Semantic-Rich Facial Emotional Expression Recognition

Keyu Chen  Xu Yang  Changjie Fan  Wei Zhang  Yu Ding†

Abstract—The ability to perceive human facial emotions is an essential feature of various multi-modal applications, especially in the intelligent human-computer interaction (HCI) area. In recent decades, considerable efforts have been put into researching automatic facial emotion recognition (FER). However, most of the existing FER methods only focus on either basic emotions such as the seven/eight categories (e.g., happiness, anger and surprise) or abstract dimensions (valence, arousal, etc.), while neglecting the fruitful nature of emotion statements. In real-world scenarios, there is definitely a larger vocabulary for describing human's inner feelings as well as their reflection on facial expressions. In this work, we propose to address the semantic richness issue in the FER problem, with an emphasis on the granularity of the emotion concepts. Particularly, we take inspiration from former psycho-linguistic research, which conducted a prototypicality rating study and chose 135 emotion names from hundreds of English emotion terms. Based on the 135 emotion categories, we investigate the corresponding facial expressions by collecting a large-scale 135-class FER image dataset and propose a consequent facial emotion recognition framework. To demonstrate the accessibility of prompting FER research to a fine-grained level, we conduct extensive evaluations on the dataset credibility and the accompanying baseline classification model. The qualitative and quantitative results prove that the problem is meaningful and our solution is effective. To the best of our knowledge, this is the first work aimed at exploiting such a large semantic space for emotion representation in the FER problem.

Index Terms—Facial Emotion Recognition, Affective Computing, Image Analysis.

I. INTRODUCTION

Understanding and recognizing human facial emotional expressions has been an attractive research topic for decades, lying in the intersection area of affective science and human-computer interaction. Despite the natural perception ability that humans obtained from evolution [1], it is never straightforward for computer-based systems to sense and interpret emotions from human facial performances automatically. On one side, the challenge of facial emotion recognition (FER) problem partially comes from the sophisticated facial muscle system, leading to complicated facial behaviors w.r.t. individual’s emotional statements, especially under the in-the-wild uncontrolled conditions. On the other side, most of the current FER researches only focus on the abstract level of emotion concepts, but are struggling to cover the entire emotion space [2] sufficiently.

Fig. 1. Facial image samples belong to the same category (surprise) defined by the basic emotion model but with contrastive emotional expressions (amazement and astonishment). The obviously different facial performances indicate the necessity of proposing more fine-grained representation model to handle the abundant emotion semantics.

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Typically, the categorical model is one of the most popular representations in the FER area, composed of several basic emotion classes, e.g., happiness, anger and surprise. Depending on the psychological conceptualization on specific natural emotions, multiple emotion theorists suggest a variety of category lists individually [3], [4], [5], [6]. However, due to the highly abstract manner of such definitions, there are some arguable ambiguities. For example, given two individual emotion terms, amazement and astonishment, which are both subject to the surprise class [7], their triggered facial expressions are obviously different as amazement is rather positive and close to happiness while astonishment is more negative and associated with fear (Fig. 1). Therefore, simply categorizing the various facial expressions into several abstract classes is incapable of representing the numerous and fine-grained emotional statements.

To tackle this issue, several annotated FER datasets are proposed by mixing the basic expressions into compound ones [8], [9], [10], replacing the discrete representations with multi-label distributions [11], [12], or enlarging the emotion sets with a few more classes [13], [14]. Besides, another category of methods follows the circumplex emotion modeling idea [15], whose dimensions are represented by the principle emotion factors, i.e., valence, arousal, dominance, etc. The shortcoming of the dimensional model comes from its difficulty of annotating accurate continuous labels, such as [16], [17]. Nevertheless, the semantic richness issue of recognizable emotion concepts still remains an open problem, which is really challenging to the whole FER community.
In this paper, we aim at studying the FER problem on a semantic-rich level. Different from the previous methods that simply blend or add more emotion classes to enhance the FER quality, we thoroughly exploit the linguistic space and leverage a reasonable lexicon to describe the emotion concepts. Inspired by previous psychological research [7], we extend the recognizable emotions to an exhaustive set, covering 135 English words which can semantically describe most of all distinctive emotional feelings or inner statements of humankind. From the perspective of psychological and linguistic research, the 135 words expand an almost complete semantic atlas of the emotion domain [18], [19]. Accordingly, we argue that the 135-class emotion model is desirable for semantic-rich FER research.

