Assessing Accuracy of Ensemble Learning for Facial Expression Recognition

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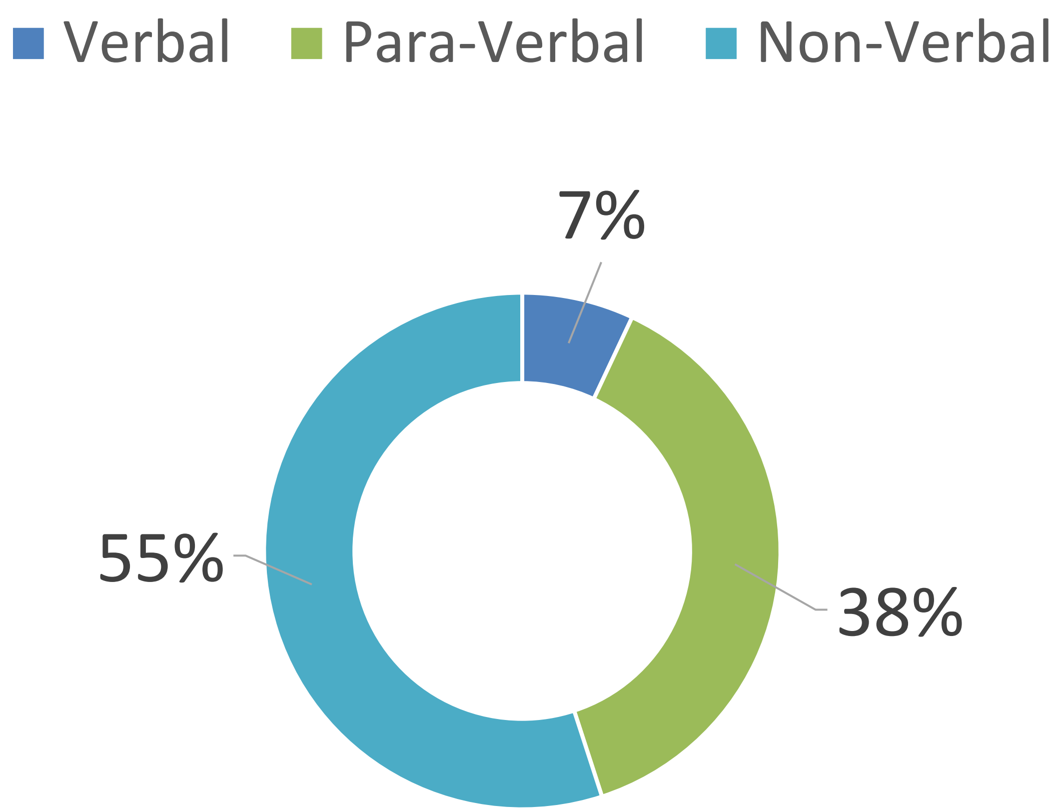
How We Communicate Our Feelings



Facial Expressions of Emotions

Paul Ekman and Friesen Wallace
Constants across cultures in the face and emotion
Journal of personality and social psychology 17.2 (1971): 124.

- **Universality** of Facial Expressions of Emotion
- Definition of a List of **Basic Emotions**

from http://ocw.mit.edu/courses/brain-and-cognitive-sciences/9-00sc-introduction-to-psychology-fall-2011/emotion-motivation/discussion-emotion

Automatic Facial Expression Recognition

A challenging task:
- Facial Expressions Recognition (FER) from **facial images *in-the-wild***

Fields of **Applications**:
- Human Comuputer Interaction
- Sentiment Analysis
- Behaviomedics
- Deceit Detection
- Emotional Health
- Data Analyitics

Outline

1. Introduction to the traditional and modern approaches to the FER problem
2. Motivations and Objectives
3. Our Experimental Setup
   - FER2013 *in-the-wild* dataset
   - Ensemble Design Strategies under different scenarios
4. Results and Conclusions

