MAFER: A Multi-resolution Approach to Facial Expression Recognition

Fabio Valerio Massoli∗
fabio.massoli@isti.cnr.it

Donato Cafarelli
donato.cafarelli@isti.cnr.it

Claudio Gennaro
claudio.gennaro@isti.cnr.it

Giuseppe Amato
giuseppe.amato@isti.cnr.it

Fabrizio Falchi
fabrizio.falchi@isti.cnr.it

Istituto di Scienza e Tecnologie dell’Informazione “Alessandro Faedo” – CNR, Pisa, Italy

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ABSTRACT

Emotions play a central role in the social life of every human being, and their study, which represents a multidisciplinary subject, embraces a great variety of research fields, e.g., from psychology to computer science, among others. Especially concerning the latter, the analysis of facial expressions represents a very active research area due to its relevance to human-computer interaction applications, for example. In such a context, Facial Expression Recognition (FER) is the task of recognizing expressions on human faces. Typically, face images are acquired by cameras that have, by nature, different characteristics, such as the output resolution. Moreover, other circumstances might involve cameras placed far from the observed scene, thus obtaining faces with very low resolutions. It has been already shown in the literature that Deep Learning models applied to face recognition experience a degradation in their performance when tested against multi-resolution scenarios if not properly trained. Since the FER task involves analyzing face images that can be acquired with heterogeneous sources, thus involving images with very different quality, it is plausible to expect that resolution plays an important role in such a case too. Stemming from such a hypothesis, we prove the benefits of multi-resolution training for learning models tasked with recognizing facial expressions. Hence, we propose a two-step learning procedure, named Multi-resolution Approach to Facial Expression Recognition (MAFER), to train Deep Convolutional Neural Networks to empower them to generate robust predictions across a wide range of resolutions. A relevant feature of MAFER is that it is task-agnostic, i.e., it can be used complementarily to other objective-related techniques. Specifically, only the first step of the training concerns a multi-resolution environment, while the second one is problem-objective oriented and can be adapted to specific needs. To assess the ef-

∗Corresponding author
Figure 1: Sketch of the multi-resolution training approach we use to pre-train the VGGFace2 model [5] on the Aff-Wild2 [34] dataset.

Effectiveness of the proposed approach, we performed an extensive experimental campaign on three different publicly available datasets, namely FER2013 [22], RAF-DB [41], and Oulu-CASIA [73]. Concerning a multi-resolution context, we observe that with our approach, learning models improve upon the current state-of-the-art while reporting utterly comparable results regarding fix-resolution contexts. Finally, we analyze the performance of our models and observe the higher discrimination power of deep features generated from them.

Keywords Deep Learning, Facial Expression Recognition, Multi Resolution

1 Introduction

In the last two decades, the automatic analysis of facial expressions revealed a very active research area. Especially, due to the key role that affective analysis plays in several research and industrial applications such as human-computer interactions [29, 6, 58], customer marketing [67, 19], health monitoring [17, 56, 51], etc. Historically, different formalizations of human expressions have been proposed in the literature. On the one hand, they can be considered as points in a continuous space [54, 55, 65, 14], and in such cases, the focus is on arousal and valence. On the other hand, expressions can be interpreted as discrete occurrences that can be used to classify the emotional status of human beings [13].

In this manuscript, we focus on the latter interpretation. Specifically, we consider the so-called six universal expressions [9, 10, 36], i.e., anger, fear, sadness, happiness, disgust, and surprise. In the Machine Learning (ML), and especially in the Deep Learning (DL) scientific community, the ability to discern among different facial expressions is a task known as Facial Expression Recognition (FER). In such a context, learning models aim at classifying the human expressions starting from a face image of the given person.

Face Recognition (FR) is a task that, as FER, involves analyzing facial images. Indeed, even though they have different goals, both tasks aim to classify a person or an expression, starting from the analysis of an image of a human face. Typically, face images are acquired by cameras that have, by their nature, different characteristics such as the output resolution. Moreover, other circumstances might involve cameras placed far from the observed scene, thus returning faces with very low resolution. If such heterogeneity of the input data is not accounted while formulating the training procedure for Deep Convolutional Neural Networks (DCNNs), then it is not guaranteed that the learning models will perform as well as they do in the so-called “controlled” environment, e.g., when images have high resolutions (a context typically realized in lab experiments). Indeed, it has been already shown in the literature [48], that DCNNs suffer from performance degradation when tested against multi-resolution scenarios if not properly trained. Based on such an observation and the similarities between the FER and the FR tasks, we hypothesize that DL models could benefit from multi-resolution training concerning the FER objective too.

