

STATISTICAL, SPECTRAL AND GRAPH REPRESENTATIONS FOR VIDEO-BASED FACIAL EXPRESSION RECOGNITION IN CHILDREN

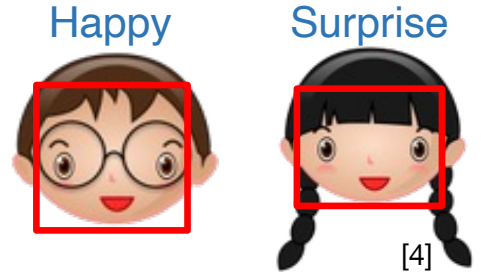
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Introduction

- Accurately recognising facial expressions can provide a deeper insight into **human nonverbal behaviours** [1], especially for people that do **not** have advanced **verbal communication skills**, e.g., children.
- Very few machine learning-based **facial expression classification** approaches [2] [3] have specifically investigated facial expression analysis in **children**.
- Understanding child facial expression analysis is important for developing **affect models** for future **child-agent interaction** research.



Why construct child-specific facial expression frameworks?

01

Models trained on adult expression datasets do not generalize well on child facial expression recognition tasks [6].

02

Facial expressions of children are often exaggerated, incomplete and unique as compared with their adult counterparts [2].

03

Child facial expressions are very dependent on demographic factors such as gender, age and ethnicity [3].

Novelty of our Proposed Approach

1.

First approach that constructs video-level heterogeneous graph representation for facial expression recognition in children.

2.

First approach that predicts children's facial expressions using the automatically detected Action Units (AUs).

Advantages of using Facial AUs

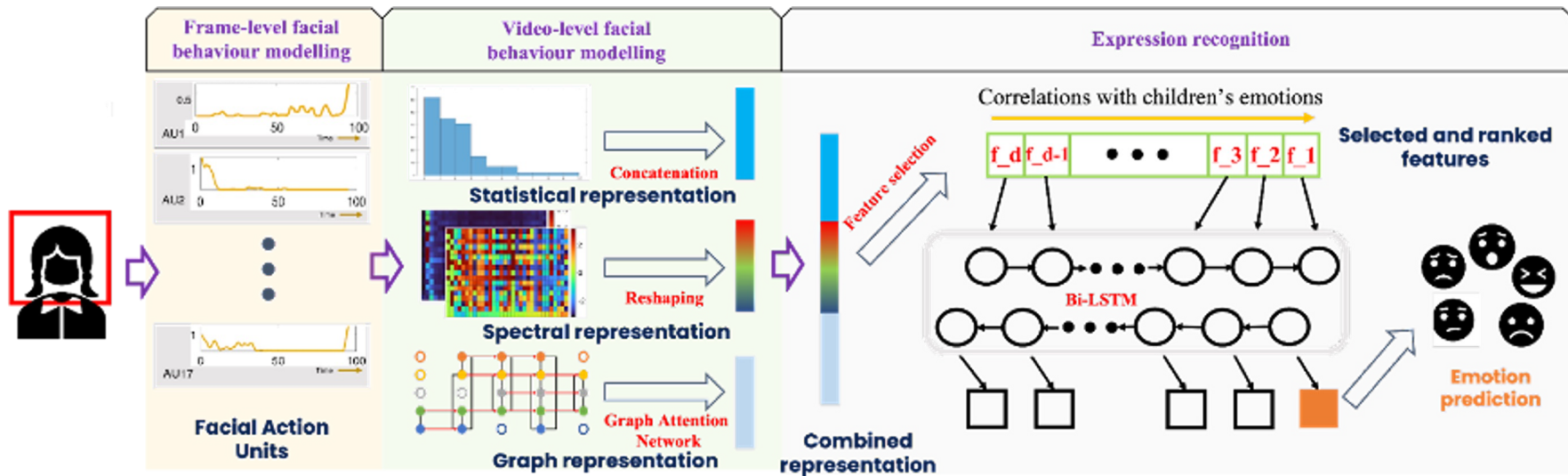
01

Objective and descriptive representation for measuring facial behavioral changes.

02

Ethical advantage over using raw images and videos for vulnerable demographic groups including children and the elderly by discarding video data after AU detection in real-time.

