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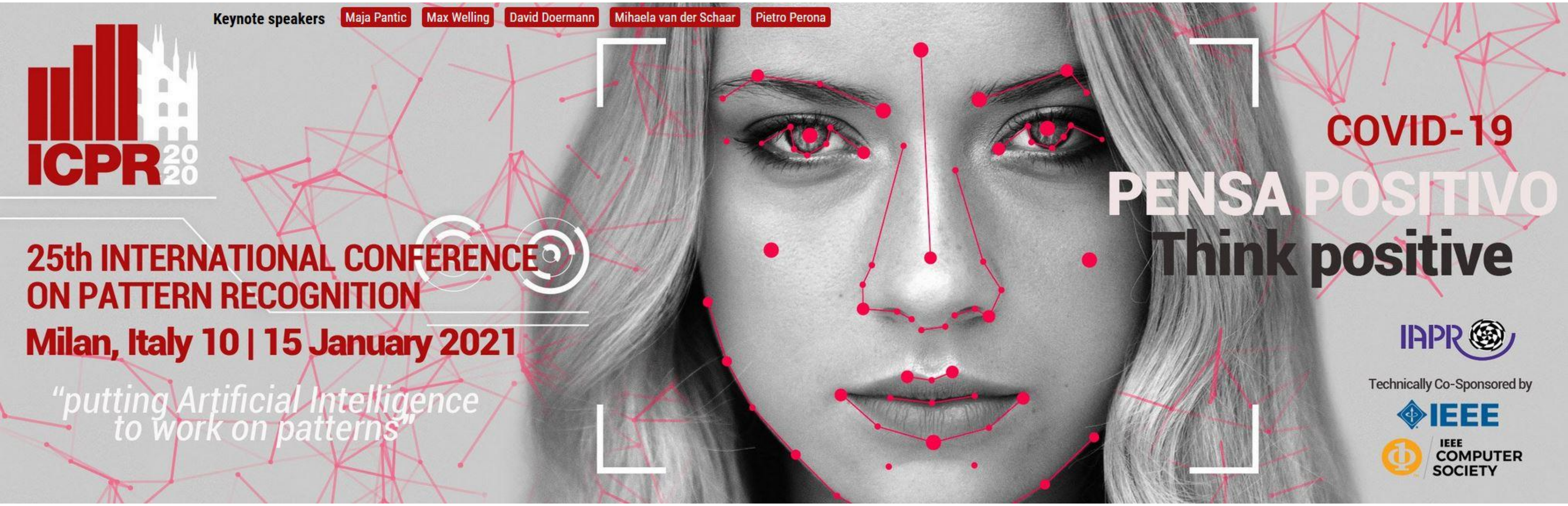

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Using Meta Labels for the Training of Weighting Models in a Sample-Specific Late Fusion Classification Architecture

Agenda

- Late Fusion Architectures
- Proposed Approach
- Results
- Conclusion & Future Work

LATE FUSION ARCHITECTURES

Late Fusion Architectures – Formalisation

- $X \subset \mathbb{R}^d$, $d \in \mathbb{N}$: d-dimensional data set
- $\Omega = \{\omega_1, \ldots, \omega_c\}$, $c \geq 2$: class label set
- $m \in \mathbb{N}$: number of feature subsets

- CM_i: classification model that is trained on feature subset i
- The outputs of $\{CM_1, \ldots, CM_m\}$ are combined for the final prediction

- In general: each CM_i is a **strong** model (LF combines *ensembles*)

Late Fusion Architectures – Example

Affect recognition or pain detection tasks with person-specific data

- Audio
- Video
- Physiology

$\Rightarrow m = 3$

Train 3 strong models in combination with each modality

PROPOSED APPROACH

Proposed Approach – Basic Idea

- Divide the training subsets $X_1, \ldots, X_m$ into
  - $T_1, \ldots, T_m$: Training Sets
  - $V_1, \ldots, V_m$: Validation Sets
- The output of CM_i on V_i defines the labels for Weighting Model WM_i

$$\tilde{y}_{i,j} := \begin{cases} 1, & \text{if } \mathrm{CM}_i(v_j) \rightsquigarrow y_j, \\ 0, & \text{otherwise.} \end{cases}$$