In such a context, we propose a learning approach, named Multi-resolution Approach to Facial Expression Recognition (MAFER), to train DCNNs to empower them to generate robust predictions across a wide range of resolutions.
A relevant feature of MAFER is that it is task-agnostic, i.e., it can be used complementarily to other techniques. Specifically, MAFER accounts for a two-step training procedure. A first one, in which the learning model is trained in a multi-resolution environment, and a second one, entirely devoted to the given FER objective at hand. To our aim, the first step is the most interesting since it accounts for the multi-resolution technique. Instead, concerning the second step, we use a standard approach to learn a classifier without designing any specific technique, thus emphasizing the real contribution from the multi-resolution training.

We conceive two flavors for the first training phase. On the one side, we exploit the very same approach presented in [48] and report the performance gain due to the multi-resolution training compared to a base model. Subsequently, we formulate a lighter version of the mentioned approach, which is less resource-demanding, thus making MAFER suitable to any type of FER-related task. Concerning the last formulation, we report a schematic view in Figure 1.

As shown in the red box in Figure 1, to simulate a multi-resolution dataset, MAFER exploits two random extractions. The first one is used to decide whether to downsample the image, and the second one to pick the specific resolution. We refer the reader to section 4 for more details about the multi-resolution training step.

To assess the benefits of our approach, we test the models trained with MAFER against the FER task on three different publicly available datasets, namely, FER2013 [22], RAF-DB [41], and Oulu-CASIA [73]. We observe that with our approach, a learning model improves upon the current state-of-the-art when tested against multi-resolution scenarios. Moreover, we investigate the quality of the deep features generated by models trained with MAFER by visually inspecting them using the t-SNE [46] technique and evaluating commonly used metrics in the context of Content-Based Image Retrieval [12, 62] (CBIR).

Regarding the current manuscript, we can summarize our contributions as follows:

- we propose a multi-resolution procedure, named MAFER, to empower DCNNs to generate robust predictions among a wide range of input face resolution for the FER task;
- we formulate two flavors concerning the first step of MAFER. On the one side, we exploit the same technique as in [48], and on the other, we use that approach as a reference to propose a lighter version for the multi-resolution training step;
- to assess the benefits of MAFER, we test the performance of learning models on the FER2013 [22], RAF-DB [41], and Oulu-CASIA [73] publicly available datasets;
- we show that with our approach, a learning model improves upon the current state-of-the-art when tested against multi-resolution scenarios while it obtains comparable results on fix-resolution contexts;
- we analyze the performance of our models and visually compare the quality of the representations generated by models trained with and without MAFER;
- we perform CBIR experiments to show the effective discrimination capability of the features generated by models trained with MAFER and compare it to the base model.

The remaining part of the manuscript is organized as follows. In section 2, we briefly report works related to our study, while in section 3 we describe the datasets we use. In section 4 and section 5, we report the training procedure and the experimental results, respectively. Finally, in section 6 we outline our conclusions.

2 Related Works

In the last two decades, several approaches have been studied to solve the FER task based on different techniques: handcraft features, shallow and deep models. Although each technique came with its pros, generally, the DL-based ones reach the highest performance.
Local Binary Pattern (LBP) [75, 23], Gabor wavelets [3, 38], Histogram of Oriented Gradients (HOG) [75, 7], distance and angle relation between landmarks [49], to cite a few, are examples of handcraft-features based approaches. Instead, [59, 39, 21] concerns shallow models based approaches.

Although the mentioned approaches reached modest performance, in recent years, DL-based algorithms have become state-of-the-art to tackle the FER task [53]. In 2013, [60] won the ICML face expression recognition challenge [22] by learning an SVM classifier on top of deep architectures used as backbone features extractors. In [28], two CNN are used to detect seven emotions on the Extended Cohn-Kanade [44] Dataset (CK+), Oulu-CASIA [73] and MMI [52] datasets. In [24], the authors use a 3D DCNN followed by a Long Short-Term Memory (LSTM) to analyze and classify facial expressions in videos. To overcome the issues related to typical 2D CNN models, Jeong et al. [27] propose to use a 3D convolution and multiple frames with the normalized LBP feature to extract spatial and temporal features at the same time. In [32], the authors propose a CNN-RNN architecture for valence-arousal (VA) recognition on the Aff-Wild database [70]. A Multi-Task learning algorithm is introduced in [35], to perform action unit (AU), expression (EX), and Valence Arousal (VA) recognition. In [37], the authors propose a multi-task CNN combined with a recurrent neural network for VA and EX recognition.

