Human-centered Trait Predictions with Explanations

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Outline

- Human Traits
- Non-verbal behaviour cues
- Head Matters
- Explainable Human-centered Traits
- References

Human-Centered Traits: Introduction

Two key dimensions of an individual’s personality : Traits and Behavior

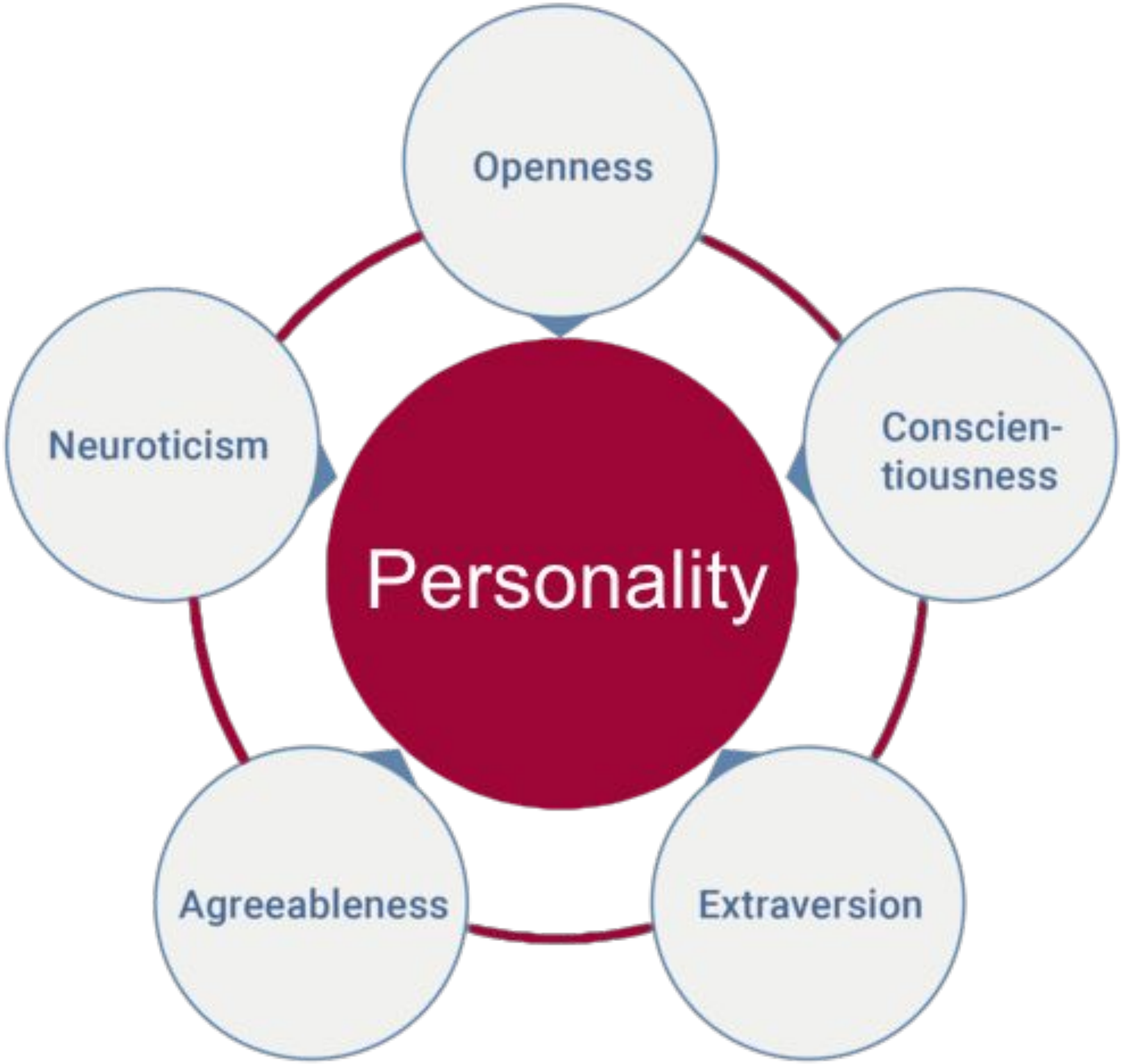

Figure 1: Big Five Personality Traits [28].

Human Centered Traits

- Hirability Traits
- Relational Traits: Anxious and avoidant.

Figure 2: Interview Specific Traits.

Hirability Traits: Iftekhar Naim, Md. Iftekhar Tanveer, Daniel Gildea, and Mohammed Ehsan Hoque. 2018. Automated Analysis and Prediction of Job Interview Performance. IEEE Transactions on Affective Computing 9, 2 (2018), 191–204. https://doi.org/10. 1109/TAFFC.2016.2614299

Relational Traits: Dimitra Karanatsiou, Pavlos Sermpezis, Dritjon Gruda, Konstantinos Kafetsios, Ilias Dimitriadis, and Athena Vakali. My tweets bring all the traits to the yard: Predicting personality and relational traits in online social networks. ACM Transactions on the Web (TWEB) 16(2):1–26, 2022

Non-verbal Behaviour: What

- Human communication acts distinct from speech

- Everything from facial expression and gesture to fashion and status symbol

Figure 3: Non-verbal behaviour [29].

Non-verbal Behaviour: Types

- Facial expressions
- Gestures
- Paralinguistics
- Body language
- Proxemics or personal space
- Eye gaze
- Haptics (touch)
- Appearance and
- Artifacts.

Figure 4: Emoticons: a form of non-verbal communication [30].

Non-verbal Behaviour: Why

- “Actions speak louder than words”

- Studies show that over half of your message is carried through nonverbal elements

Head Matters: Explainable Human-centered Trait Prediction from Head Motion Dynamics

Madan Surbhi, Monika Gahalawat, Tanaya Guha, and Ramanathan Subramanian. "Head Matters: Explainable Human-centered Trait Prediction from Head Motion Dynamics." In *Proceedings of the 2021 International Conference on Multimodal Interaction*, pp. 435-443. 2021.

Introduction

- Importance of non-verbal behavioral cues towards human-centric trait estimation
- The utility of head motion units for predicting personality and interview trait.
- 3D rotation angles: yaw, pitch and roll.
- Also, Action Units are utilized for trait prediction

Related Work

- **Personality and Interview Trait Prediction:**
  - **While many works examine prediction of personality and interview traits and explain predictions via statistical analysis or visualizations:**
    - Modeling, Recognizing and explaining apparent personality from videos- [7]
    - Study on determining the Big-Five personality traits of an individual based on facial expressions – [8]
    - Multimodal first impression analysis with deep residual networks – [9]
    - Interpreting CNN models for apparent personality trait regression – [10]
  - **The explanations in these papers are limited to discovering salient facial features.**

Related Work: Cont'd

Deep learning models need to improve in terms of explainability and interpretability.