Based on the 135-class emotion model, we construct a large-scale FER dataset in a labor-free manner. First, we use the 135 emotion terms as class labels, collect more than one million web images from the internet. Then, we design an automatic data cleaning process by efficiently evaluating the expression consistency of the collected images. To evaluate the label credibility of our categorical dataset, we set up a manual verification test in which multiple participants are required to give their judgments on given images and different emotion labels. In this way, we successfully build up the Emo135 dataset, which contains 135 emotion categories and 728,946 facial images in total.

Next, we propose a baseline method to validate the feasibility of conducting FER on the semantic-rich representation. Considering the number of emotions to be recognized, there inevitably exist synonyms among the 135 emotion concepts/terms, making it neither reasonable nor possible to regard these categories as individual sets. Our corresponding solution is to evaluate the cross-label correlations via two metrics, i.e., computing the word embedding and facial expression embedding similarity distances. The similarity scores are then transformed into two weight matrices for storing the correlations among 135 emotion classes. Finally, we make the weight matrices as prior knowledge and inject them into the recognition network training softly.

To the best of our knowledge, this is the first work aimed at handling the FER problem with such a large number of emotion categories. The psychological backing of the utilized 135 emotion concepts makes adequate support on our claimed semantic richness of the FER problem. In sum, the contributions of this research are three-fold:

- We propose the first semantic-rich facial emotional expression recognition work, with an exhaustive emotion set including 135 concepts comprehensively described the entire emotion domain.
- We automatically construct a large-scale FER dataset Emo135, containing 135 fine-grained emotion categories and 728,946 facial images. We believe the open-released dataset could benefit the other research works in the FER community.
- We carefully design a correlation-guided method for fine-grained facial emotional expression recognition. The quantitative and qualitative experiment results indicate that our method can well handle the complicated nature of so many emotions and generate reliable FER predictions with rich semantics.

II. RELATED WORK

This section briefly reviews some related literature to our work, including facial emotion expression representations, datasets, and automatic recognition methods.

A. FER Representation and Dataset

Facial emotional expression embodies non-verbal communication of our daily life. In order to technically model the inner emotion statements that are conveyed by facial expressions, there are three common-used emotion representations being proposed, including the categorical model [6], the action unit model [20], and the circumplex model [15]. Among these models, the categorical one consisting of several basic emotion terms is most popular. Typically, it is defined by seven or eight universal recognizable emotions, namely neutral, anger, disgust, fear, happiness, sadness, surprise, contempt, etc. As a matter of fact, most current FER datasets are built upon these discrete categories, varying on the specific definition of emotion concepts, such as JAFFE [21], CK+ [22], KDEF [23], SFEW [24], FER2013 [25], FER-Wild [26], Affect-Net [16], and Aff-Wild2 [27].

However, until recent years, the basic categorical model has been challenged for its incapability of modeling fine-grained emotion variances. The following researches suggest improving the representation capacity of the emotion model, for example, introducing compound emotion classes [8] and transferring the discrete emotion labels into continuous distributions [11]. Based on these ideas, some novel FER datasets are proposed, like RAF-DB [10] and EmotioNet [9] which includes 18 and 23 basic/compound emotion classes respectively, and RAF-ML [12] with continuous label distribution annotations. Furthermore, the latest research work tries to extend the emotion concepts to 54 classes and proposes a corresponding dataset F^2ED [14].