- The class-support vector for input $x \in \mathbb{R}^d$ is calculated as

$$\mu(x) = \sum_{i=1}^{m} s_i^{(1)}(x) \cdot \mathrm{CM}_i(x)$$

Proposed Approach – Training Phase

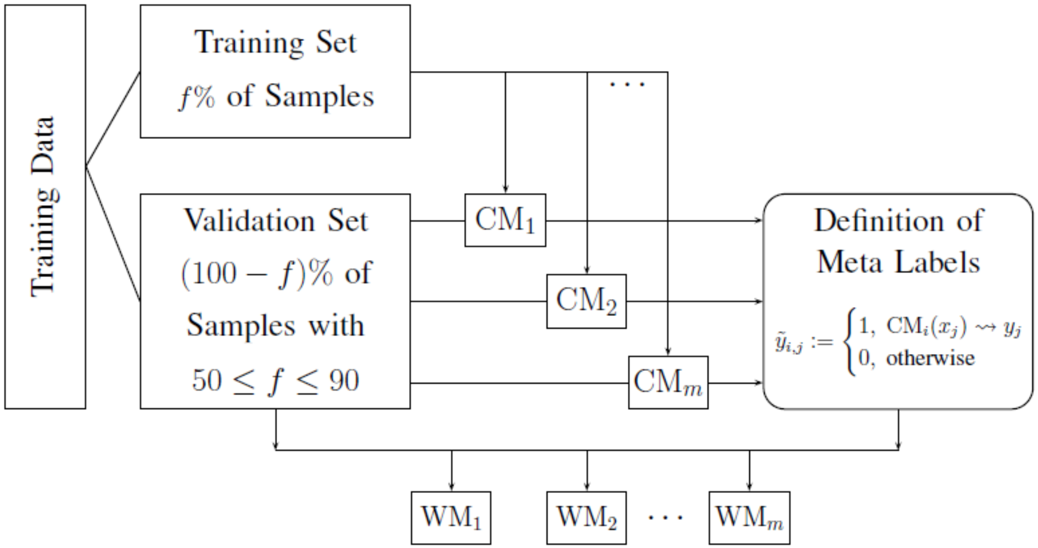

Fig. 2: **Training Phase of our Approach - System Diagram**. CM_i: Classification model i. WM_i: Weighting model i. Each model WM_i is trained on the validation set, in combination with an individual vector of corresponding meta labels.

$$\mu(x) = \sum_{i=1}^{m} s_i^{(1)}(x) \cdot \mathrm{CM}_i(x)$$

RESULTS

Data Sets Overview

Data Set	# Classes	# Samples	# Features	# Channels
BioVid	2	3480	194	3
Mfeat	10	2000	649	6
Arrhythmia	2	452	274	4
Fisher Iris	3	150	4	4

Experimental Settings

- **Classifier Choice** Bagged Decision Tree (DT) Ensemble
- **Classification Models**
  - BioVid 200 DTs per Channel
  - Remaining Sets 100 DTs per Channel
- **Weighting Models** 100 DTs per Channel
- **Measure** Accuracy

Results – Accuracy Performance

TABLE V: **Mean accuracy and standard deviation values in %.** The best performing method is depicted in bold. CV: Cross Validation. LOPO: Leave-One-Participant-Out. The early fusion corresponds to Breiman's bagging approach.

Data Set	CV	Early Fusion	Late Mean	Our Approach
BVDB	LOPO	81.90 ± 15.2	82.93 ± 16.0	$\mathbf{83.94 \pm 15.3}$
Mfeat	20-fold	96.02 ± 1.64	97.60 ± 1.47	$\mathbf{98.00 \pm 1.34}$
ARR	20-fold	74.62 ± 7.86	75.15 ± 10.6	$\mathbf{76.48 \pm 8.93}$
Iris	10-fold	94.39 ± 4.10	95.33 ± 5.49	$\mathbf{96.67 \pm 4.71}$

Results – Operational Cost

TABLE VI: **Averaged training and testing time in s**. The faster performing method is depicted in bold.

Approach	BVDB	Mfeat	ARR	Iris
Late Mean	21.8 ± 0.3	$\mathbf{12.5 \pm 0.3}$	$\mathbf{2.53 \pm 0.2}$	$\mathbf{1.45 \pm 0.1}$
Our	$\mathbf{20.2 \pm 0.3}$	13.9 ± 0.3	4.29 ± 0.3	3.00 ± 0.2

Conclusion & Future Work

- The proposed approach is a valid alternative for trainable LFs
- This approach can be formulated as a plain ensemble method

- In Future work we aim to analyse the effectiveness of confidence

$$\tilde{s}_i(x) = \begin{cases} s_i^{(1)}(x), & \text{if } s_i^{(1)}(x) \geq \theta, \\ 0, & \text{otherwise.} \end{cases}$$

$$\tilde{s}_i(x) = \begin{cases} +s_i^{(1)}(x), & \text{if } s_i^{(1)}(x) \geq \theta_2, \\ 0, & \text{if } s_i^{(1)}(x) \in (\theta_1, \theta_2), \\ -s_i^{(1)}(x), & \text{if } s_i^{(1)}(x) \leq \theta_1. \end{cases}$$

THANK YOU VERY MUCH FOR LOOKING AT THE SLIDES ☺

PLEASE FEEL FREE TO POST YOUR QUESTIONS!