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An Audiovisual Child Emotion Recognition System for Child-Robot Interaction Applications

Panagiotis P. Filntisis[1], Niki Efthymiou[1], Gerasimos Potamianos[2], and Petros Maragos[1]

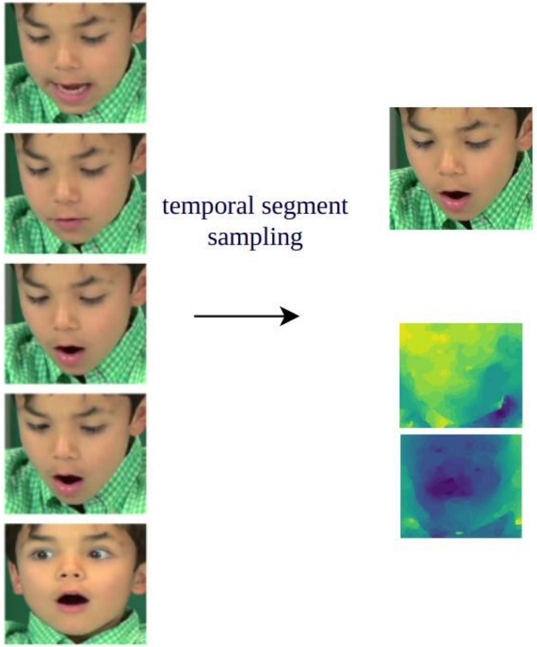
[1]School of ECE, National Technical University of Athens, 15773 Athens, Greece
[2]Department of ECE, University of Thessaly, 38221 Volos, Greece

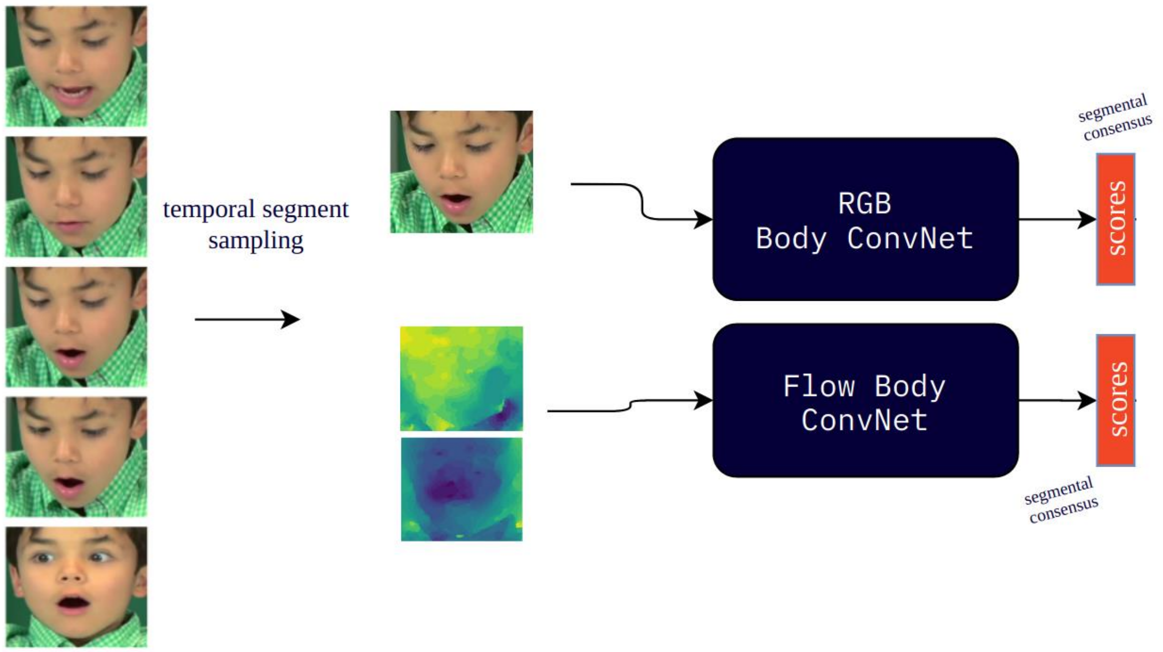
Motivation & Challenges

- Emotion is a fundamental aspect of human communication
- Empathic Robots create stronger bonds with children
- Children present different behavioral patterns compared to adults
  - Use of multiple modalities can help
- Human-robot communication requires real time performance