In [42], the issue of low-resolution face images is tackled. The authors proposed a novel Hierarchical Convolutional Neural Network (HCNN) that hierarchically assembles shallow CNNs with deep CNNs for effective image super-resolution. Instead, [57] proposes an end-to-end network structure for tiny FER, which also exploits super-resolution techniques and encapsulates multiple facial attributes with a feedback mechanism. [45] deals with the problem of facial expression recognition in-the-wild with Convolutional Visual Transformers, while in [1], the authors investigate the effect of facial expressions on the face biometric systems’ reliability. A lightweight mobile architecture and a multi-kernel feature facial expression recognition network, which can take into account the speed and accuracy of real-time facial expression recognition is proposed in [40].

In [8], the authors address the FER task by proposing a hybrid CNN with a Dense Scale Invariant Feature Transform (Dense SIFT) aggregator model that exploits the combination of deep and handcrafted features to increase the accuracy result on the FER2013 [22] and the CK+ [44] datasets. Authors in [47], propose a FER method based on a CNN model with a specially designed pooling layer, which has learnable weights. Using learnable pooling layers with a Gaussian RBF kernel allowed them to outperform state-of-the-art results on the RAF-DB [41] dataset. The problem of intra-class variations and inter-class similarities in FER datasets is addressed in [16] with the introduction of a Deep Attentive Center Loss (DACL) method that adaptively selects a subset of significant feature elements for enhanced discrimination. In [64], the authors propose a Region Attention Network (RAN) to address the problem of occlusion and pose variations in the FER task. This network adaptively captures the importance of facial regions. Furthermore, they annotate several in-the-wild FER datasets with pose and occlusion attributes. The paper [18] propose a method called Annealed Label Transfer for FER task, which makes use of labeled and unlabelled data. Two FER methods are proposed in [71], namely, Weighted Mixture Deep Convolution Neural Networks (WMDCNN) and deep CNN long short-term memory networks of double-channel weighted mixture (WMCNN-LSTM). The first is based on static images, while the second on image sequences. The WMDCNN network model can provide static facial expressions features to the WMCNN-LSTM network, which exploits them to acquire the temporal features of the image sequence in order to realize the accurate recognition of facial expressions.

3 Datasets

In this section of the manuscript, we briefly describe the datasets we employ in our study. Specifically, we use the Aff-Wild2 [34] dataset for training purposes only since it is currently used in the “Affective Behavior Analysis in-the-wild (ABAW) 2020 competition” [33] and for that reason, the ground truth for the test set is not available yet.
3.1 Affect-in-the-Wild 2 (Aff-Wild2)

The Aff-Wild2 [34] dataset is the first-ever database annotated for all of the three main behavior tasks: Valence Arousal (VA), Action Unit (AU), and EXpression (EX) classification. Concerning the last task, the dataset consists of 547 videos (collected from YouTube) for a total of \(\sim 2.5M\) frames shared among the seven available expressions: neutral, anger, disgust, fear, happiness, sadness, surprise. Specifically, “neutral” means that the specific expression cannot be classified as belonging to any of the remaining available six classes. A pool of seven experts manually annotated frame-by-frame all the available images. The dataset is split into three subsets: training, validation, and test, consisting of 253, 71, and 223 videos, respectively. Moreover, cropped and aligned images are already available in the dataset with a resolution of 112x112 pixels. As mentioned above, since the Aff-Wild2 [34] dataset is currently employed in the ABAW 2020 competition [33] the ground truth for the test is not available. Thus, we use this dataset for training purposes only. We refer the reader to section 4 for more details on this topic.

3.2 Facial Expression Recognition 2013 Dataset (FER2013)

FER2013 [22] is a large-scale and unconstrained database containing 28,709 training, 3,589 validation (public test), and 3,589 (private test) test images belonging to seven different classes: anger, disgust, fear, happiness, sadness, surprise, neutral. Images were collected automatically by the Google image search API, and they are characterized by the same resolution equals to 48x48 pixels. In Figure 2, we report a few examples of facial images from the FER2013 [22] dataset.

![Example of face images from the FER2013 dataset](image)

**Figure 2:** Example of face images from the FER2013 [22] dataset. On top of each image, we report the corresponding ground truth expression.

