remain an under-researched problem for regression.

### V. Open Problems and Opportunities

This section describes the challenges for FER in the context of WSL. Although developing a robust FER system raises many challenges such as identity bias and data sparsity [5], [101], we emphasize the challenges and research directions for FER in the context of weak annotations.

#### A. Open Problems

(a) **Training with Limited Reliable Annotations.** As the data capture conditions change from controlled laboratory environments to uncontrolled real-world environments, the visual appearance of facial expressions exhibits a wide range of variations between people, depending on age, civilization, ethnicity, cosmetics, eyeglasses, capture conditions, etc. Moreover, facial expressions may be sparse in videos, as they are often expressed in a subset of the frames along with neural frames. The problem is accentuated by ambiguous or uncertain annotations, as they further reduce the number of training samples with reliable labels. The performance of the ML/DL models is typically influenced by the quantity of representative data. Given a limited number of training samples with reliable annotations, the potential of DL models is not fully explored due to the overfitting and generalization capability. Though large-scale unlabeled or noisy annotated data are leveraged for the context of incomplete [45], [47], [50] and inaccurate annotations [61], [63], [69], exploring the potential of DL models with weak annotations for FER is not fully explored.

(b) **Localizing AUs with Weak Image-Level Annotations.** Localizing AUs with image-level AU annotations can be formulated in the context of inexact annotations. Some approaches have recently been proposed for localizing AU regions based on facial landmarks [102], [104]. However, these approaches rely on prior knowledge of predefined AU attentions, which restrict the capacity of predefined AUs, and fail to capture the wide range of non-rigid AUs. Given the potential of local features related to AU and the tedious process of obtaining localized AU regions, there is a need to formulate the problem of localizing AU patches without predefined AU attention. To our knowledge, only two approaches have addressed the problem of AU localization without any prior information on pre-defined AU attention. [105] integrated the relations among AUs with an attention mechanism in an end-to-end DL framework by extracting multiscale features, while [106] explored self-supervised learning for localizing AUs...
using optical flow and further deployed in a cross-domain setting.

(c) Data Bias with Incomplete Annotations. Leveraging large-scale face recognition (FR) datasets is a promising direction to address the limitations of labeled FER datasets. However, leveraging FR datasets as unlabeled data poses the problem of a distribution mismatch between small-scale FER datasets and large-scale unlabeled FR datasets, which can deteriorate system performance. To the best of our knowledge, only two works attempted to solve this issue. [107] addressed the problem of class imbalance along with the mismatch of data distributions using base and adaptation networks in an iterative feedback mechanism, while [50] explored self-supervised learning with contrastive learning. Therefore, dealing with data set bias to cope with FER data with limited annotation remains a challenging open problem, which can be further explored to improve system performance.

(d) AU Recognition with Noisy Annotations. Most approaches for AU recognition have been explored in the context of inexact annotation (using expression labels) [38]–[40] or incomplete annotations (missing or incomplete labels) [52], [55]. Annotating AUs is more challenging compared to categorical expressions because of the increased range of facial behavior. Moreover, the annotation of AUs requires domain expertise certified by the FACS coding system, which is laborious, and thereby prone to annotation errors. Given the complex annotation process for AUs, most of the existing AU datasets are constrained by the number of coded AU samples. Although the number of facial images on the web has been growing at an exponential rate, leveraging large-scale datasets captured in the wild for AU recognition is relatively unexplored in the literature. Most current approaches for AU recognition with inexact or incomplete annotations rely on classical facial landmarks based on geometric features [38], [40]. Though few works explored RBMs for AU recognition [39], leveraging DL models for AU recognition with weak annotations requires a large-scale dataset. Therefore, there is a scope for research on AU recognition with inaccurate annotations using large in-the-wild datasets. Only two works [70], [71] (see Sections 3.3.2) have been explored in the literature for AU recognition with inaccurate annotations, which leaves much room for further improvement.