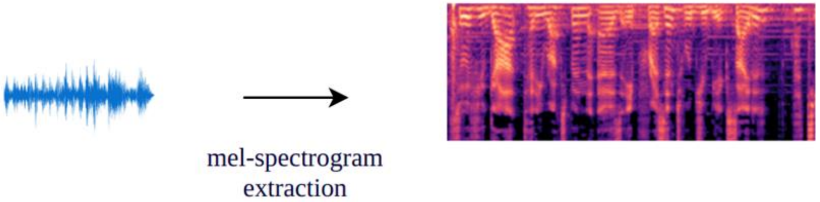

Method

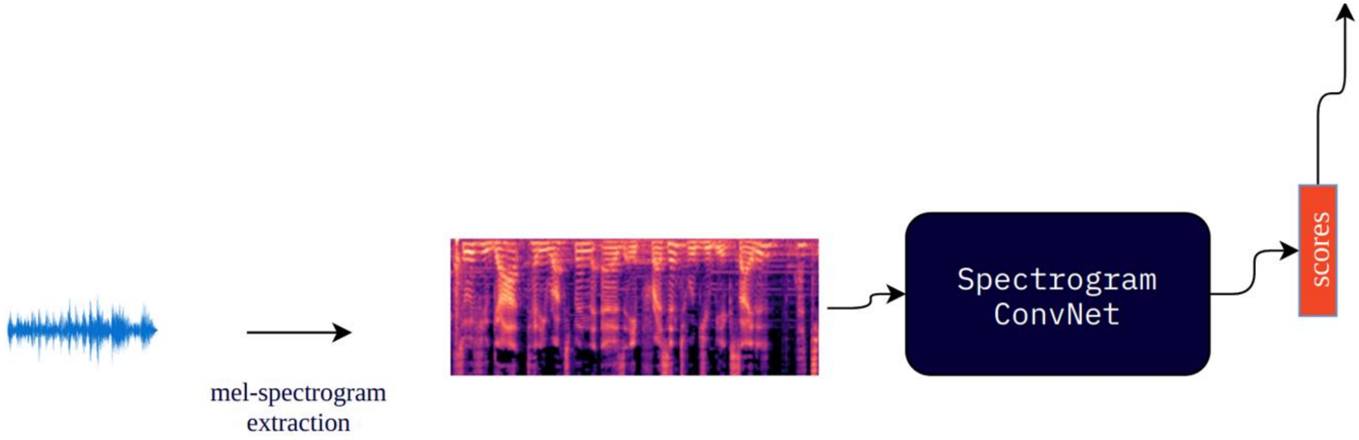
Visual Branch




temporal segment sampling
RGB Body ConvNet
Flow Body ConvNet
segmental consensus
scores
scores
segmental consensus