- A CNN-based approach for interpretability is explored, where the authors observe a correlation between AUs and CNN- learned features [31]
- Another work [32] trains a deep residual network with audiovisual descriptors for personality trait prediction, where predictions are elucidated via face image visualization and occlusion analysis.

Recent studies alleviate this issue by interpreting the results of deep learning models.

Related Work: Cont’d

Numerous studies have also examined the relationship between a candidate’s personality traits and their job interview performance:

- Conscientiousness is positively correlated with job and organizational performance [33] [34]
- Conscientiousness and Extraversion impact interview success [13], [14] and job ratings [35]
- Emotional stability, Conscientiousness, and Agreeableness are positively related to job performance[36]

These correlations between personality and interview traits have been discovered via statistical measures only. Very few studies have explored the relationships between non-verbal behavioral cues and personality-cum-interview traits

Related Work: Cont’d

- **Head Motion for Behavioral Analytics:**
    - **While head motion patterns have been identified as critical non-verbal behavioral cues in interactive scenarios:**
        - Low-level Characterization of Expressive Head Motion through Frequency Domain Analysis [3]
        - On the role of head motion in affective expression [4]
        - Dimensional Emotion prediction from spontaneous head gestures for interaction with sensitive artificial listeners [5]
        - Modeling dynamics of expressive body gestures in dyadic interactions [6]
    - **Head motion patterns have not been employed for personality or interview trait prediction**
    - **We novelly attempt explanations for personality and interview traits from kinemes which are inherently explanatory**

Research Contribution

- Head motion, are effective non-behavioral cues and predictive of personality and interview traits. .

- Apart from being predictive, kinemes and AUs enable behavioral *explanations* for the target traits.

- Datasets: FICS[7] and MIT interview[2].

- Examining trait prediction using thin-slice approach.

Proposed Framework

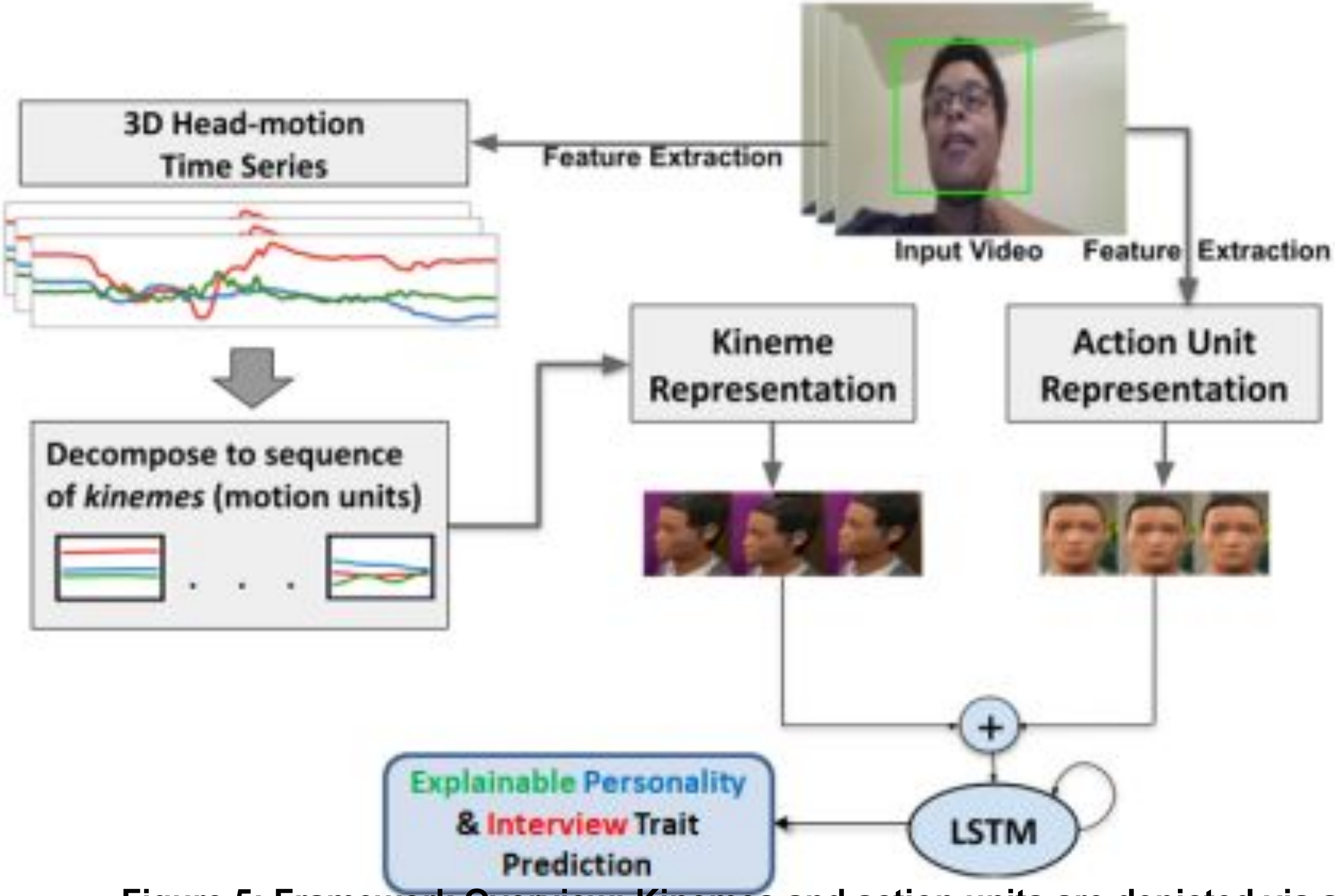

Figure 5: Framework Overview: Kinemes and action units are depicted via a 3D model.

Methodology: Kineme Formulation

- Head motion is represented as multivariate time-series.
- Model is proposed to represent the head-motion as a sequence of fundamental and interpretable motion units termed “Kinemes”.