B. Facial Expression Features and Classifiers

Image-based facial emotion recognition has been extensively studied for decades. In general, a complete FER method is composed of two algorithm modules, i.e., feature extractor and classifier. Traditional FER approaches usually apply hand-crafted features, such as Gabor Wavelets [28], Local Binary Patterns [29], and Histogram of Oriented Gradients [30]. With the rapid development of deep learning techniques, some pre-trained backbones like ResNet [31] are adopted for extracting high-level features. In terms of the specificity of FER tasks, there are also some expression embedding models [32], [33] which can eliminate the invariant attributes like pose, identity, and image background from the captured features.

On the other hand, the classifiers integrated into the FER systems have also achieved promising performances in recent years. To solve the occlusion issue caused by large poses, the region-based network [34] is proposed with an attention mechanism. Besides, there are some FER methods considering
the facial priors, such as the muscle moving masks [35] and the geodesic distance on 3D shapes [36]. Except for the extensive methods [37], [38], [39], [40], [41] which focus on solving the FER problem independently, there is also another category of methods trying to explore the benefits from multi-task settings [42], [43].

III. METHODOLOGY

In this section, we first review the background of our leveraged emotion model, which contains 135 lexicon terms representing the semantic atlas of the emotion domain. Then we introduce the data acquisition and processing details that help us construct a large-scale facial image dataset. Finally, we propose a baseline approach for fine-grained facial emotion recognition by considering the cross-label relationships among the multiple emotions.

A. Semantic-rich Emotion Categories

Emotion knowledge plays an important role in social interaction. Without too much training, even infants can naturally perceive and express emotional feelings at a basic level, e.g., happiness, fear, and anger. Although numerous empirical cognitive studies have demonstrated that ordinary people can reliably name the emotions being expressed from facial images [44], it has been a struggle for psychologists to agree on a formal semantic structure of the human emotion space. To efficiently associate the cognitive emotions with linguistic descriptions, some emotion theorists suggest applying the prototype approach [45] to determine the emotion concepts with a finite set of words [3].

Depending on the definition of emotion varieties, there are different kinds of emotion taxonomies, i.e., emotion representations consisting of different sets of semantic terms (words with specific emotion meanings). Some research works focus on the abstract level of emotion episodes, claiming several universal categories forming the overall structure of the emotion space, such as the seven or eight basic emotions [6].

Another branch of methods digs into the language space to search for every distinctive word representing a particular emotion concept. It is first proposed by Averill who collects 558 English words conveying emotion connotations [46]. Then the 558 words are further cleaned up by grammar roots and evaluated with the emotion-sorting study [7]: one hundred twelve participants make their judgments on each word, with a prototypical rating from “I definitely would call this an emotion.” to “I definitely would not call this an emotion.” [7]. Finally, there are 135 words left with high enough ratings, and it is responsible for saying that they extensively form the semantic space of the emotion domain. Therefore, in this paper, we refer to the 135 emotion words/categories as the semantic-rich emotion representation. A full list of the 135 words given by Shaver et al. is transcribed in the appendix section.

We would like to point out that, given the human language is a living entity, some recent studies [47], [48], [49] propose a variety of emotion classes that defend/revise the Shaver’s model [7]. Nevertheless, as language research goes on, the ideal emotion semantic atlas shall be updated as well.

B. Emo135 Dataset

With the semantic-rich emotion representation, we establish a facial image dataset Emo135 according to the 135 emotion words. Technically, our dataset construction process involves two automatic steps, data collection and cleaning. Data acquisition. We use the 135 emotion category names as keywords, accompanying several other suffix words such as expression, feeling, and face, to query for web images with matching titles by internet search engine indexing. While downloading the valid images from the internet, we also apply face detection by dlib library\(^3\) and crop the face area from the entire image into 224 × 224 size. In this way, we collect 135 image categories with more than one million facial expression images. An illustration of our data collection results is shown in Fig. 2.