3.3 Real-world Affective Faces (RAF-DB)

The RAF-DB [41] database comprises 29,672 facial images retrieved from the Internet. Concerning the basic emotion recognition task, the images are manually annotated and distributed in seven different classes: surprise, fear, disgust, happiness, sadness, anger, neutral. Moreover, the dataset comprises twelve classes concerning compound emotions. Regarding the basic emotions only, there are in total 15,339 images divided into two groups: training (12,271 samples) and test (3,068 samples). All the aligned face images have the same resolution of 100x100 pixels. In Figure 3, we report a few examples of facial images from the RAF-DB [41] dataset.

3.4 Oulu-CASIA NIR&VIS facial expression database (Oulu-CASIA)

The Oulu-CASIA [73] database consists of 2,880 video sequences involving 80 different subjects aging from 23 up to 58 years old. Face expressions are divided into six classes: surprise, happiness, sadness, anger, fear, and disgust. Each video was captured with two imaging systems, i.e., near-infrared (NIR) and visible light (VIS), considering three different illumination conditions, namely normal, weak, and dark. The resolution of the frames extracted from the videos is 320x240 pixels. Specifically, such a resolution concerns the entire frame and not the face only. Indeed,
Figure 3: Example of face images from the RAF-DB [41] dataset. On top of each image, we report the corresponding ground truth expression.

differently from the previous two datasets, i.e., FER2013 [22] and RAF-DB [41], the Oulu-CASIA [73] dataset allows to test in a natively multi-resolution context since the cropped faces have different resolutions. In Figure 4, we report a few examples of facial images from the Oulu-CASIA [73] dataset.

Figure 4: Example of face images from the Oulu-CASIA [73] dataset. On top of each image, we report the corresponding ground truth expression.

To show the difference among the various datasets that we use to test our training approach, we report the resolution distributions in Figure 5.

As one can notice from Figure 5, both FER2013 [22] and RAF-DB [41] contain face images at the same resolution, namely, 48x48 and 100x100 pixels, respectively. Instead, Oulu-CASIA [73] is characterized by images with different resolutions, thus allowing us to test our approach on a genuine multi-resolution environment.

4 Training Approach

In this section, we describe in detail our experimental procedure. First, we introduce the architecture of our models and then describe the training approach.

Concerning the learning models, we exploit a ResNet-50 [25] architecture, equipped with Squeeze-and-Excitation [26] blocks, that generates 2048-dimensional deep features vectors used to fulfill the classification task.

As mentioned in section 1, our contribution stems from the idea that the FER task might benefit from a multi-resolution training. Thus, we propose the MAFER approach to explicitly leverage images at different resolutions while training a DL model. Specifically, such an approach accounts for a two-step training procedure. First, the DCNN is trained with multi-resolution input data to empower it to generate resolution-robust deep features. Then, a second training step is performed to account for the specific FER task.
Figure 5: Distribution of face resolution concerning the FER2013 [22], RAF-DB [41], and Oulu-CASIA [73] datasets. The distributions are evaluated considering 2000 images for each dataset.

4.1 Multi-resolution Training

Concerning the first training phase, we formulate two different flavors for it. First, we leverage the same procedure as in [48], and then we use it as a reference to propose a lightweight version of the multi-resolution step to make it less resource-demanding. Specifically, a schematic view of the proposed simplified procedure is shown in Figure 1. Compared to the original approach in [48], there are two main differences. On the one hand, we do not use the “Teacher” supervision signal, and on the other, we use the Aff-Wild2 [34] dataset instead of VGGFace2 [5]. We want to stress here that we use the Aff-Wild2 [34] dataset for training purposes only because the ground truth for the test is not available yet as the dataset is currently employed in the ABAW 2020 competition [33]. We refer the reader to subsection 3.1 for more details on the Aff-Wild2 [34] dataset.

4.2 Simplified Multi-resolution Training

We can now focus on the simplified approach to the multi-resolution step proposed in this manuscript (Figure 1). The two random extractions in the red box are used to decide whether to downsample an image and pick its final resolution. The first one is related to the use of the curriculum learning paradigm [4], i.e., we define a growing upper bound for the probability of an image to be downsamplied. Thus, there is a growing probability for the model to be fed with different resolution images while the training proceeds. Instead, the second extraction is used to pick the resolution at which an input image has to be scaled. However, the face is not modified if the extracted resolution is higher than the
Neutral Anger Disgust Fear Happiness Sadness Surprise

| Dataset                | Neutral | Anger | Disgust | Fear | Happiness | Sadness | Surprise |
|------------------------|---------|-------|---------|------|-----------|---------|----------|
| Aff-Wild2 [34]         | 0.365   | 0.975 | 0.986   | 0.988| 0.837     | 0.891   | 0.958    |
| FER2013 [22]          | 0.827   | 0.861 | 0.985   | 0.857| 0.749     | 0.832   | 0.890    |
| RAF-DB [41]           | 0.795   | 0.942 | 0.941   | 0.977| 0.611     | 0.838   | 0.895    |
| Oulu-CASIA [73]       | -       | 0.827 | 0.836   | 0.826| 0.833     | 0.837   | 0.842    |

Table 1: Classes’ weight for each dataset. The values reported are referred to the training set only. Note that weights do not need to sum up to one. The lower the weight, the higher the cardinality of the corresponding class.

initial one. Finally, we want to stress that in the case of the “simplified” flavor, we use the Aff-Wild2 [34] dataset in the first training step.