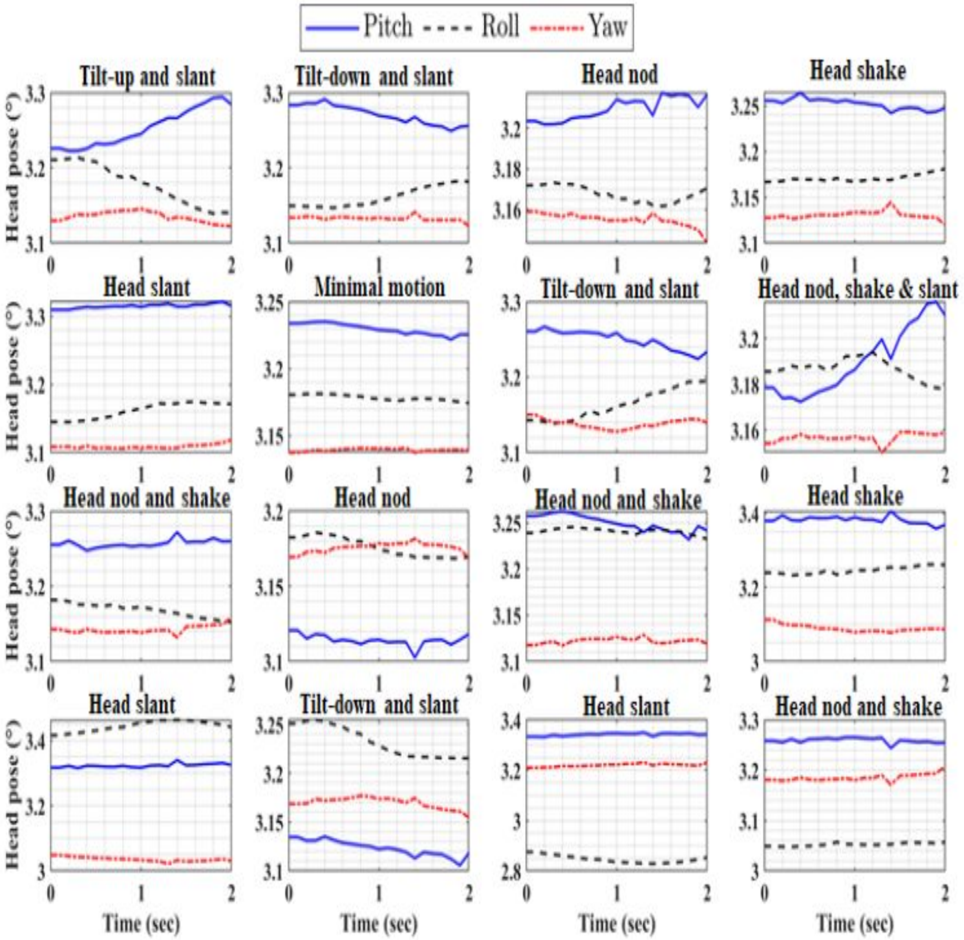

Figure 6: Plots of 16 kinemes extracted for the FICS dataset follow raster ordering (left to right, top to bottom).

Methodology: AU Extraction

- An AU is marked as dominant if within the window maximum value exceeds threshold.
- Thus resulting in 17-D vector for each window.

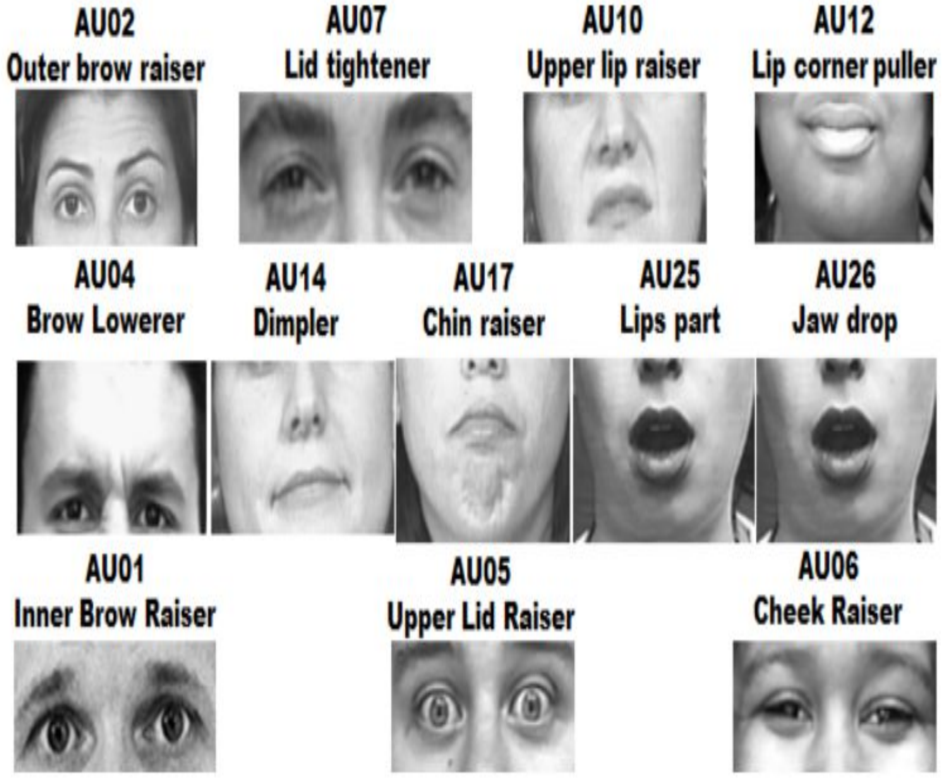

Figure 7: Common AUs in the FICS and MIT datasets.

Datasets

1. **First Impression Candidate Screening (FICS)**
   - Comprises 10K *YouTube* self-presentation videos[7]
   - Labeled via crowdworkers for OCEAN personality traits

2. **MIT Interview Dataset**
   - Comprises of 138 mock interview videos with average length 4.7 minutes [2]
   - Rated by crowdworkers on 16 traits
   - The paper focuses on the following traits: Excited, Eye Contact, Friendly and Recommended Hiring along with the Overall interview score

Figure 8: FICS (top) and MIT (bottom) video examples.