Data cleaning. In order to eliminate the noisy samples of each emotion category (which could be titled or indexed with wrong

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2https://www.\{bigstockphoto;alamy;photocase;shutterstock\}.com

3http://dlib.net
we find it is quite sensitive to the specified hyper-parameters, codes are lying on a 16-dimensional unit sphere. described in Algo. 1. In practice, the expression embedding with a predefined threshold. The detailed algorithm steps are distance between each sample and its $K$ nearest neighbors. Based on the same category and evaluate the embedding density of these expressions, they will be mapped closely in the latent space, while enforcing the dissimilar ones away from each other. Even more, it can capture subtle expression variations between facial attributes like identities, poses, or image backgrounds. Specifically, we adopt an advanced facial expression embedding model [33] for expression similarity evaluation. The advantage of the embedding model is that it can produce expression embedding codes that are invariant to the other facial attributes like identities, poses, or image backgrounds. Even more, it can capture subtle expression variations between different faces. For example, if two faces have similar expressions, they will be mapped closely in the latent space, and vice versa (See Fig. 4). Within that latent space, we gather the expression embedding codes of all images in the same category and evaluate the embedding density of these codes. Based on the $k$-nearest neighbors algorithm, we can efficiently detect the embedding outliers by filtering the mean distance between each sample and its $K$ nearest neighbors with a predefined threshold. The detailed algorithm steps are described in Algo. 1. In practice, the expression embedding codes are lying on a 16-dimensional unit sphere.

While we employing the knn-based data cleaning method, we find it is quite sensitive to the specified hyper-parameters, i.e., the neighborhood size $K$ and the threshold distance $\sigma$. Generally, larger neighborhood size and smaller threshold distance will encourage more strict elimination policy and thus reduce the dataset size (eliminating even matched images), and vice versa. To preserve the label quality as well as the image quantities, we empirically choose $K = 10$ and the threshold distance $\sigma = 0.2$.

**Algorithm 1** Data cleaning process

**Input:** Image category $C = \{I_n\}_{n=1}^N$; Neighbouring number $K$; Filter threshold $\sigma$; 

**Output:** Remove/keep decision on each image sample;

**Step:**
1. Generate expression embedding of each image,
$$E : I_n \mapsto V_n ,$$
$$E(C) = \{V_{n_k}\}_{k=1}^K .$$
2. Find the $K$ nearest neighbors for each embedding vector,
$$\text{KNN}(V_n, E(C)) = \{V_{n_k}\}_{k=1}^K .$$
3. Calculate the mean distance between $V_n$ and its $K$ nearest neighbors,
$$d_n = \frac{1}{K} \sum_{k=1}^{K} \|V_n - V_{n_k}\|^2 .$$
4. Compare $d_n$ with $\sigma$,
$$d_n < \sigma : \text{keep image } I_n \text{ in } C ,$$
$$d_n \geq \sigma : \text{remove image } I_n \text{ from } C .$$

In Fig. 3, we visualize the expression embedding distributions of the single class hope before/after the data clean process. It can be observed that our designed approach is significantly helpful in terms of reducing data noise and improving label accuracy to the dataset. Besides, we also visualize the multi-class expression embedding distributions before/after the automatic data cleaning procedure in Fig. 3. After the removal operation, each emotion class is more compact, which makes it possible for us to analyze their correlations. In sum, 31% of original data is automatically cleaned during this process, leaving in total of 728,946 valid facial images.

**Dataset statistics.** In Tab. I, we compare our proposed Emo135 dataset with some other existed FER datasets. It can
be observed that our dataset Emo135 has the most fine-grained annotations in terms of emotion classes and comparable large quantities of facial images.

Besides, we also illustrate the image quantity distribution per each emotion category in Fig. 5. Considering the different emotions may involve different degree of presence in our daily life, some rare emotion classes (e.g., vengefulness) generally contain less image samples than those common ones (e.g., excitement). Therefore, our dataset distribution is not absolutely uniform but including the maximum category with 12,794 images and the minimum category with 994 images.