Traditional approaches to the multi-class Image Classification Problem

Pre-Processing

- Face Detection
- Face Registration

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Features Extraction

- **Hand Crafted Features**
- Useful, Discriminative Representation

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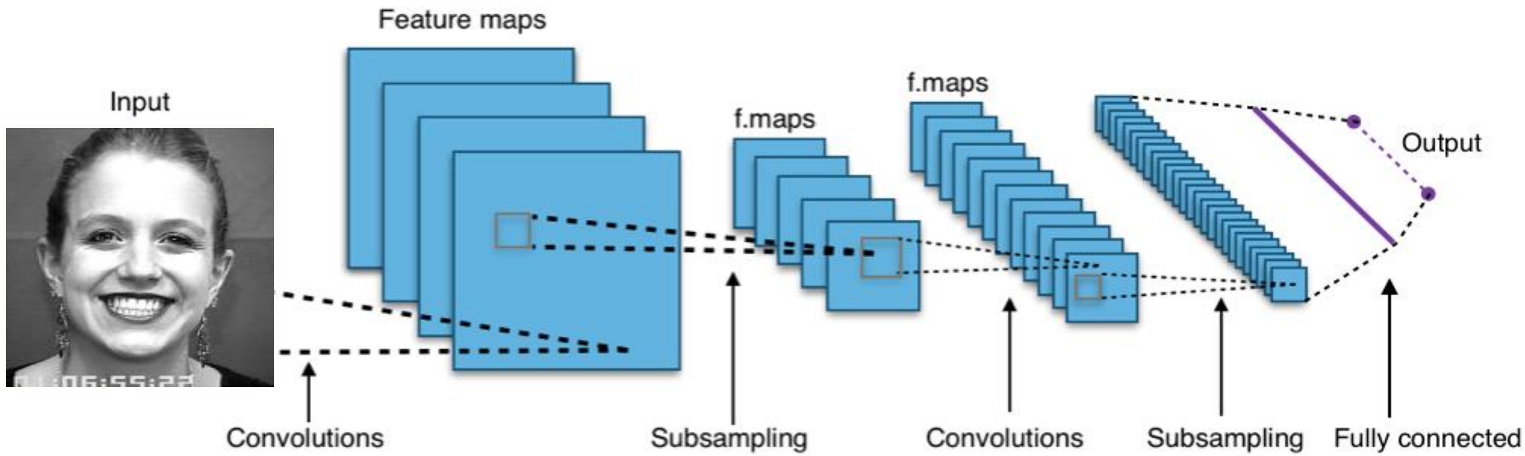
Classification

- N-Way Classification

Deep Learning approach



Convolutional Neural Networks (CNNs)