4.3 Full Training Procedure

As mentioned previously, we use two different formulations for the multi-resolution training phase. Concerning the approach from [48], we use the VGGFace2 [5] dataset, while in the case of the simplified one, we use the Aff-Wild2 [34] dataset. As we report in section 5, the two approaches offer comparable results.

Following the multi-resolution training step, we fine-tuned each model on a given dataset, namely, FER2013 [22], RAF-DB [41], and Oulu-CASIA [73]. We refer the reader to section 3, for a description of the databases used in this study. Since we aim to show the benefits of a multi-resolution approach to the FER objective, we do not apply any special type of training specifically designed for FER, therefore emphasizing the benefits of using a multi-resolution approach. Hitherto, we show in section 5, that our models reach, and in some cases improve upon, state-of-the-art results concerning carefully designed techniques to fulfill the FER task. Moreover, to better emphasize the impact of the multi-resolution training, we train a base model on the second step of MAFER only and report its performance as a baseline for our study.

4.4 Training Hyperparameters

Concerning the first training step on the Aff-Wild2 [34] dataset, we use the Adam [31] optimizer, set the learning rate to $1.e^{-2}$ and $1.e^{-3}$ for the classifier layer and all the convolutional layers, respectively, and the weight decay to $1.e^{-4}$. We validate the model every 200 train iterations so to avoid overfitting, and we drop the learning rates by a factor of 10 every time the accuracy on the validation set sets on a plateau for more than 2000 training iterations. We set the batch size to 256 and consider images with a resolution down to 16 pixels (on the shortest side). Instead, regarding the first training step on the VGGFace2 [5] dataset, we utilize the same protocol as in [48].

Subsequently, we specialize the models on each of the datasets we use to assess its performance. In all these experiments, we use the Adam [31] optimizer, set the learning rate to $1.e^{-2}$ and $1.e^{-4}$ for the classifier layer and all the convolutional layers, respectively, and set the weight decay to $5.e^{-4}$. The only difference here is that, concerning the base model, i.e., the one trained only with the second phase of MAFER, we set the learning rate to $1.e^{-3}$ and $1.e^{-5}$. We use a batch size of 256 and validate the model at the end of each training epoch. Finally, we drop the learning rates by a factor of 10 every time the accuracy on the validation set sets on a plateau for more than ten epochs.

Finally, to allow other researchers to reproduce our results, we will made our code and all the models’ checkpoints available on github².

²https://github.com/fvmassoli/mafer-multires-facial-expression-recognition
4.5 Data Preprocessing and Balancing

Since the datasets we use are not very large, we use data augmentation to preprocess the input data to improve the generalization capabilities of the neural networks. To account for the different properties of the various datasets, we use slightly different transformations for each of them. However, the majority of them are common to all of the datasets. We refer the reader to our GitHub repo for the specific code.

Concerning the common transformations, we resize the images to 224 pixels and then we randomly apply the horizontal flip, image gray-scaling, color jitter, and perspective transformations. Finally, we normalize the pixels value.

In almost all the datasets we consider, the number of images for the various expressions is not balanced. For such a reason, we employ a balancing strategy to avoid the models overfitting on the most populated classes. Specifically, we assign to each expression a weight, in the range $[0, 1]$, evaluated as the inverse of its cardinality. Such weights are then used to balance the cross-entropy loss. In Table 1, we report the class cardinality and weights for each of the datasets we employ.

5 Experimental Results

In this section, we report the results of our experimental campaigns. However, we first briefly describe the various metrics we employ.