C. Modeling Correlation Matrix for 135 Emotions

After obtaining the Emo135 dataset, we propose to analyze the cross-emotion similarities for the 135 emotions. Different from the previous FER methods established on only a few discrete emotion classes, the problem setting of this work is more challenging since there are as many as 135 emotion categories, and most of them do not have sharp boundaries, which means it is even impossible to absolutely distinguish any emotion term from the others. This phenomenon suggests we have to carefully consider the correlations of different classes. The idea of modeling cross-emotion distances can date back to the 1980s [15], [50]. Until recently, the emotion correlations are considered in several automatic facial affective recognition methods [51], [52], [53]. In this task, the similarity of different emotions can be evaluated in two ways, one based on their triggered facial expressions and the other by the semantic word embeddings. Specifically, the facial expression evaluations focus on the performance/expressiveness level of different emotions, which is useful for extracting solid facial image features. In contrast, the semantic word embeddings are adopted from the language modeling area, capable of revealing the intrinsic synonymous distances between different emotion labels. Thus we can make them facilitate the emotion label prediction process.

To begin with, let us denote the 135 emotion categories as $C_1, C_2, ..., C_{135}$. For each category $C_k (k = 1, 2, ..., 135)$, it contains in total of $N_k$ facial images $I_n^k (n = 1, ..., N_k)$. Because of some inevitable synonyms like anger and fury existed in the 135 emotion classes, and even words in hierarchical relationship like astonishment and amazement which are both subject to surprise, we are motivated to quantitatively calculate the distances between different emotions and moreover apply this knowledge to help our network training.

Facial expression similarities. We first adopt the facial expression embedding model [33] to evaluate the facial images between different emotion categories. Specifically, we first send every image $I_n^k$ into the pre-trained facial expression embedding model and generate the corresponding expression embedding vector $V_n^k \in \mathbb{R}^{16}$. We utilize Directed Hausdorff Distance to measure the one-sided similarity from $C_i$ to $C_j$, which can be formulated as following:
Notably, this metric is asymmetric as $d_H(C_i, C_j)$ does not necessarily equal to $d_H(C_j, C_i)$, and thus it is suitable for the similarity modeling purpose. This is because sometimes the emotion $C_i$ could be absolutely recognized as $C_j$ (e.g., amazement → surprise) but the inverse is not true (e.g., surprise → {amazement, astonishment, etc}).

Next, we pack the calculated results into a facial expression similarity matrix $F^{exp} \in \mathbb{R}^{135 \times 135}$, in which each element $F^{exp}_{ij}$ is given as:

$$F^{exp}_{ij} = \frac{1}{d_H(C_i, C_j)^2} \quad (i \neq j). \quad (2)$$

Particularly, the diagonal element $F^{exp}_{ii}$ is computed by adding the rest entries within the $i$-th row like:

$$F^{exp}_{ii} = \sum_{j \neq i} F^{exp}_{ij}, \quad i \in \{1, 2, ..., 135\}. \quad (3)$$

Finally, we normalize the correlation matrix along each row into sum 1.0. The technical meaning of our constructed matrix is that, if emotion $C_i$ is very close to emotion $C_j$, the value of element $F^{exp}_{ij}$ would be significantly large. In this way, we can use $F^{exp}$ to efficiently guide the recognition process to be aware of the cross-emotion relationships.

**Word embedding distances.** The other metric we adopted for evaluating cross-emotion similarities is the semantic word embedding. Firstly, we adopt a Word2Vec model [54], [55] which is pre-trained on large-scale dataset including English blogs, texts, and comments. Then the model will take input as every pair of 135 emotion terms and output the corresponding embedding distance of each. Similar to the facial expression similarity matrix, the word embedding distances are stored in a coefficient matrix $F^{word}$. For every pair of emotion categories $(C_i, C_j)$, the word embedding distance is calculated as follows and then normalized in rows as well:

$$F^{word}_{ij} = Word2Vec(C_i, C_j) \quad (i \neq j). \quad (4)$$

$$F^{word}_{ii} = \sum_{j \neq i} F^{word}_{ij}, \quad i \in \{1, 2, ..., 135\}. \quad (5)$$

In practice, we deem the word embedding distances as label correlations. For example, if emotion $C_i$ and $C_j$ are close in the word embedding space, then when an image is classified into class $C_i$ with a high probability, it should also possess a similarly high probability within class $C_j$.