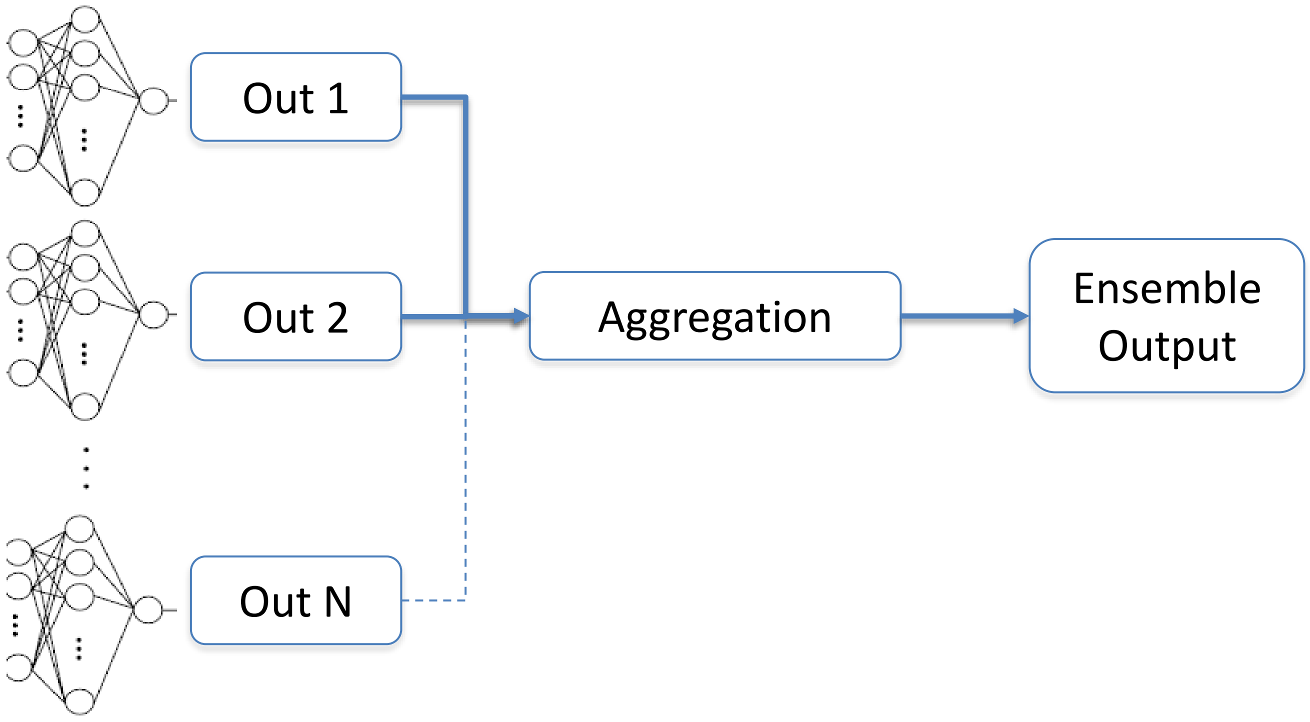
- Automatic learning a **hierarchical features representation**
- **Excellent results** in a wide variety of similar problems
- Represent state-of-the-art also for FER

Drawback:

- Typically rely on ***large* collection of labeled data** for training
- Available FER datasets have limited size