Experimental Settings

- **Prediction Type:**
  - **Chunk-level prediction:**
    - Segmented the original videos into smaller chunks based on the thin-slice approach for behavioral trait prediction
    - For FICS dataset, 3, 5, and 7 sec chunks are considered
    - For MIT data, different chunk sizes are considered from 5-60 sec
    - Computed performance metrics over all chunks
  - **Video-level prediction:**
    - Performance metrics computed over all videos by assigning the majority label over the chunks to each video

Models

- **Linear Regression with principal components**
- **Hidden Markov Model for Classification**
- **Long Short-Term Memory for Regression and Classification**
- **2D CNN for Regression and Classification**
- **Decision fusion for Regression and Classification**

Fusion Model

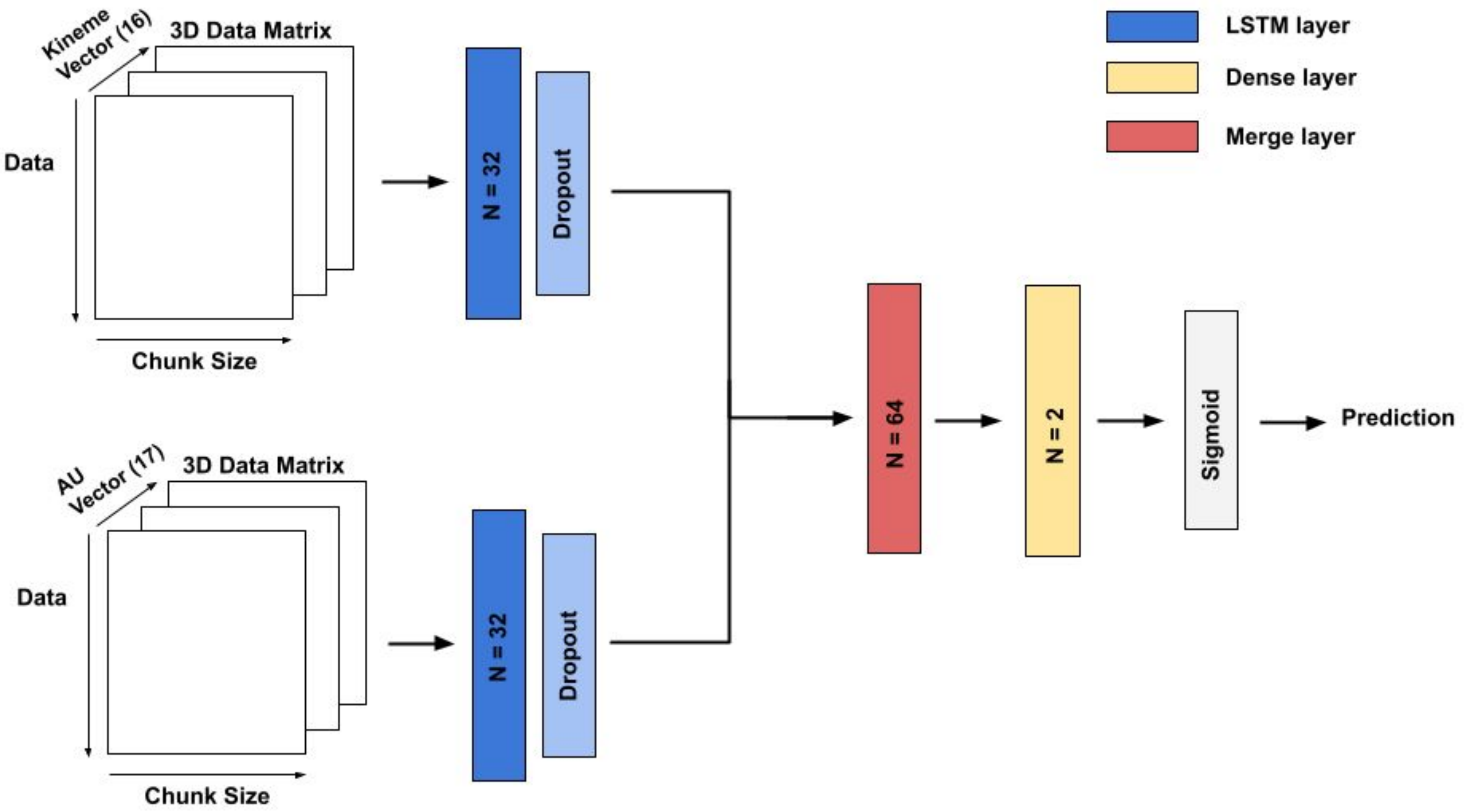

Figure 9: Kineme+AU LSTM classification architecture.

Results and Discussion

Table 1: FICS Regression results: Accuracy and PCC values for different methods are tabulated.

Trait	PCA Lin-Reg		LSTM Kin		LSTM AU		LSTM Kin+AU (FF)		LSTM Kin+AU (DF)		2D-CNN	
	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC
Open	0.884	0.085	0.872	0.060	0.889	0.370	0.892	0.368	0.893	0.382	**0.906**	**0.392**
Con	0.875	0.086	0.864	0.027	0.882	0.317	0.880	0.304	0.882	0.282	**0.908**	**0.295**
Extra	0.877	0.060	0.869	0.048	0.891	0.491	0.893	0.474	0.891	0.485	**0.907**	**0.492**
Agree	0.892	0.035	0.885	0.046	0.897	0.251	0.892	0.253	0.896	0.275	**0.906**	**0.283**
Neuro	0.877	0.071	0.867	0.051	0.885	0.370	0.884	0.365	0.887	0.387	**0.903**	**0.395**

Results and Discussion

Table 2: MIT Classification results: Accuracy and F1 values are tabulated.

Trait	HMM		LSTM Kin		LSTM AU		LSTM Kin+AU (FF)		LSTM Kin+AU (DF)		2D-CNN	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
Ov	0.56±0.17	0.48±0.18	0.83±0.11	0.82±0.13	0.82±0.14	0.81±0.15	0.80±0.14	0.80±0.14	0.85±0.13	**0.85±0.14**	0.65±0.09	0.64±0.08
RH	0.55±0.14	0.34±0.27	0.79±0.12	0.79±0.12	0.83±0.13	0.83±0.14	0.81±0.12	0.80±0.12	0.84±0.11	**0.83±0.12**	0.59±0.07	0.58±0.07
Ex	0.57±0.14	0.51±0.10	0.82±0.13	0.82±0.13	0.82±0.12	0.82±0.10	0.79±0.13	0.79±0.13	0.83±0.11	**0.82±0.12**	0.72±0.08	0.71±0.08
EC	0.53±0.17	0.44±0.24	0.79±0.13	0.79±0.13	0.81±0.12	0.80±0.13	0.78±0.12	0.76±0.13	0.84±0.13	**0.83±0.14**	0.57±0.07	0.55±0.09
Fr	0.57±0.18	0.54±0.12	0.80±0.15	0.80±0.16	0.86±0.09	0.85±0.09	0.84±0.10	0.84±0.11	0.87±0.11	**0.86±0.12**	0.61±0.08	0.61±0.08