**D. Baseline Approach**

**Network design.** Our proposed fine-grained emotion recognition network includes two modules, a pre-trained facial expression embedding model and a correlation-guided classification model (Fig. 6). The expression embedding model is responsible for extracting expression-related features, and the classification model aims to regress the target emotion distributions with the help of the calculated correlation matrix $F^{exp}$. Notably, the pre-trained facial expression embedding model [33] is trained for fine-grained expression similarities. The model incorporates many expression triplet data and learns a continuous expression embedding space. It is capable of capturing minor expression similarities and thus suitable for building the 135-class representations. We also illustrate the detailed network structures in the appendix section.

Given a training image $I \in \mathbb{R}^{224 \times 224 \times 3}$ and its one-hot ground-truth vector $Y \in \mathbb{R}^{135 \times 1}$, we first input the image into the expression embedding model for feature extraction. The expression feature will then be sent into the classification model consisting of several alternative fully connected and correlation layers. In particular, we implement the three
correlation layers by initializing them with \( F^{exp} \). The detailed network design can be found in the appendix.

**Loss function.** The final output of our model is a prediction vector \( P \) in size of \( \mathbb{R}^{135 \times 1} \). Before comparing \( P \) with the one-hot ground-truth label \( Y \), we take the word embedding correlation matrix \( F_{\text{word}} \) into consideration by applying the transformed cross entropy (TCE) loss:

\[
L_{TCE} = -\sum (F_{\text{word}} \cdot Y) \log P + (1 - F_{\text{word}} \cdot Y) \log (1 - P))
\]

It is worth noting that despite the formulation of Eq. 6 is similar to the standard label smoothing strategy [56], they are different in terms of relaxing weights. In the label smoothing operation, each zero-value term within the ground-truth \( Y \) is uniformly modified with the same soft parameter, e.g., \( \alpha = 0.1 \). While in our method, the label relaxing is dependent on the emotion word embedding analysis. Therefore our produced correlation label \( F_{\text{word}} \cdot Y \) can better satisfy the emotion nature and enhance the recognition process with the prior semantic knowledge.

**IV. Experiment**

In this section, we first give some implementation details about our experiments. Then we report the subjective survey results on evaluating the Emo135 dataset. Finally, we compare our proposed baseline framework with other feasible approaches and prove the efficiency of our method.

**A. Implementation Detail**

We randomly split the Emo135 dataset into training, validation, and testing set by 70%, 15%, 15%, respectively. There are in total of 510,262 images for training and 109,342 for validation/testing. We implement our training framework based on Pytorch\(^4\). The training costs around 30 hours on an NVIDIA RTX 3090 graphics card of 24 GB memory, with a learning rate of 0.005 and batch size 240. We use a stochastic gradient (SGD) optimizer for optimization and train the entire framework for 100 epochs.

**B. Dataset Evaluation**

To ensure the image emotion labels are convincing and credible, it is necessary to conduct a manual evaluation on the Emo135 dataset. Therefore, we make a subjective survey by recruiting 62 participants to validate the semantic correspondence of our collected facial images and their emotion labels. Specifically, we offer the participants three rating choices including “I agree the given word faithfully conveys the facial emotions”, “I prefer another similar word to describe the facial emotion”, and “I prefer another dissimilar word to describe the facial emotion”, respectively for different accuracy levels of the emotion terms.

Considering the large size of our constructed dataset (roughly 700k images), we choose to carry out the aforementioned manual evaluation by sampling the whole Emo135 dataset. We blindly select examples from each category according to its size. For instance, we extract 198 images from the largest category (containing 12,794 images) and 16 images from the smallest category (containing 994 images). In return, we receive 33,651 ratings on 11,217 images, in which each image and its label are evaluated by three different raters.

As the histograms shown in Fig. 7, the image labeling results are, in most cases, in agreement with the common sense of human affective cognition. On average, 81.2% raters agree that the given emotion labels perfectly match the corresponding images. Besides, there are 12.9% raters suggesting similar words for description, while 5.9% disagree with the given labels and suggest something different. Among the 135 emotion categories, pride gets the lowest satisfying rate at 41.8% from raters. The other less satisfying (< 50%) classes are annoyance, humiliation, and suffering. In contrast, there are relatively more consistent categories, such as amusement (92.6%), amazement (91.1%), grumpiness (91.1%) and sorrow (89.6%).