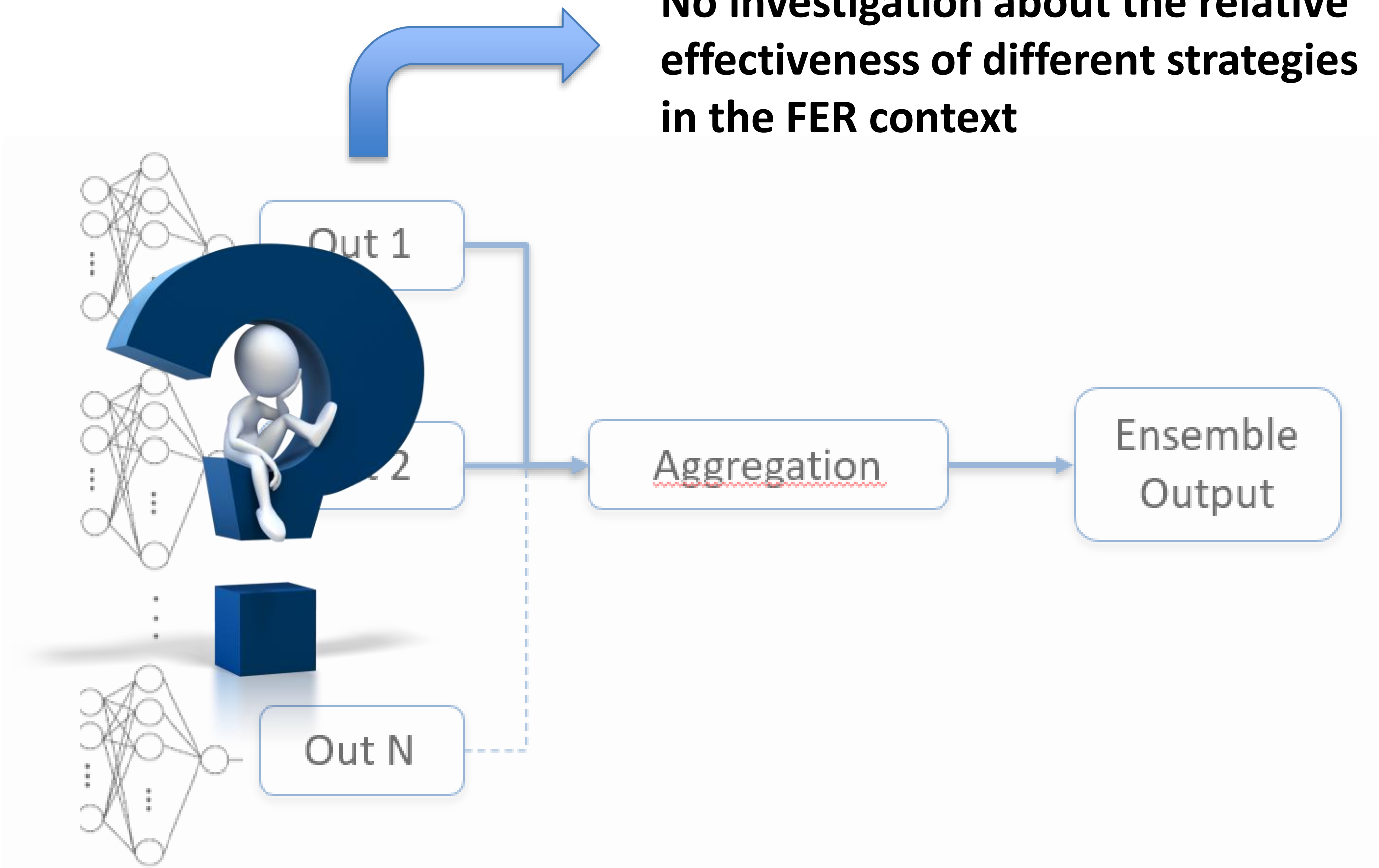
Ensemble Techniques

- Widely exploited in Neural Networks to **boost classification performances**
- Exploit diversity of base classifiers



Ensemble Techniques

No investigation about the relative effectiveness of different strategies in the FER context



Objectives of our work

- Tackling FER problem
  exploiting Ensembles of Deep Convolutional Neural Networks

- Comparative study: Assessing accuracy of two simple techniques to generate diversity across the base classifiers of an ensemble

- Medium-size dataset: Considering two distinct scenarios:
  1. Training from scratch an ad-hoc architecture
  2. Fine-tuning a pre-trained state-of-the-art model

FER-2013: Facial Expressions Dataset

- One of the **largest collection of *in-the-wild* facial images**
- Consisting in **35.876 images** from **7 classes:**