Audio Branch





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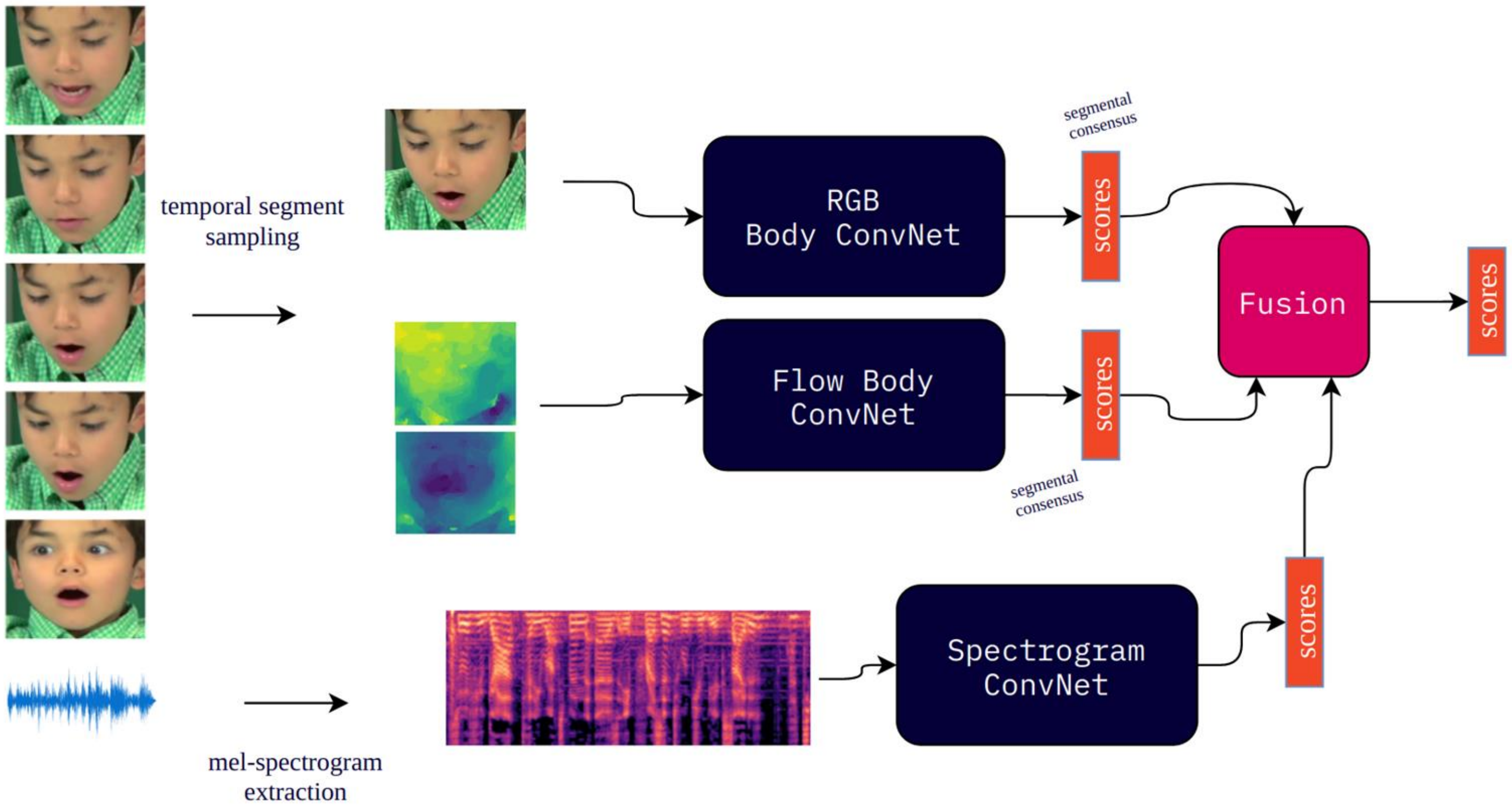
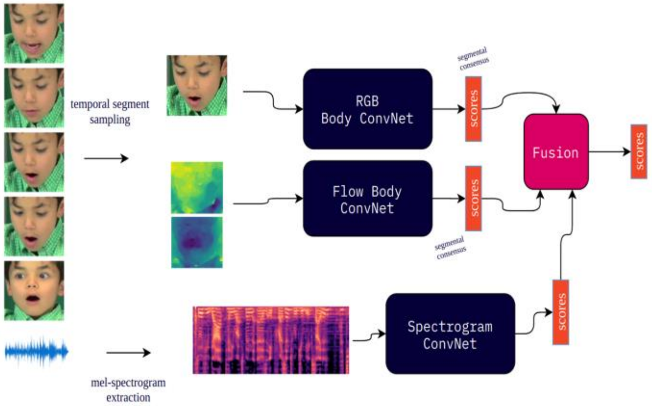

temporal segment sampling
segmental consensus
RGB Body ConvNet
scores
Fusion
scores
Flow Body ConvNet
scores
segmental consensus
scores
Spectrogram ConvNet
mel-spectrogram extraction