(e) Dimensional Affect Model with Weak Annotations. As described in Section 3.3, the problem of FER with inaccurate annotations is explored mainly in the context of classification. Although the problem of noisy annotations is more pronounced in the case of dimensional or ordinal annotations due to subtle variations between consecutive frames, few works have addressed the problem of inaccurate annotations in the dimensional model [108], [109]. Given the complexity of obtaining annotations in the dimensional model and the lack of techniques to handle noisy dimensional annotations, most of the datasets are developed for the task of classification of facial expressions or AUs, which is mentioned in Section 3.4.1. Though few datasets have been explored for the task of ordinal regression (as described in Section 4.3.1), the development of datasets for continuous dimensional models is rarely explored. To our knowledge, only two datasets, i.e. [11] and [9] have been explored for FER in a continuous dimensional model, however, several multimodal datasets are available [110]–[112]. Ordinal annotations of DISFA [77] are obtained by two FACS-certified experts and noisy annotations are reduced by evaluating the correlation between their annotations. For UNBC-McMaster [74], the ordinal annotations are obtained from three FACS coders, which were then reviewed by a fourth FACS coder and validated using Ekman-Friesen formulae [113]. Similarly, [9] relies on 12 expert annotators, and the annotations were further reviewed by two independent annotators. [11] obtained annotations from six trained experts and were doubly reviewed by two more annotators. Finally, the final labels are considered as the mean of the annotations for each sample. They have also conducted statistical analysis to evaluate the inter-annotator correlations. Therefore, modeling the dimensional labels remains a highly challenging open problem due to the high level of ambiguity in the annotations.

B. Potential Research Directions

(a) Domain Adaptation. Unsupervised Domain Adaptation (UDA) for FER is a promising line of research to deal with the problem of limited samples with reliable annotations, by adapting a model using unlabeled videos from relevant external datasets to counteract the problem of overfitting deep models. It also allows adapting the model to the target operational environment. It has been widely used for many applications related to facial analysis such as face recognition [114], facial expression recognition [85], [115], etc. Similarly, domain generalization (DG) methods can also be exploited to improve the robustness of source models (without target data), especially for WSL with inexact or incomplete WSL scenarios. One example in this direction is the work of Wang et al. [116], who proposed an UDA approach for small target datasets using GANs, where GAN-generated samples are used to fine-tune the model pre-trained on the source dataset. Another work done by Zhu et al. [117] explored an UDA approach in the feature space, where the mismatch between the feature distributions of the source and target domains is minimized while improving the discrimination among the face images related to facial expressions. Shao et al. [118] exploited the collection of constrained images from the source domain with both AU and landmark labels, and an unpaired collection of unconstrained wild images from the target domain with only landmark labels. The features extracted from source and target images are disentangled to shape and text features, and the shape features (AU label information) of source images are fused with the texture information of the target feature. Therefore, the performance of FER can be enhanced using UDA along with DL to handle data with limited annotations still harnessing the potential of deep networks.

(b) Deep Learning Models. Given their success, many researchers have leveraged DL models for various computer vision applications such as object detection, face recognition, etc., and showed significant improvement in performance over the traditional approaches in real-world conditions. However, the performance of deep models is not fully explored in the context of facial behavior analysis due to the limited
training data and laborious task of annotations which demands human expertise. Despite the complex process of obtaining annotations for facial behavior, most of the existing approaches to FER based on DL have been focused on fully supervised settings. Li et al. [12] provided a comprehensive survey on DL approaches for FER in the framework of supervised learning, and provided insight into the advantages and limitations of deploying deep models for FER. Recently, DL models have been explored in the context of incomplete and inaccurate annotations by leveraging the unlabeled and noisy wild datasets [45], [46], [61] for expression recognition. However, it is still at a rudimentary level for the recognition of AUs. Most of the approaches for AU recognition used geometric features based on facial landmark [39], [40], [43] or classical features such as LBP [42], SIFT [38], etc. In the case of regression tasks, very few works explored deep models by leveraging large-scale pre-trained models [97] or CNN with limited hidden layers [22]. [39] and [43] have explored RBMs to model the domain knowledge of dependencies among AUs and the relationships between expressions and AUs. For AU intensity estimation, two works [92], [95] used CNN with 3 layers, and two more works [94], [97] used Resnet-18, where [97] explored large-scale pre-trained models with self-supervised learning. To the best of our knowledge, no work has been done on expression detection with inexact annotations using deep models.