5.1 Metrics

To properly compare our results with other authors, we adopt the most commonly used metrics found in the literature. Concerning the FER2013 [22], we report the accuracy on the test set, while on the Oulu-CASIA [73] dataset, since it is not shipped with a test partition, we use a k-fold protocol to evaluate the average accuracy. Specifically, we set $k=10$. Finally, concerning the RAF-DB [41], we evaluate the accuracy considering two different protocols: overall accuracy, evaluated on all the classes at once, and average accuracy, evaluated on every single class separately and averaged among them. First, we report the accuracy of the whole test set, then we evaluate the accuracy of each class and then quote the average among them. Finally, we evaluate the Precision@k and the mean Average Precision (mAP) concerning the CBIR context. The Precision@k is defined as the portion of the retrieved items in the k-set that are relevant and is given by:

$$\text{Precision}@k = \frac{(k - \text{Retrieved} \cap \text{Relevant})}{k - \text{Retrieved}}$$  \hspace{1cm} (5.1)

Instead, the mAP quantifies how good the model is at answering the query. Mathematically, it is defined as:

$$\text{mAP} = \frac{\sum_{q=1}^{Q} \text{AP}(q)}{Q}$$  \hspace{1cm} (5.2)

where $Q$ is the number of queries and AP(q) is the Average Precision for a given query “q”. The AP measures the average relevance scores for a set of items returned as answer to a query. Concerning the set of k-retrieved items, the AP is given by:

$$\text{AP} = \frac{1}{GTP} \sum_{i=0}^{k} (p@i \cdot \text{rel}@i)$$  \hspace{1cm} (5.3)
where GTP is the total number of relevant items, k is the number of retrieved items (that can be equal to the size of the whole dataset), p@i is defined in Equation 5.1, and rel@i is a relevance function which is 1 if the i-th item is relevant and 0 otherwise.

5.2 Experimental Results

Concerning the FER task, we report the experimental results on the FER2013 [22], Oulu-CASIA [73], and RAF-DB [41] datasets in Table 2, Table 3, and Table 4, respectively. In all of the mentioned tables, we report the performance of the models trained with MAFER alongside the best results available in the literature.

Regarding our models, we quote the results from four different experiments on each dataset. First, we apply the second step only to the “base” model to have a baseline to compare with. In our case, we use the Se-ResNet-50 from [5] as the base model. Subsequently, we consider three different training configurations. Concerning the first step of MAFER, we first employed the same technique as in [48], and we name the model “CR”. Then, we formulated a lightweight version for the multi-resolution step and named the model as “CR-Simplified”. Finally, to ensure that the gain in the performance of our models is not due to the given dataset used in the first training step, we finetune the “CR” model on the Aff-Wild2 [34] dataset and name it “CR+AffWild2”. Then, all the models are specialized on the given FER dataset during the second step of MAFER.

| Authors          | Accuracy (%) |
|------------------|--------------|
| Tang et al. [60] | 71.20        |
| Mahmoudi et al. [47] | 71.35 |
| Yu et al. [69]+† | (72.00)      |
| Kim et al. [30]† | (72.72)      |
| Connie et al. [8] | 73.40        |
| Luan et al. [43] | 74.14        |
| Luan et al. [43]+† | (76.82)    |
| base             | 60.82        |
| MAFAR            |              |
| CR               | 73.06        |
| CR-Simplified    | 72.33        |
| CR+AffWild2      | 73.45        |

*Results from [20]
†Should not be directly compared with others since the results come from ensembles of models.

Table 2: Results on the FER2013 [22] dataset. We emphasize in bold the performance of the best model.

As we can see from Table 2, Table 3, and Table 4, the results reported by the three configurations we tested are compatible among them, thus witnessing that the main source of improvement upon the base model is due to the multi-resolution nature of the training and not to the specific dataset used in such a first training step. We can derive two more fundamental conclusions from our results. First, we acknowledge that our models perform better than the current state-of-the-art when considering natively multi-resolution test scenarios. We can appreciate such a result from Table 3. Indeed, among the considered test datasets, Oulu-CASIA [73] is the only one that is shipped with images at very different resolutions, as reported in Figure 5. Especially, we acknowledge that on the Oulu-CASIA [73] dataset, our best model improves upon the current state-of-the-art by \( \sim 6\% \). Instead, concerning fix-resolution scenarios, i.e., FER2013 [22] and RAF-DB [41], our models deliver utterly comparable performance. Again, it is important to stress that our training approach is completely agnostic of the final task, while the ones we are comparing to were specifically designed for the task at hand. Finally, we can particularly pay attention to the results reported by Mahmoudi et al. [47]
### Authors Accuracy (%)

| Authors             | Accuracy (%) | 10-fold Averaged |
|---------------------|--------------|-------------------|
| Zhao et al. [74]    | 84.59        |                   |
| Ding et al. [11]    | 87.71        |                   |
| Zhang et al. [72]   | 86.25        |                   |
| Zhang et al. [71]   | 86.00        |                   |
| Ming et al. [50]    | 89.60        |                   |
| Yu et al. [68]      | 90.40        |                   |
| Yang et al. [66]    | 92.89        |                   |
| base                | 59.84 ± 1.29 |                   |