Training Set	28699
Validation Set	3588
Test Set	3589

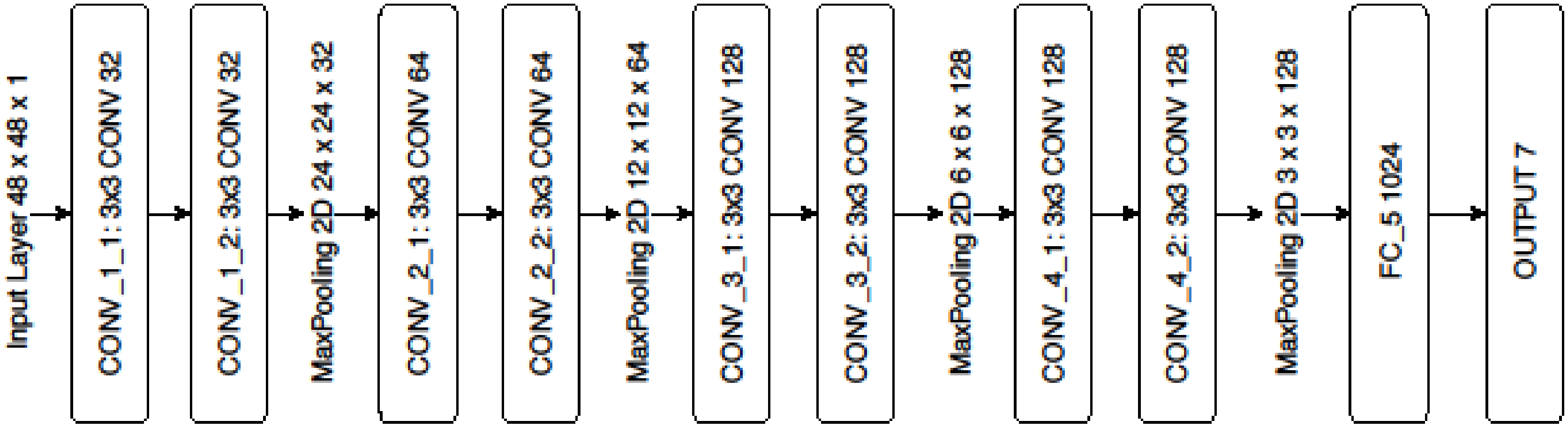
Neutral	6197
Anger	4945
Disgust	547
Fear	5121
Happiness	8988
Sadness	6076
Surprise	4001

- Average Human Accuracy: 65%
- State-of-the-art Accuracy: 75.2% [1]

[1] C. Pramerdorfer and M. Kampel, "Facial expression recognition using convolutional neural networks: State of the art," arXiv preprint arXiv:1612.02903, 2016

First Scenario: CNN10-S

- **Training from scratch an Ad Hoc Architecture**
  - 10 layers, ~ 1.7M parameters
  - Mimics VGG-B architecture, inspired to [1]

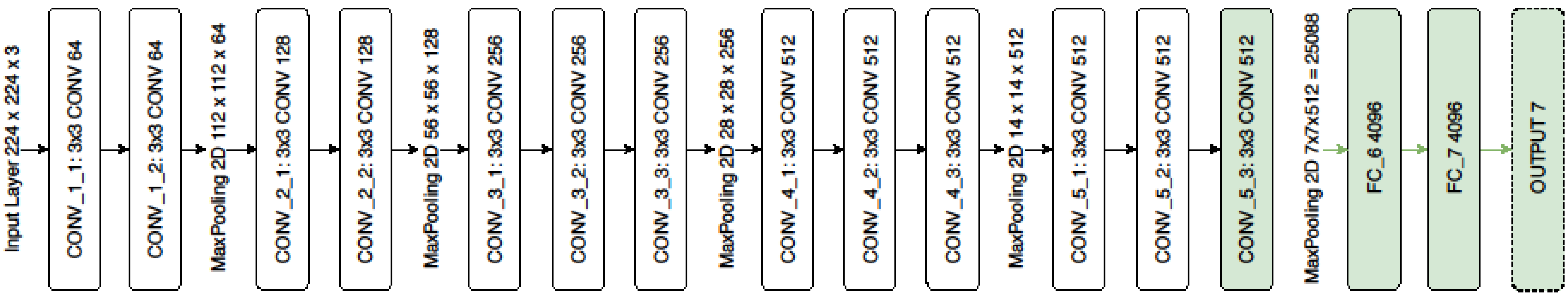


[1] C. Pramerdorfer and M. Kampel, "Facial expression recognition using convolutional neural networks: State of the art," arXiv preprint arXiv:1612.02903, 2016

Second Scenario: VGG16-FT

- **Fine-tuning a Pretrained Model**
  - VGG16 architecture
  - 16 layers, ~130M parameters
  - *Pretrained* on a Face Recognition dataset [1] of 2.6M images

A) Remove original output layer. Add custom output layer (7 units)
B) Train the output layer. Freeze all hidden layers
C) Fine-tune the final (green) layers. Freeze the white layers



O.M. Parkhi et al., Deep face recognition. *BMVC*. Vol. 1. No. 3. 2015.