Results and Discussion

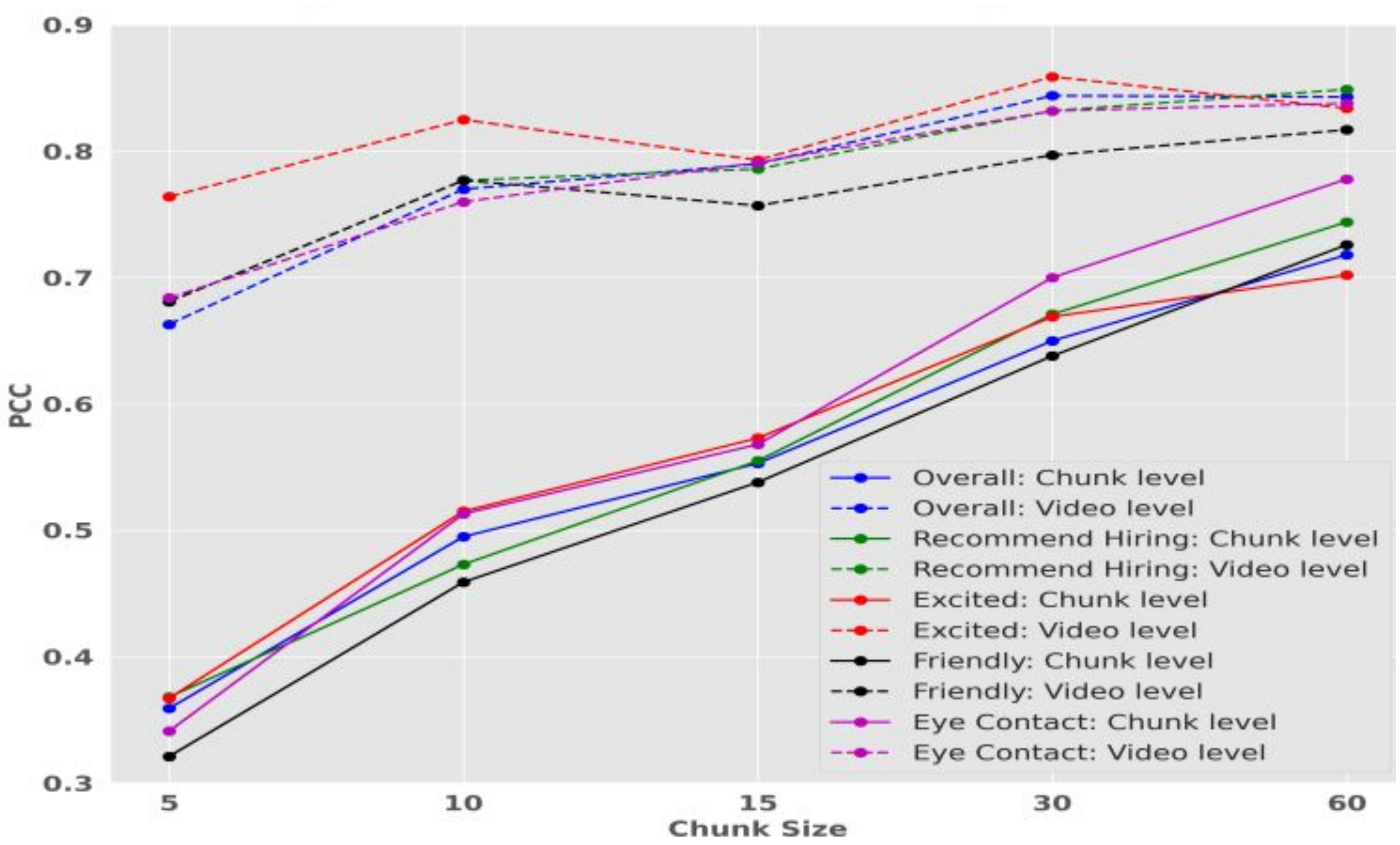

Figure 10: Chunk vs video-level predictions with kinemes.

Explainability

TABLE 3: Explaining OCEAN and interview traits via kinemes and AUs.

Dataset	Trait	Dominant Kin	Dominant AUs	Inferences
FICS	O (H)	2, 8, 10, 16	7, 12, 14, 25, 26	Persistent head movements (as noted in [56]) with nodding and smiling.
	C (H)	1, 8, 10, 16	7, 12, 17, 25, 26	Upward head-tilt indicative of upright demeanor and head nodding.
	E (H)	2, 10, 14, 16	10, 12, 17, 25, 26	Head tilt-down with nodding, and facial gestures related to speaking.
	A (H)	3, 8, 10, 16	7, 12, 14, 25, 26	Frequent head nodding and smiling (associated with courteous behavior [57], [58]).
	N (H)	2, 8, 10, 16	7, 12, 17, 25, 26	Frequent head movements with nodding and smiling.
	O (L)	1, 6, 11, 16	4, 10, 14, 17, 26	Relatively fewer head movements and frowning.
	C (L)	2, 4, 8, 16	4, 7, 10, 14, 25	Head tilt-down avoiding eye-contact, head shaking and frowning.
	E (L)	1, 4, 10, 16	4, 7, 10, 14, 17	Tilt-up, head shaking and frowning.
	A (L)	1, 8, 9, 16	4, 14, 17, 25, 26	Frequent head movements and frowning.
	N (L)	1, 5, 12, 16	4, 7, 10, 14, 25	Few head movements, head shaking and frowning.
MIT	RH (H)	**16**, **14**, 3, 4	5, 10, 12, 14, 25	Head nodding and smiling, and being expressive.
	Ex (H)	**14**, 3, 4, 9	5, 10, 12, 14, 25	Head nodding and exhibiting persistent head motion. Smiling and expressive.
	EC (H)	**14**, 12, 4, 5	6, 7, 10, 14, 25	Head up, nodding and showing limited facial emotions.
	Fr (H)	**16**, 3, **11**, **14**	5, 10, 12, 14, 25	Frequent head movements and smiling.
	RH (L)	**11**, 1, 2, 5	6, 7, 12, 14, 25	Head shaking and exhibiting minimal facial expressions.
	Ex (L)	**11**, **16**, 2, 3	4, 6, 7, 14, 25	Head shaking and nodding. Frowning and showing minimal facial expressions.
	EC (L)	13, 7, **16**, **11**	6, 7, 10, 12, 25	Frequent nodding is perceived as avoiding eye-contact.
	Fr (L)	3, **11**, 4, 9	1, 4, 6, 7, 25	Head shaking, frowning and otherwise being minimally expressive.