**MAFAR**

|          |               |                  |
|----------|---------------|------------------|
| CR       | 98.40 ± .11   |                  |
| CR-Simplified | 96.72 ± .24  |                  |
| CR+AffWild2 | 98.95 ± .15  |                  |

**Table 3:** Results on the Oulu-CASIA [73] dataset. We emphasize in bold the performance of the best model. If we improve upon the current state-of-the-art with more than one model, we underline the highest performance.

| Authors             | Overall | Average          |
|---------------------|---------|------------------|
| Vo et al. [63]      | 88.98   | 80.78            |
| Farzaneh et al. [16]| 87.78   | 80.44            |
| Farzaneh et al. [15]| 86.90   | 79.71            |
| Florea et al. [18]  | 84.50   | 76.50            |
| Mahmoudi et al. [47]| 93.21   |                  |
| Wang et al. [64]    | 86.90   |                  |
| base                | 77.09   | 65.39 ± 9.83     |

**MAFAR**

|          | Overall | Average          |
|----------|---------|------------------|
| CR       | 88.43   | 81.90 ± 4.12     |
| CR-Simplified | 88.14   | 83.16 ± 2.92     |
| CR+AffWild2 | 88.07   | 82.40 ± 3.74     |

**Table 4:** Results on the RAF-DB [41] dataset. We emphasize in bold the performance of the best model. If we improve upon the current state-of-the-art with more than one model, we underline the highest performance.

In Table 2 and Table 4, we see that the mentioned authors reported a value for the overall accuracy higher than ours concerning images at a resolution of 100x100 pixels. Interestingly, from Table 2, we see that our models perform better than theirs. We can interpret such results by saying that a multi-resolution approach gives more robust features at low resolutions, as in the case of the FER2013 [22] dataset, than models that are trained at a specific resolution. Perhaps, we can explain such behavior by observing that images at lower resolutions carry less discriminative information than the ones at higher resolutions. Thus, training focused on such input data might lead the model to a worse optimizer compared to when images at high resolution are used, too, as in our case.

### 5.3 Models Analysis

In this subsection, we delve deeper into our DCNNs’ performances by analyzing their predictions. In Figure 6, Figure 7, and Figure 8, we report the confusion matrices for all the four models we trained on the FER2013 [22], Oulu-CASIA [73], and RAF-DB [41] datasets, respectively. By looking at the figures, a common pattern emerges. All the multi-resolution-trained models perform better than the base one on all of the classes. Moreover, we can appreciate that the models behave properly on all classes, meaning that we properly balanced them during the training. The only
exception is accuracies on the “fear” and “disgust” classes of the RAF-DB [41] dataset. Specifically, concerning the two mentioned expressions, most mistakes are due to their misclassification as “sadness”.

![Figure 6](image1)

Figure 6: Confusion matrices for the classes’ accuracy on the FER2013 [22] dataset. The title of each plot refers to the analyzed model. We emphasize with the symbol “†” the least populated (minority) classes.

![Figure 7](image2)

Figure 7: Confusion matrices for the classes’ accuracy (10-fold averaged) on the Oulu-CASIA [73] dataset. The title of each plot refers to the analyzed model.

![Figure 8](image3)

Figure 8: Confusion matrices for the classes’ overall accuracy on the RAF-DB [41] dataset. The title of each plot refers to the analyzed model. We emphasize with the symbol “†” the least populated (minority) classes.

Subsequently, we exploit the t-SNE [46] technique to visually inspect and compare the deep representations generated by the base model and the ones trained with MAFER. The results are reported in Figure 9 concerning the Oulu-CASIA [73] dataset.