Two Ensemble Design Strategies: SE - PS

- Fixed size ensemble of **nine networks**
- **Three repetitions** for each strategy and for each scenario

Seed Strategy (SE)

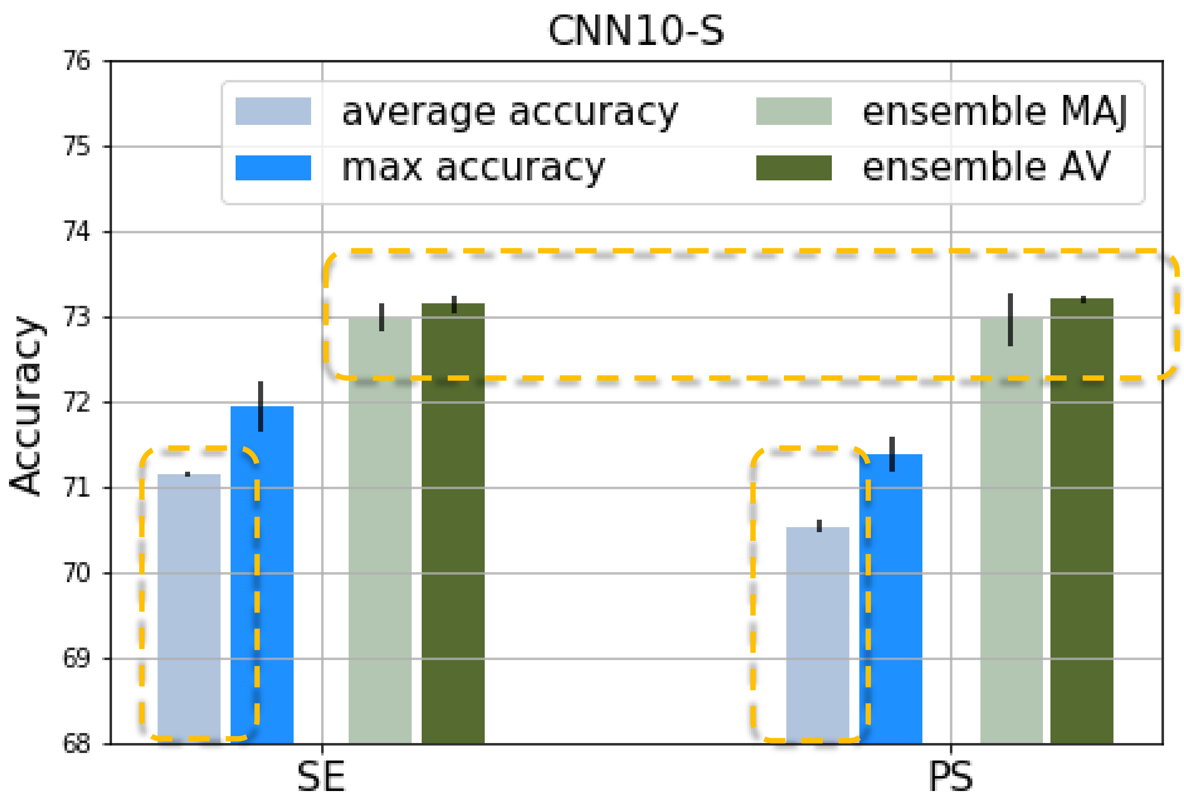
SEED 1	NET 1
SEED 2	NET 2
SEED 3	NET 3
SEED 4	NET 4
SEED 5	NET 5
SEED 6	NET 6
SEED 7	NET 7
SEED 8	NET 8
SEED 9	NET 9

Preprocessing Strtegy (PS) [1]