(c) Temporal Dynamics. In most approaches for FER in WSL, only short-term dynamics across the temporal frames are exploited. [119] and [120] used LBP-TOP features [18] while [33], [30], and [121] used frame aggregation – the maximum of feature vectors of the frames for modeling temporal dynamics. [35] capture the temporal order of the templates of the sequence by appending frame-level features of the sequence, while [92] captures temporal dynamics using contrastive appearance difference, i.e., the difference between apex frame and neutral frame. Recently, several DL models have been proposed to leverage the temporal dynamics of facial expressions over video sequences [122], [123]. Convolutional 3D (C3D) models [124] are also gaining much attention in computer vision for modeling spatio-temporal information across frames. Compared to a 2D-CNN with RNN, C3D is efficient in capturing short-term temporal information. Though LSTM and C3D techniques are widely explored for FER in fully supervised settings [125], [126], it is not yet effectively explored for the framework of WSL for FER. Therefore, LSTM and C3D techniques when deployed in a WSL setting for FER are expected to further enhance the performance of existing state-of-the-art approaches. Leveraging transformers to model the temporal dynamics by exploiting self-supervised learning to mitigate the problem of limited annotations is also expected to improve the performance of FER in WSL [127].

(d) Modeling Perception Uncertainty. A challenge that is relevant for FER with weak annotations is modeling perception uncertainty to closely reflect human perception of emotions. Most approaches in the literature rely on the assumption that annotations obtained from crowd-sourcing will be more accurate, yet this assumption is not verified in realistic scenarios. Even when multiple annotators are engaged, producing multiple diverse annotations, label uncertainty still remains in the emotion target as the number of annotators cannot be infinite. This inevitably introduces noise in annotations, which may degrade system performance. Motivated by this observation, [128] introduced the idea of modeling the uncertainty of emotion perception using soft labels instead of hard labels. Although the problem of modeling the perception uncertainty is unexplored in the literature, there is great potential for further exploration.

(e) Continuous Affect Models. The continuous dimensional model conveys a wider range of expressions than ordinal regression and plays a crucial role in capturing the subtle changes and context sensitivity of emotions. Compared to the task of classification and ordinal regression, WSL-based approaches for facial expressions or AUs are hardly explored in the context of continuous dimensional space though few endeavors have been made in the context of fully supervised learning [129], [130]. Hatice et al. [7] investigated the potential of a continuous dimensional model, and provided insight on state-of-the-art approaches and challenges associated with automatic continuous analysis and synthesis of emotional behavior. Given the intricate and error-prone process of obtaining annotations, there is an imperative need to formulate the problem of the continuous dimensional model in the framework of WSL to handle noisy annotations and alleviate the negative impact of unreliable annotations. Huang et al. [131] investigated the impact of annotation delay compensation and other post-processing operations for continuous emotion prediction of multi-modal data. As far as we know, there is only one work [132] based on WSL for the prediction of a continuous dimensional model, using valence and arousal in a multi-modal framework. They have reduced the noise of unreliable labels by introducing temporal label, which incorporates contextual information by considering the labels within a temporal window for every time step. They have further used a robust loss function that ignores small errors between predictions and labels in order to further reduce the impact of noisy labels. Therefore, there is much room for improvement to augment the performance of the FER system in the continuous dimensional model using WSL-based approaches.

(f) Multimodal Learning. Multimodal analysis has gained much attention in recent years to enhance the overall accuracy and robustness of FR systems over uni-modal approaches. Exploring multiple modalities may provide more diverse and comprehensive information, which can help reduce the cost of annotation, as well as annotation error or low-quality annotated datasets [133]. Inspired by their performance, several data sets are developed to validate multimodal approaches under challenging real-world scenarios [110], [134]. To encourage progress in multimodal emotion recognition, several datasets including audio, visual, text, etc. have been introduced [11], [110], [111], [135]. Several works have been done based on audio-visual fusion for emotion recognition [136], [139] in the framework of supervised learning. To our knowledge, only one work [132] has been published on WSL approaches for multimodal affect recognition using audio and visual features. Inspired by the invariance of thermal images to illumination, some approaches have been proposed to exploit thermal im-
ages with RGB images in a complementary fashion to augment the performance of the FER system [140], [141]. Another line of research is dealing with noisy data caused by facial pose or occlusion, which may lead to ambiguous annotations. To overcome the problem of pose-variance and occlusion, 3D data has been explored to obtain the comprehensive information displayed by the face and capture the subtle changes of facial AUs in detail using the depth of the facial surface. For instance, AU18 (lip pucker) is hard to differentiate from AU10+AU17+AU24 in a 2D frontal view. Sandach et al. [142] provided a comprehensive survey on datasets and FER systems relevant to 3D or 4D data. Inspired by the performance of optical flow in action recognition, a few approaches have been proposed to capture facial muscular movements using optical flow as it converts the sequence of motion information to static textures [143], [144]. Benjamin et al. [145] investigated the effectiveness of optical flow in recognizing full expressions, as well as micro-expressions, in near-frontal images. As far as we know, only one work [146] has explored optical flow for FER with minimal annotations i.e., sequence-level labels.