Conclusion

- Combining facial AUs information with kinemes enables more efficient trait prediction and intuitive explanations.
- Trait explainability can also be utilized for developing assistive technologies to help users improve their public speaking and interactional skills.
- The proposed behavioral analytic tools are intended to support and complement human decision-making.

Explainable Human-centered Traits from Head Motion and Facial Expression Dynamics

Surbhi Madan, Monika Gahalawat, Tanaya Guha, Roland Goecke, and Ramanathan Subramanian

Manuscript is under preparation and will be submitted to IEEE Transactions on Affective Computing by Jan 2023.18

Introduction

- We utilize kinemes, action units, and audio features to estimate these human-centered traits.

- Along with decision and feature fusion, we explore additive attention fusion.

Proposed Framework

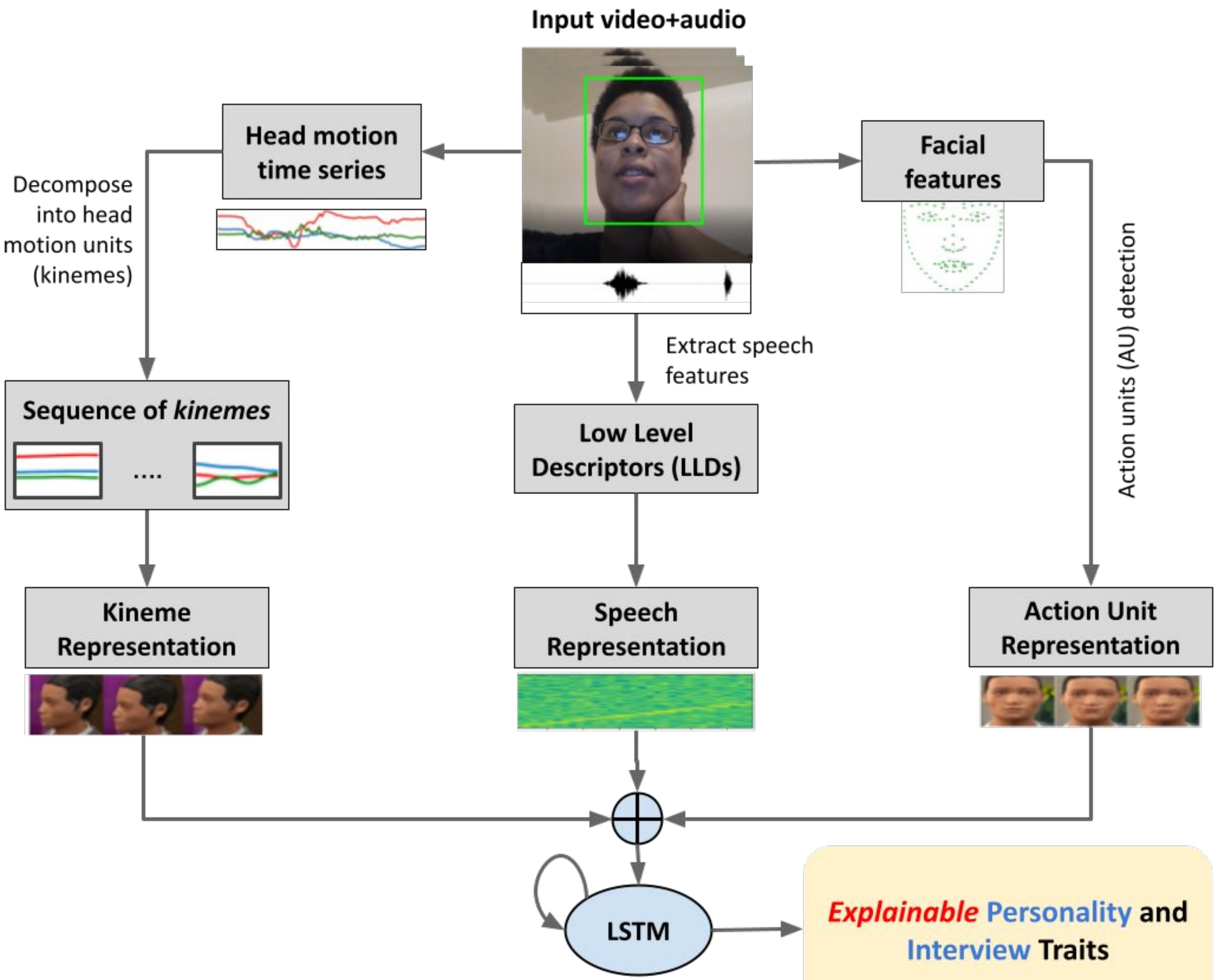

Figure 11: Overview of the proposed framework: Kinemes (elementary head motions), action units (atomic facial movements) and speech features employed for explainable trait prediction.

METHODOLOGY: Speech Feature Extraction

1. Low-level audio descriptors (LLDs) via the Librosa library [11]: F0, VP, ZCR and MFCCs..

1. 23-dimensional feature vector for each 2s segment.