Architecture Benefits

1. models long-range temporal structure
2. temporal sampling
   a. avoids overfitting
   b. acts as a type of data augmentation
3. small computational cost compared to other architectures



The EmoReact Database

- 63 children, aged 4-14
- 1102 youtube videos (432 train, 303 val, 367 test), audio and visual expressions
- 8 emotions (curiosity, uncertainty, excitement, happiness, surprise, disgust, fear, frustration)

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Experimental Details

- Resnet50 CNN Backbone
- Visual backbone pretrained on the AffectNet Dataset
- 60 epochs
- 0.01 learning rate SGD (reduced at 20 and 40 epochs)
- evaluation with ROC-AUC

3 ablation studies

- computational burden and performance against segments
- feature fusion vs score fusion
- per emotion/modality performance

ROC AUC AND AVERAGE TIME ELAPSED PER EPOCH WITH VARYING NUMBER OF SAMPLED SNIPPETS.

Segments	ROC AUC		sec/train epoch	sec/val epoch
	Balanced	Unbalanced		
RGB				
1	0.685	0.773	11	7
3	0.713	0.786	27	20
5	0.709	0.787	40	26
10	0.715	0.788	73	51
Flow				
1	0.585	0.741	37	23
3	0.596	0.744	101	70
5	0.623	0.757	166	115
10	0.627	0.759	294	210

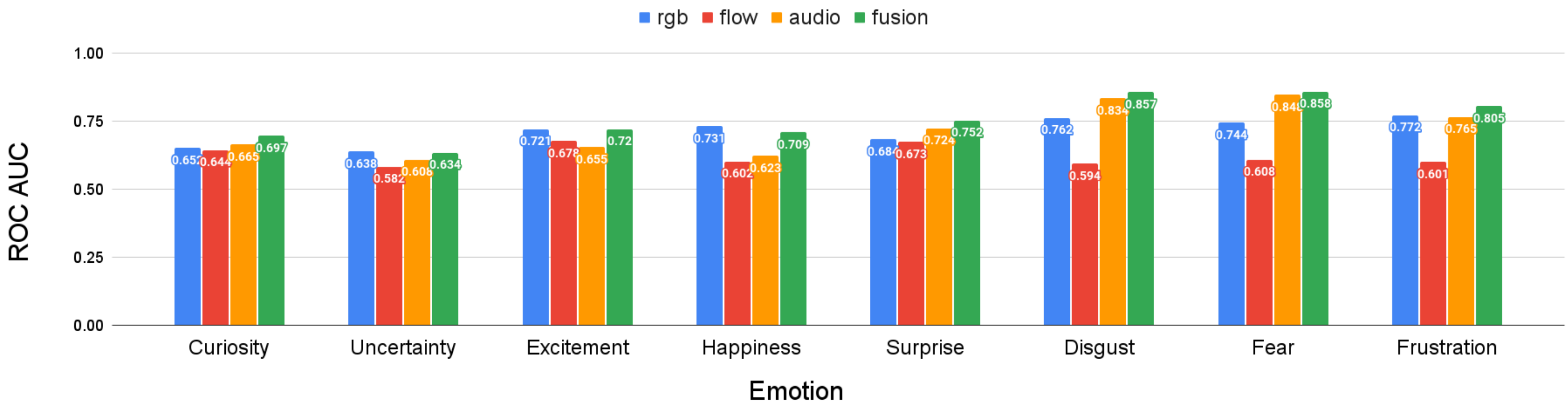
- increasing # segments above a threshold → small performance increase, large computation
    - choosing a trade-off at 3 RGB segments and 5 Flow segments

RESULTS ON THE EMOREACT DATASET FOR DIFFERENT FUSION AND TRAINING SCHEMES BETWEEN THE RGB-AUDIO AND FLOW-AUDIO MODALITIES.