As we can see from Figure 9, the base model cannot separate well the various classes while the other models do a pretty good job. Such a result is of fundamental relevance since we generate the representations using images from the Oulu-CASIA [73] dataset that natively offers a multi-resolution test environment being its images characterized by different resolutions Figure 5. Moreover, by comparing the multi-resolution models, we can see that “CR-Simplified” performs comparably to the others, thus sustaining our proposal of a simplified version of the multi-resolution training step.
5.4 Content-Based Image Retrieval

Finally, we conclude the section on the experimental results by testing our models against the CBIR task [12, 62, 2, 61, 12] on the Oulu-CASIA [73] dataset. We choose such that dataset since, as reported in subsection 3.4, it contains images at different resolutions. As reported in subsection 5.1, we evaluate the Precision@k and mAP. Concerning the first one, we report results considering \(k \in \{1, 5, 10, 50, 100\}\). To our knowledge, we are the first to perform such a test. Thus we cannot compare to results from other authors. However, we assess the benefits of the multi-resolution training by comparing the “base” model results. Concerning the CBIR protocol, we apply the following procedure. We randomly select 20 correctly classified images for each expression class for each model to use as queries. Then, the remaining faces are used to train a k-NN classifier. Concerning the k-NN, we use the implementation available from the python package scikit-learn, use the euclidean distance as a similarity measure, and set \(k=3\).

Concerning the Precision@k and mAP, we report the results in Table 5.

| Model         | Precision@k (%) | mAP      |
|---------------|-----------------|----------|
|               | 1   | 5   | 10 | 50 | 100 |       |
| base          | 83.3 ± 3.4 | 67.0 ± 2.9 | 60.2 ± 2.5 | 49.0 ± 1.8 | 42.2 ± 1.4 | 35.4 ± 1.1 |
| MAFAR         |     |     |     |     |     |        |
| CR            | 95.8 ± 1.8 | 92.2 ± 2.0 | 89.8 ± 2.2 | 84.4 ± 2.5 | 80.3 ± 2.4 | 70.8 ± 1.5 |
| CR-Simplified | 100 ± 0.0 | 98.5 ± 0.8 | 96.9 ± 1.0 | 91.5 ± 1.8 | 88.0 ± 2.0 | 78.6 ± 1.5 |
| CR+AffWild2   | 99.2 ± 0.8 | 98.5 ± 0.7 | 97.8 ± 0.8 | 93.6 ± 1.3 | 89.5 ± 1.5 | 79.6 ± 1.7 |

Table 5: Precision@k and mAP for the Oulu-CASIA [73] dataset. Concerning the Precision@k, we report results for \(k \in \{1, 5, 10, 50, 100\}\). Each value represents the average over 120 queries (20 for each class). We emphasize in bold the performance of the best model.

As we can from Table 5, the performances of the models trained with MAFER are superior to the base model, thus confirming the effectiveness of a multi-resolution approach. Moreover, we can appreciate that the model learned with the “simplified” version of the training reports comparable performance to the other “CR-” models, thus confirming our hypothesis that, in the case of FER, it is possible to simplify the approach proposed in [48]. Especially, we observe that the performances of the “CR-Simplified” and “CR+AffWild2” agree within the errors.

6 Conclusion

Within the deep learning community, the automatic analysis of human facial expressions is an active research area, primarily due to its relevance to several applications as human-computer interactions, customer marketing, and health
monitoring, among others. In such a context, we conjecture that deep learning models tasked with FER might benefit from a multi-resolution training approach. To prove that it is indeed the case, we conducted an extensive experimental campaign on publicly available datasets, namely, FER2013, RAF-DB, and Oulu-CASIA. Thus, we propose a two-step training procedure, named MAFER, which directly leverages a multi-resolution learning technique. By adopting MAFER, our models improve upon the current state-of-the-art in multi-resolution scenarios and obtain utterly comparable performance in fix-resolution contexts. Notably, we acknowledge the \(\sim 6\%\) improvement of the accuracy on the Oulu-CASIA dataset. To better emphasize the benefits of the multi-resolution training step, we trained our models with four different configurations, namely, “base”, “CR”, “CR-Simplified”, and “CR+AffWild2”. By looking at the obtained results, we can conclude that the multi-resolution training empowers deep learning models to generate predictions for FER that are robust against a wide range of resolutions. Finally, we analyze our models to assess their performance better. As a first remark, we observe that the behavior of our models is well balanced among the various classes. Then, we visually inspect the quality of the deep features, i.e., how well they can be separated when belonging to different classes, by exploiting the t-SNE technique. From such an analysis, one can notice that the features generated by the model trained with MAFER are much better separated than the ones generated by the “base” model. We can interpret such a result by asserting that MAFER empowers deep learning models to generate discriminative features robust against variations in the resolutions of the input images. Finally, to numerically sustain the higher discriminability of deep representations generated by models trained with MAFER compared to the base model, we quote the Precision@k, Recall@k, and mAP in the context of CBIR. To perform such tests, we use the OULU-Casia dataset since it contains images at different resolutions. The experimental results confirm, also in this case, that the image resolution plays a relevant role in the context of FER and that learning models benefit from a multi-resolution approach.

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