	SEEED 1	**SEEED 2**	**SEED 3**
DEFAULT 	NET 1	NET 2	NET 3
HISTEQ 	NET 4	NET 5	NET 6
INOR 	NET 7	NET 8	NET 9

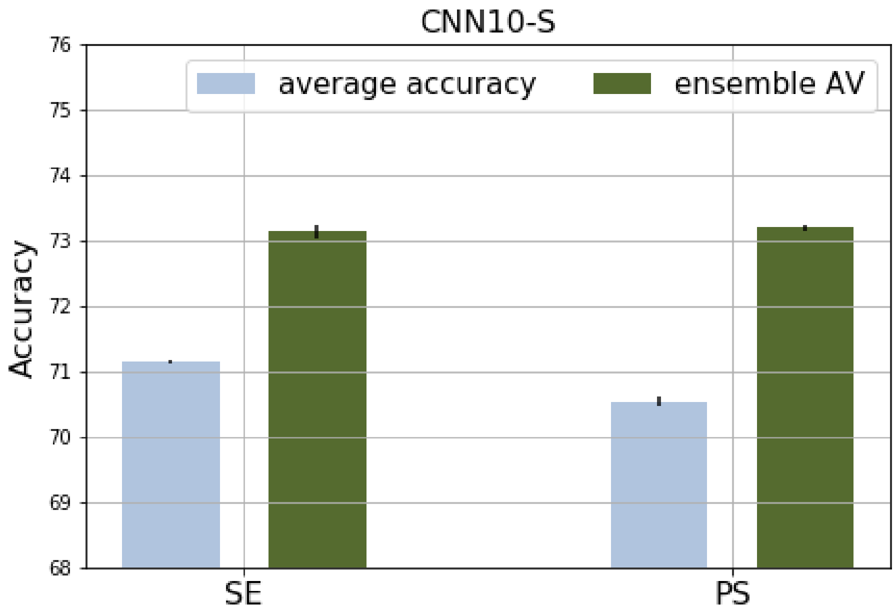
[1] B.-K. Kim et al., Fusing aligned and non-aligned face information for automatic affect recognition in the wild: A deep learning approach, Proc. Of the IEEE Conf. on Computer Vision and Pattern Recognition Workshops, 2016, pp. 1499{1508. doi:10.1109/CVPRW.2016.187.

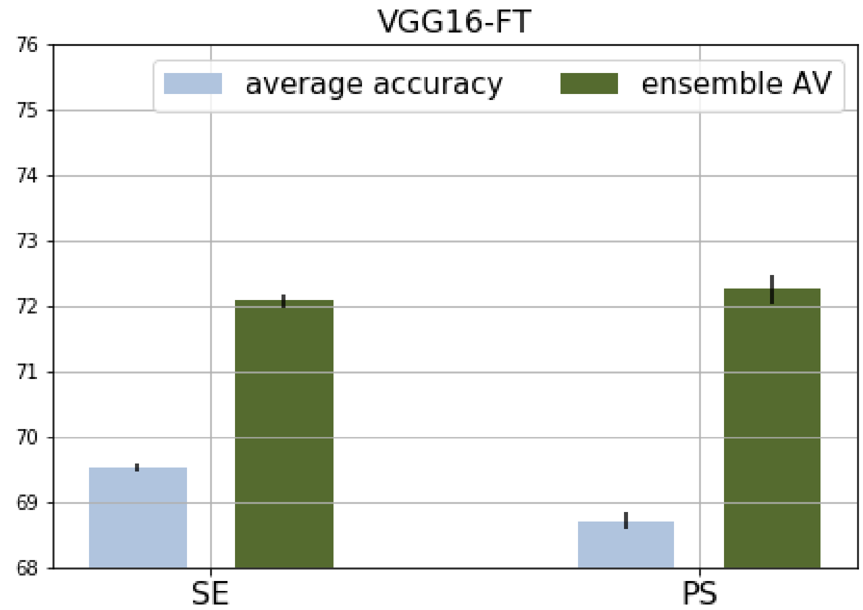
Experimental Results



- Average and Majority voting lead to comparable results
  - The higher variability among networks, the higer ensemble gain