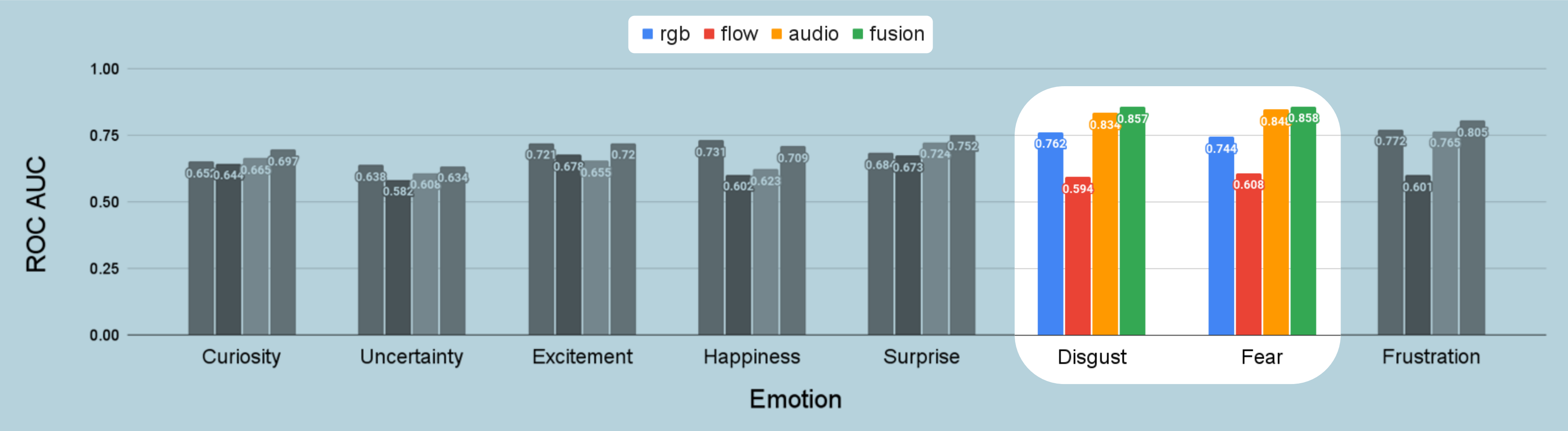
Fusion	**Training**	**ROC AUC**	
		Balanced	Unbalanced
Single Modality	Audio	0.715	0.750
	Visual (RGB)	0.713	0.786
	Visual (Flow)	0.623	0.757
Score Fusion RGB-audio	Joint Training	0.720	0.756
	Independent Training	**0.747**	**0.799**
Score Fusion Flow-audio	Joint Training	0.719	0.746
	Independent Training	0.725	0.787
Feature Fusion RGB-audio	Joint Training	0.719	0.769
Feature Fusion Flow-audio	Joint Training	0.707	0.744