(g) Auxiliary Spaces for label Uncertainty Exploring the auxiliary label space of relevant tasks has recently gained much attention for dealing with label uncertainty. The idea is to leverage the information available in the auxiliary label space of related but distinct tasks to refine the label uncertainty of the main FER task. Chen et al. [147] explored the labels of AU recognition and facial landmark detection to effectively learn the label distributions based on the assumption that neighboring facial images in the auxiliary label space should have similar expression distributions. Le et al. [148] showed that leveraging the neighborhood information in the valence-arousal space helps to obtain more semantic label distributions, and further improves system performance. Unlike the above two approaches, Liu et al. [149] exploited the auxiliary tasks of AU detection and valence-arousal measurement to learn to relabel uncertain samples and mitigate the class imbalance respectively. Therefore, leveraging the auxiliary label space is a promising line of research to deal with the problem of label uncertainty, and can also be extended to deal with limited annotations.

(h) Few Shot Learning Few-Shot Learning (FSL) is another emerging machine learning paradigm that deals with the problem of learning from limited annotated samples of novel classes. The basic idea of FSL is to generalize a pre-trained model to new classes by learning from a limited set of labeled samples of these classes (support set) [150]. Although FSL does not exactly correspond to any of the WSL scenarios, it overlaps somewhat with the framework of incomplete annotations, as both cases deal with the problem of limited accurate annotations. Recently, FSL has also gained attention in FER as a solution to the problem of novel classes for compound emotion recognition [127], [151]. [152]. Another line of research with FSL for FER is to adapt to new subjects as people express their emotions differently from each other [153]. Most of the existing approaches pertinent to FSL for FER have been evaluated in cross-domain settings, where the target domain may have few labeled samples of novel classes [127], [151], [152]. Xinyi et al. [151] proposed a novel emotion-guided similarity network to deal with the limited annotations of compound expressions, where the pre-trained model is generalized to limited samples of novel classes (support set) of compound emotions. Zou et al. [152] also addressed the problem of compound FER in a cross-domain setting using a cascaded decomposition network for FSL. Chen et al. [127] explored self-supervised vision transformers by jointly pertaining with multiple pretext tasks, and leveraged FSL to train the deep model with fewer labeled samples. Besides these few papers on compound emotion recognition, FSL has not been explored for AU recognition. Therefore, the use of FSL techniques is a promising line of research to deal with limited labeled samples for FER.

VI. CONCLUSION

This paper introduces different WSL scenarios for facial behavior analysis. A comprehensive review of state-of-the-art WSL methods for the recognition of expressions and AUs is provided for both classification and regression applications based on images and videos. In addition, the comparative results obtained with well-established experimental methodologies allow us to provide further insights into the benefits and limitations of these methods. Our review highlights the diversity of WSL methods available for training robust DL models for facial behavior analysis in real-world scenarios. Most of the WSL methods rely on either facial landmarks or pooling to capture the temporal dynamics, and efficient modeling of temporal dynamics with weak labels is expected to greatly improve system performance. Methods for deep WSL are still under-explored in the literature, especially for dimensional expression recognition, providing many opportunities for improving performance in WSL scenarios. Finally, we highlight the research gaps in the literature on WSL models and provide potential research directions for the development of a robust system for facial behavior analysis with weak annotations.

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