1. These features are normalized to have zero mean and unit variance.

Models

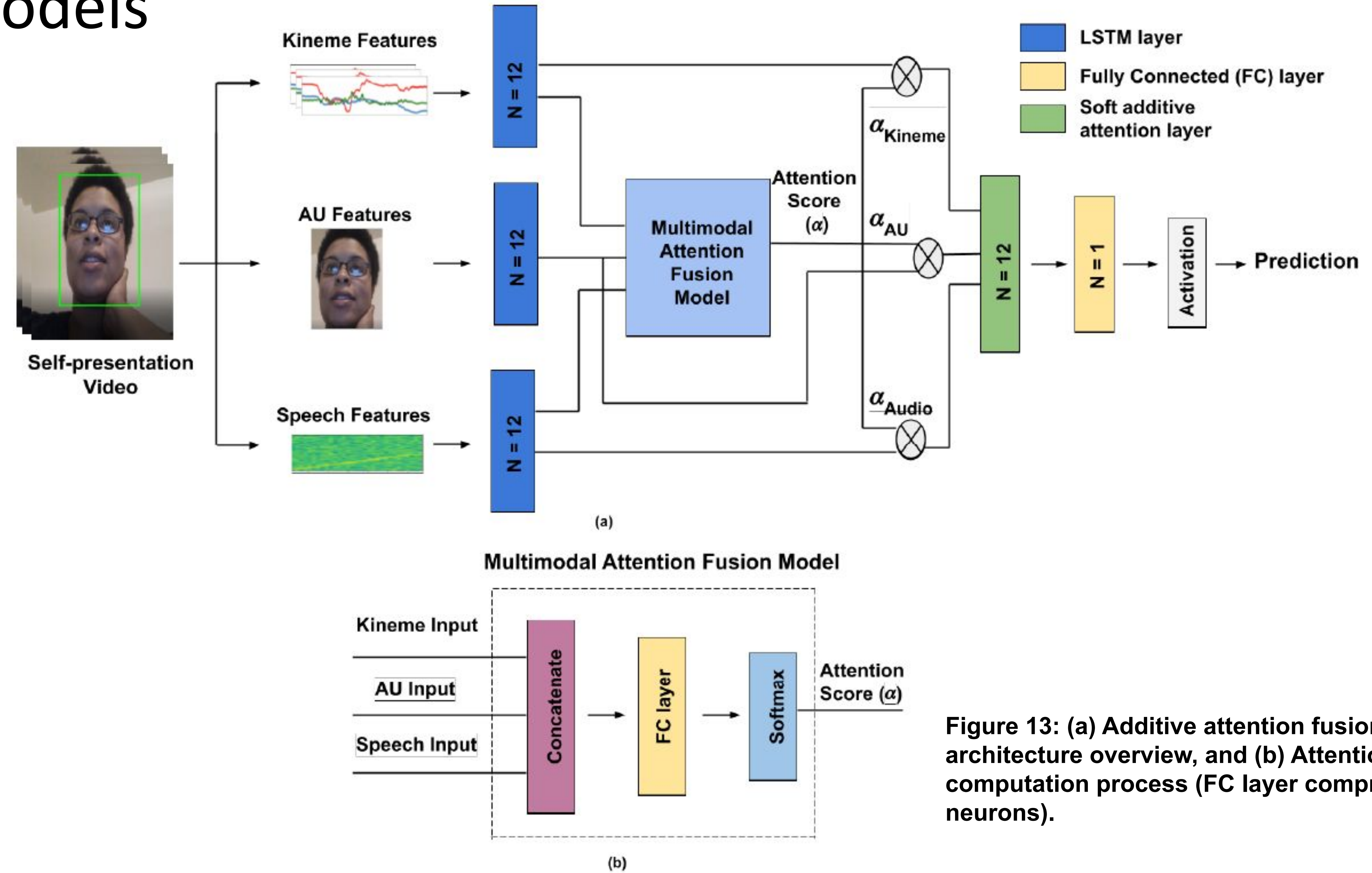

Figure 13: (a) Additive attention fusion architecture overview, and (b) Attention score computation process (FC layer comprises twelve neurons).

Results and Discussion

TABLE 4: Unimodal and multimodal regression results on the MIT dataset. Accuracy and PCC values are tabulated.

Trait	Unimodal						Trimodal					
	LSTM Kin		LSTM AU		LSTM Audio		LSTM FF		LSTM DF		LSTM AF	
	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC
Ov	0.93±0.04	0.84±0.26	0.93±0.04	0.84±0.26	0.96±0.03	0.94±0.10	0.97±0.03	0.96±0.08	0.97±0.01	**0.97±0.04**	0.98±0.03	0.95±0.16
RH	0.95±0.03	0.93±0.10	0.95±0.03	0.93±0.10	0.96±0.03	0.93±0.09	0.97±0.03	0.96±0.08	0.98±0.01	**0.97±0.03**	0.97±0.03	0.96±0.07
Ex	0.94±0.04	0.89±0.20	0.94±0.04	0.89±0.20	0.95±0.02	0.95±0.06	0.97±0.02	**0.98±0.05**	0.95±0.03	0.97±0.06	0.98±0.02	**0.98±0.05**
EC	0.94±0.04	0.89±0.13	0.94±0.04	0.89±0.22	0.95±0.03	0.94±0.08	0.96±0.03	**0.96±0.08**	0.96±0.03	**0.96±0.06**	0.97±0.03	**0.96±0.08**
Fr	0.95±0.03	0.93±0.10	0.95±0.03	0.93±0.10	0.96±0.03	0.96±0.06	0.97±0.02	**0.98±0.03**	0.98±0.01	**0.98±0.02**	0.98±0.03	0.97±0.05

Trait	Bimodal											
	Kin+AU FF		Kin+AU DF		Kin+Aud FF		Kin+Aud DF		AU+Aud FF		AU+Aud DF	
	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC	Acc	PCC
Ov	0.97±0.03	0.93±0.15	0.95±0.04	0.89±0.21	0.97±0.02	0.96±0.07	0.96±0.03	0.95±0.06	0.97±0.03	**0.97±0.07**	0.96±0.03	0.95±0.09
RH	0.96±0.04	0.92±0.16	0.94±0.04	0.90±0.19	0.97±0.03	**0.96±0.07**	0.96±0.03	0.95±0.07	0.97±0.03	**0.96±0.07**	0.96±0.03	0.95±0.08
Ex	0.96±0.04	0.93±0.15	0.93±0.04	0.91±0.14	0.97±0.02	**0.98±0.04**	0.96±0.02	0.97±0.05	0.97±0.02	**0.98±0.04**	0.97±0.02	0.97±0.05
EC	0.96±0.04	0.94±0.13	0.95±0.04	0.91±0.16	0.97±0.03	0.95±0.07	0.95±0.03	0.94±0.10	0.97±0.02	**0.96±0.06**	0.96±0.03	0.95±0.09
Fr	0.97±0.03	0.96±0.08	0.95±0.03	0.94±0.09	0.97±0.03	0.97±0.07	0.96±0.03	0.96±0.05	0.97±0.02	**0.98±0.04**	0.96±0.03	0.96±0.05

Explainability (Attention score interpretation): FICS

- Persistent head movements and facial expressions are associated with Openness [12]. Including speech features improved prediction performance[13], [14].
- Conscientiousness can be expressed through visual features[15]
- Extraversion tends to be better conveyed by exaggerated physical movements [16]
- Agreeableness can be more accurately identified through facial expressions and is positively correlated with head movements [16], [17].
- Cheerful or non-cheerful facial movements, can convey a better understanding of emotional stability [18].