Experimental Results

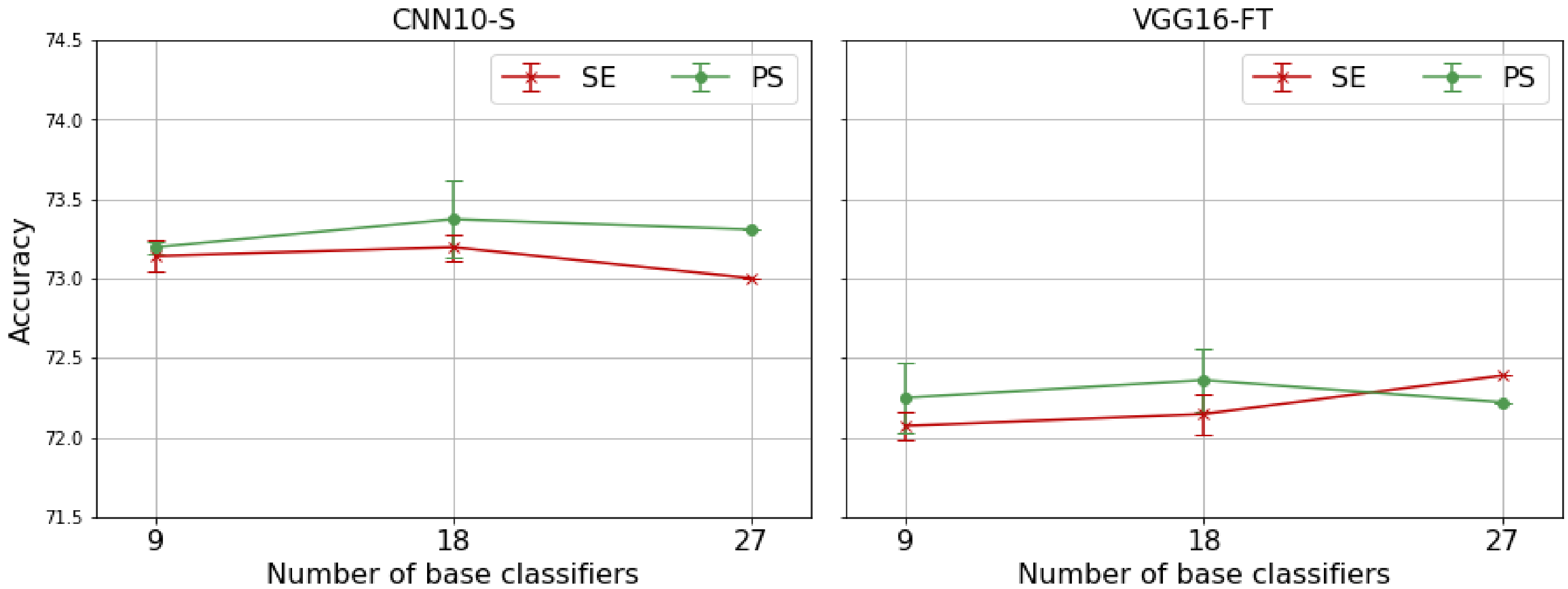




- CNN10 **trained from scratch outperforms the fine tunend** VGG16 model
  - in terms of Base Classifiers
  - In terms of Ensemble Classifiers

Increasing the number of base classifiers

- **3 repetitions** for each strategy, for each scenario → 27 networks



- In general, **no significant benefit** when increasing ensemble size

Conclusions

- Task: *in-the-wild* Facial Expression Recognition
- Assessing the accuracy of different approaches of Ensemble Learning:
  - **Two ensemble design strategies** (SEED vs PREPROCESSING) **achieve comparable results**
  - Two training scenarios (CNN10-S vs VGG16-FT): **Training an ad hoc model from scratch is an appropriate choice in the considered setting**

- Further investigation:
  - Other state-of-the-art models
  - Other pretraining datasets
  - Other factors of variation in the ensemble

Thank you for your attention

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