Proposed Methodology



The proposed pipeline for child facial expression recognition.

Proposed Methodology

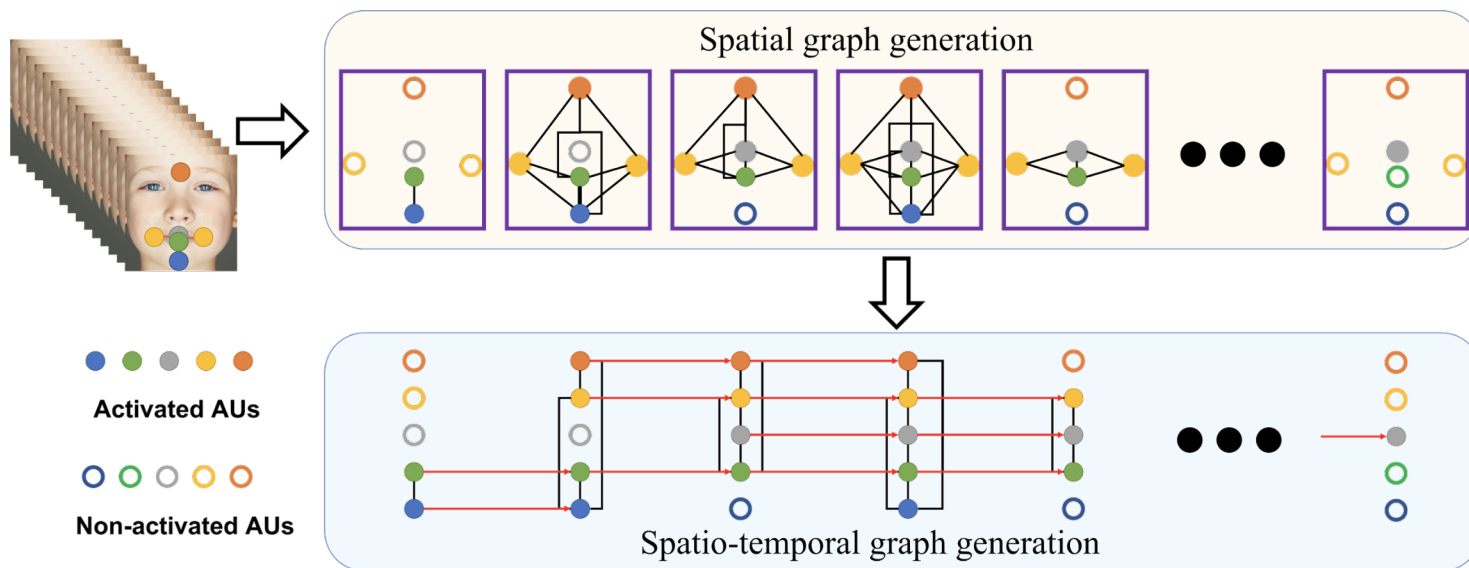


Illustration of the proposed graph representation.

Experiments

- **Dataset:** LIRIS Children Spontaneous Facial Expression Video Database (12 children of different ages, gender and ethnicities, 208 video clips) [3] [7].
- **Training details:**
 1. Excluded video clips belonging to the anger class (not sufficient number of clips), the combined categories, and the clips with very short duration (less than 3% of files).
 2. We have conducted **12-fold leave-one-child-out** cross-validation.
 3. To train the Bi-LSTM and MLP models, **cross-entropy** was used as the loss function and **Adam** was used as the optimizer with the learning rate of 0.001 and 0.005, respectively.

Results

01. Comparison between video-level representations:

Combination of all three representations provides the highest accuracy (66 % in MLP and 67.4 % in Bi-LSTM).

02. Comparison between MLP and the proposed Bi-LSTM model:

Bi-LSTM outperforms the standard MLP in all representations except in the spectral representation.

03. Comparison between expression classes:

Accurate predictions observed for happy expression class and surprise expression class while negative expressions like disgust and fear are often misclassified.