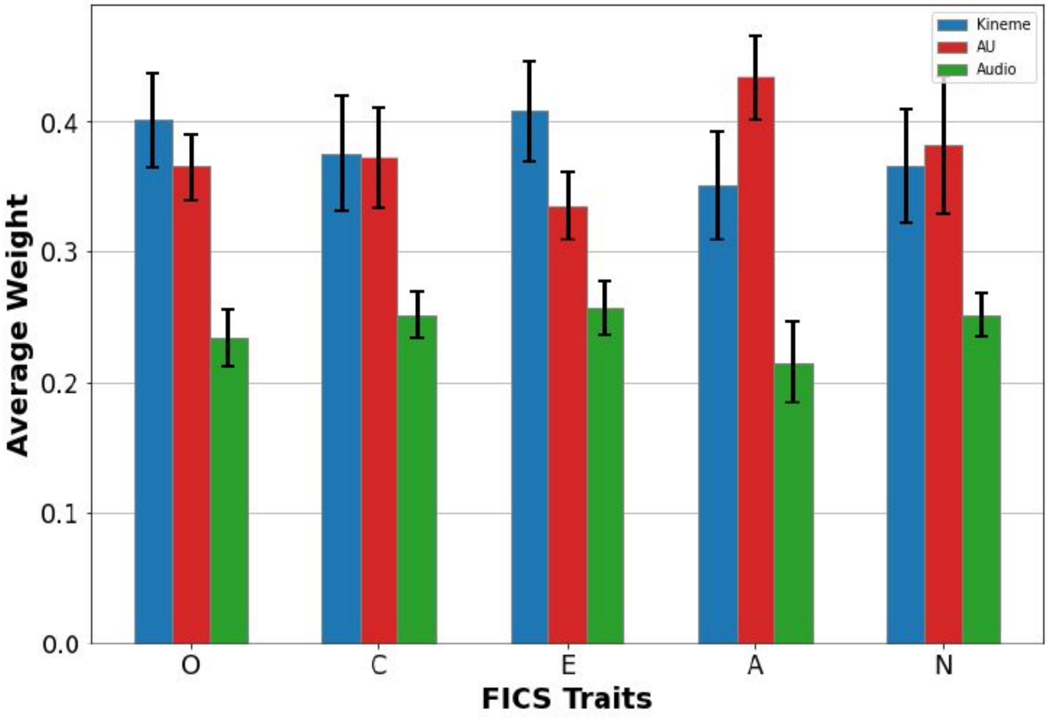

Figure 15: Average attention weights comparison of three modalities over all traits of the FICS.

Explainability (Attention score interpretation): MIT

- Positive facial expressions and frequent postural changes are seen as differentiators between the acceptance and non-acceptance of the candidate [19].

- Interview ratings correlate well with vocal attractiveness [20].

- Prosody and speaking style is essential for a person's excitement and engagement [2].

- Eye-contact trait, higher AU contribution signifies the importance of facial features for prediction.

- Visual and auditory modalities can be crucial in discerning the friendliness of the interviewee [21]

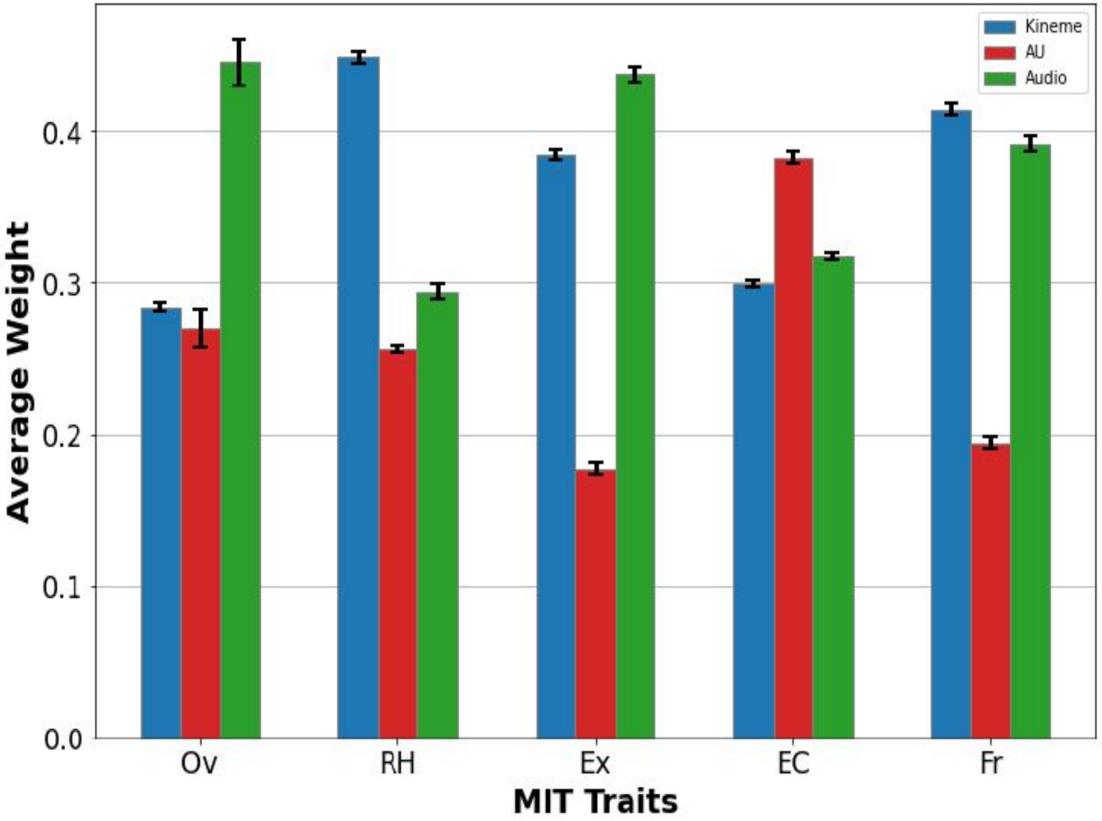

Figure 16: Average attention weights comparison of three modalities over all traits of the MIT.

Conclusion

- Efficient trait prediction can be achieved with both unimodal and multimodal approaches.
- Multimodal approaches outperform their unimodal counterpart.
- This work extracts all features over a fixed time window.

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Thank you!