score average fusion with independent of modalities training gives best result

Per Emotion Performance

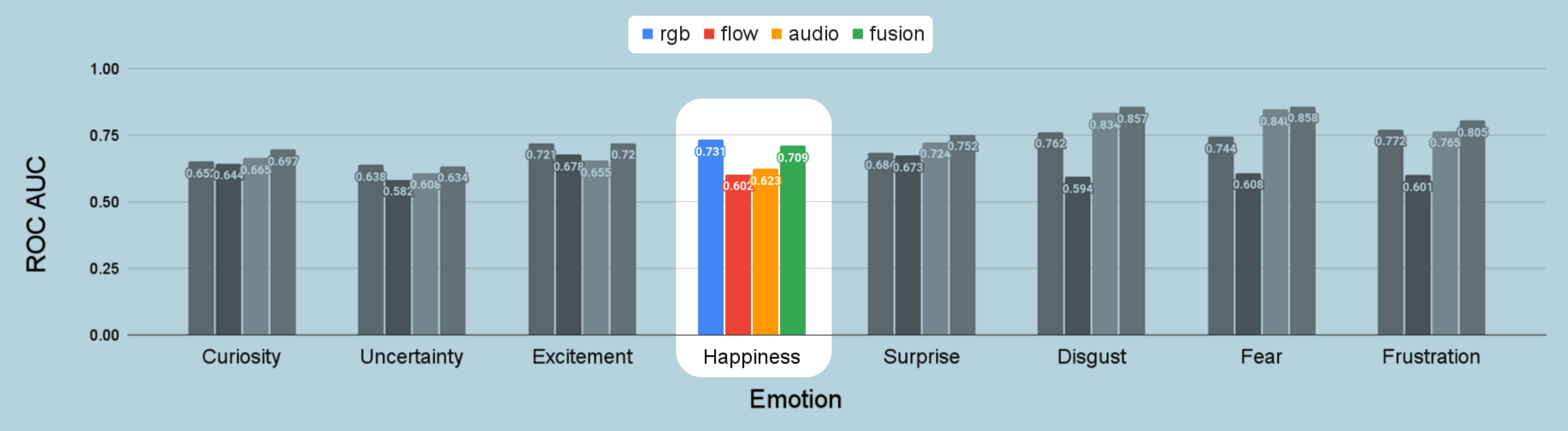


Per Emotion Performance



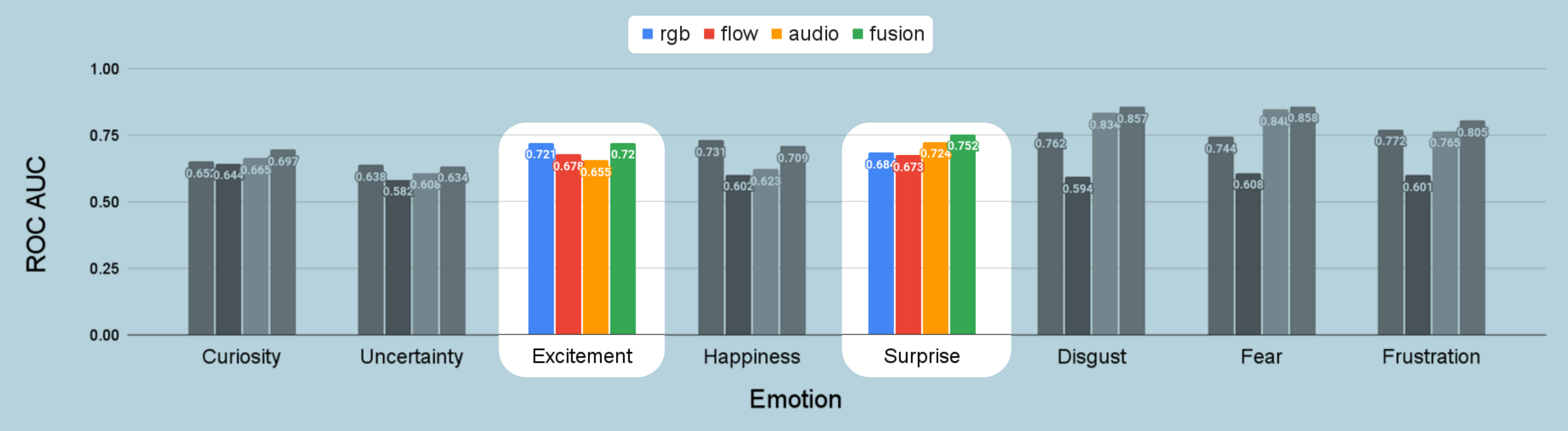
fear & disgust best identified through speech