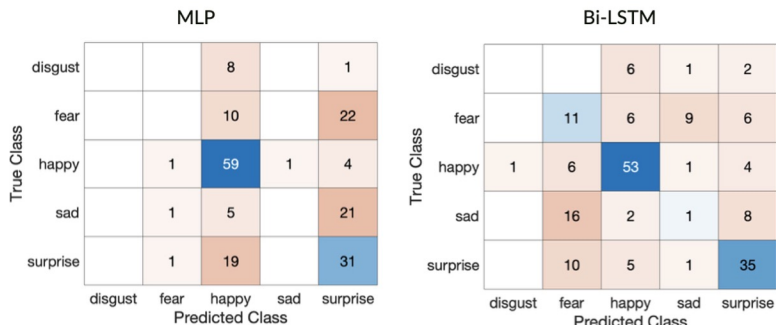
Statistical		Spectral	
MLP	Bi-LSTM	MLP	Bi-LSTM
48.9%	54.4%	62%	57.1%

Graph		Combined	
MLP	Bi-LSTM	MLP	Bi-LSTM
47.3%	51.1%	66.3%	67.4%

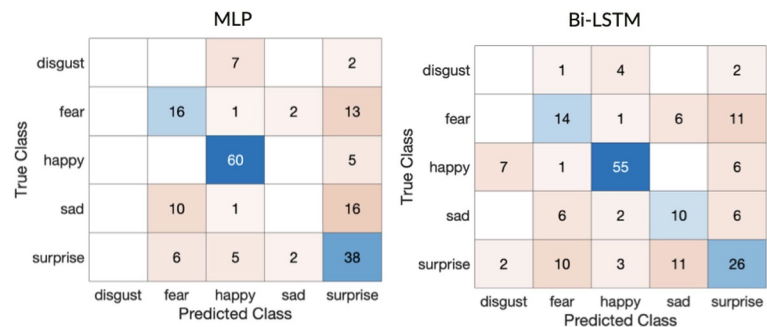
Classification accuracy obtained with different representations proposed

Results

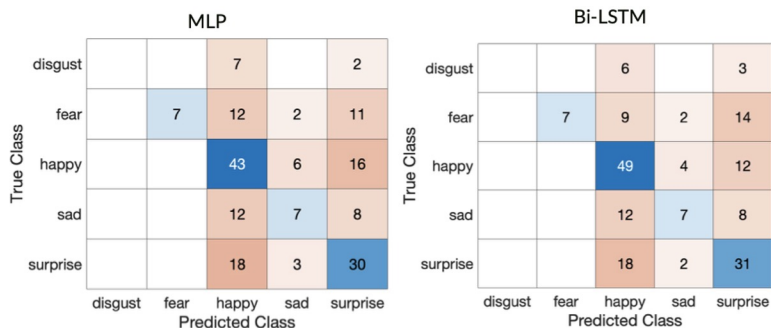
(A) Statistical



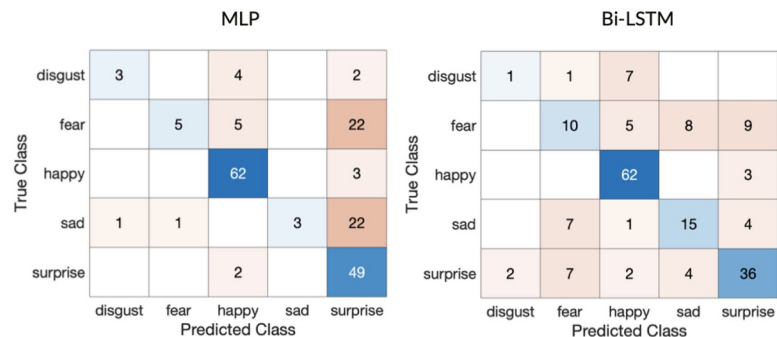
(B) Spectral



(C) Graph



(D) Combined



Confusion matrices for the different facial expression recognition frameworks proposed in this work

Conclusions

- Combination of all three representations using the Bi-LSTM model provides the highest accuracy for child facial expression recognition.
- Models developed in this work can provide a valuable stepping stone for creating affect recognition frameworks for child-agent interaction research.

Future Work

We aim to use more advanced deep-learning frameworks like **gated graph convolutional networks** and also compare other state-of-the-art end-to-end network architectures for improving the accuracy of the models proposed in this work.

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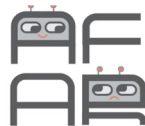


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