Furthermore, to demonstrate the test validity of the rating experiment, we also evaluate the inter-rater reliability by Krippendorff’s alpha test [57]. Following the open-source

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\(^4\)https://pytorch.org/
code\textsuperscript{5} for Krippendorff’s alpha calculation, we compute the \(\alpha\) efficient of our collected results, with a score of 0.776 (\(\alpha = 1.0\) indicates perfect reliability, \(\alpha = 0.0\) indicates the absence of reliability, and \(\alpha < 0\) means systematically disagreement). In conclusion, the statistical results of the subjective survey indicate that our adopted 135 emotion concepts, as well as the corresponding facial images, are compatible with the human emotional cognition knowledge. Nevertheless, it is worth noting that the above conclusion comes from sample survey. The annotation cost limits us to conduct a full survey at the current stage. We believe it would be meaningful to increase the manual evaluation scale in the future.

C. Model Evaluation

To evaluate our proposed model on recognizing facial emotional expressions, we conduct both performance comparison and ablative study. Since this is the first work trying to handle the 135 emotion classification problem, there is no existing method for direct comparison. Therefore, we choose two kinds of competitive models and train them on the Emo135 dataset. First, we adopt two commonly used pre-trained backbones, ResNet-50 and VGGFace2, assembled with Multilayer Perceptron (MLP) classifiers. Second, we adopt two latest FER models, ARM\textsuperscript{[58]} and DACL\textsuperscript{[59]}, which have achieved state-of-the-art performance on basic emotion recognition tasks, and modify their output layers for 135-class recognition.

**ResNet-50 baseline.** As a popular image pre-training model in computer vision community, ResNet-50\textsuperscript{[31]} has achieved significant performance in a wide range of applications, especially on the image classification/recognition topic. Therefore we integrate the most recent released ResNet-50 model trained on ImageNet-1k\textsuperscript{[60]} dataset as backbone and a 5-layer MLP to regress the image features to 135 dimensional logits.

**VGGFace2 baseline.** Compared with ResNet-50\textsuperscript{[31]}, VGGFace2\textsuperscript{[61]} is trained on specific human face images and gained even better performances in several human face centric applications, e.g., facial landmark detection, re-identification, and facial expression recognition. We also design a baseline consisting of a pre-trained VGGFace2 model\textsuperscript{[61]} and the same MLP layers as the ResNet-50 baseline.

**ARM\textsuperscript{[58]}.** ARM is one of the state-of-the-arts reaching impressive scores on the public benchmarks for 7-class discrete facial expression recognition. It introduces an auxiliary block for feature map rearrangement and enhances the de-albino effect. Moreover, a minimal random re-sampling scheme is also introduced to solve the data unbalancing issue. To fairly compare our model with ARM\textsuperscript{[58]}, we modify its regression module (final layer dimension) to make it compatible with 135-class FER.

**DACL\textsuperscript{[59]}.** DACL also reaches comparable good performance in public FER benchmarks. The core idea includes a novel sparse center loss design and an attention mechanism to weight the contribution of metric learning loss functions. Similar as ARM\textsuperscript{[58]}, we adopt the main structure of DACL\textsuperscript{[59]} including the attention net and the sparse center loss calculation module but change the target output expression dimension to 135.

**Ablative study.** Besides, we also conduct ablative studies to evaluate some key component including the expression embedding model, correlation layer, and label transformation loss of our framework. For those components, we provide vanilla alternatives to evaluate the effectiveness of our design. For example, the facial expression embedding model is replaced with VGGFace2\textsuperscript{[61]}, the correlation layer is compared with fully-connected MLP, and the label transformation loss is changed to cross entropy loss.