Per Emotion Performance



happiness best identified through RGB

Per Emotion Performance



flow high performance in excitement and surprise

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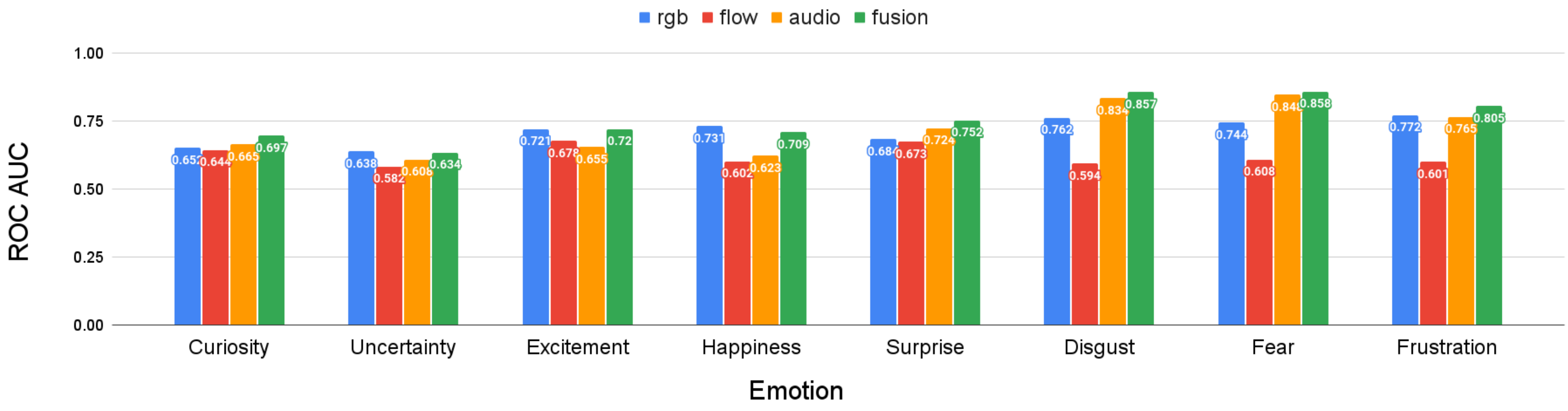
Per Emotion Performance



fusion results in higher performance in most cases

FINAL ROC AUC RESULTS ON THE EMOREACT DATASET.

	ROC AUC	
	Balanced	Unbalanced
Audio		
audio features + SVM [1]	0.610	-
dnn ensemble + SVM [2]	0.718	-
Ours (End-to-End)	0.715	0.750
Visual		
openface + SVM [1]	0.620	-
Ours (Flow)	0.623	0.757
Ours (RGB)	0.713	0.786
AudioVisual		
[1]	0.640	-
Ours (RGB+Audio+Flow)	**0.754**	**0.809**

[1] B. Nojavanasghari, T. Baltrusaitis, C. E. Hughes, and L.-P. Morency, “EmoReact: a multimodal approach and dataset for recognizing emotional responses in children,” in Proc. ICMI, 2016
[2] B. Nagarajan and V. R.M. Oruganti, “Cross-domain transfer learning for complex emotion recognition,” in Proc. TENSYMP, 2019.

Conclusions

- We proposed a novel multimodal emotion recognition system for CRI
- Tackles CRI challenges: small datasets, fast inference, low-cost training
- Ablation studies on various aspects of the system
- Achieved state-of-the-art results on the EmoReact dataset

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Email contact: filby@central.ntua.gr

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ΕΣΠΑ
2014-2020
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For more information:
http://cvsp.cs.ntua.gr/
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