In Tab. II, we compare the prediction results from each method on the test set, including F1 score and accuracy for the top 1, 5, 10 classes. It can be observed that our approach reaches the best performance of all the others, with top-1 prediction accuracy at 28.3\%, top-5 accuracy at 66.4\%, and top-10 accuracy at 78.7\%.

\textbf{D. Semantic Evaluation}

To evaluate the semantic relationships between the emotion labels and the predicted results, we design several experiments in this section. First, we compare different word embedding models in terms of their influences on the semantic similarity distances. By our problem setting, we choose three popular pre-trained word embedding model, including Word2Vec\textsuperscript{[54]}, GloVe\textsuperscript{[55]}, and BERT\textsuperscript{[62]}, to study the corresponding correlations between emotion word semantics. We use the original prototypical rating results\textsuperscript{[7]} as reference and calculate the Pearson Correlation Coefficients (PCC) between each model’s output and the original matrix (Tab. III). The results shows

\begin{table}[h]
\centering
\caption{Quantitative comparison between our method and the other approaches, including pre-trained backbones, modified SOTAs, and ablative models.}
\begin{tabular}{|c|c|c|c|c|}
\hline
\textbf{Approach} & \textbf{F1-Score} & \textbf{Top-1 Acc.} & \textbf{Top-5 Acc.} & \textbf{Top-10 Acc.} \\
\hline
\textbf{Pre-trained Model} & & & & \\
ResNet50 + MLP & 0.061 & 0.096 & 0.306 & 0.454 \\
VGGFace2 + MLP & 0.062 & 0.099 & 0.322 & 0.465 \\
\hline
\textbf{Modified SOTA} & & & & \\
ARM\textsuperscript{[58]} & 0.147 & 0.205 & 0.559 & 0.708 \\
DACL\textsuperscript{[59]} & 0.133 & 0.183 & 0.477 & 0.667 \\
\hline
\textbf{Ablative Study} & & & & \\
Ours w/o Embedding & 0.082 & 0.126 & 0.458 & 0.564 \\
Ours w/o Correlation Layers & 0.175 & 0.247 & 0.604 & 0.735 \\
Ours w/o Correlation Label & 0.219 & 0.272 & 0.605 & 0.710 \\
\hline
Ours & 0.247 & 0.283 & 0.664 & 0.787 \\
\hline
\end{tabular}
\end{table}

\textsuperscript{5}https://github.com/grrrr/krippendorff-alpha
that Word2Vec and GloVe are both capable of extracting the true semantic relationships for emotion words, while BERT performs poor on it. The reason could be that BERT is not design for specific word-level but contextual embedding.

Then we show some example testing results in Fig. 8. It is interesting to find that, even if the actual label is not recognized as the top one, our model can still produce reasonable predictions that are semantically close to the ground-truth (in red). Furthermore, we employ the chosen word embedding model [54], [55] to calculate the distances between the ground-truth and our predictions/the rest of 135 emotion terms (See Tab. IV). This phenomenon suggests that our analyzed semantic emotion relationship is helpful and reliable to improve the semantic richness of the FER results.

VI. CONCLUSION

In this work, we address the semantic-rich facial emotional expression recognition problem. Unlike the existing FER researches that only focus on a few basic emotion categories, we aim at the granularity of emotion concepts and the entire emotion space. To this end, we construct a novel FER dataset by leveraging a 135-class categorical model which can exhaustively represent the semantic atlas for the emotion domain. We further propose a baseline approach for the emotion recognition task on our built dataset. The core idea of our method is to model the fuzzy relationships between fine-grained emotions and then make it guide the network training process. We conduct thorough evaluations on both the dataset labeling quality and the baseline recognition method. The quantitative and qualitative results suggest the benefits of pushing FER to a semantic-rich level. In the future, we believe it would be meaningful to propose more dedicated methods and large-scale datasets to promote the understanding and analysis of fine-grained facial emotions.

ACKNOWLEDGMENTS

This research is supported by the Key Research and Development Program of Zhejiang Province (No. 2022C01011) and the 2022 Key Artificial Intelligence Science and Technology Innovation Project of Hangzhou Science and Technology Office.

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