Task-based Classification of Reflective Thinking Using Mixture of Classifiers*

Major Area Presentation, Spring 2022

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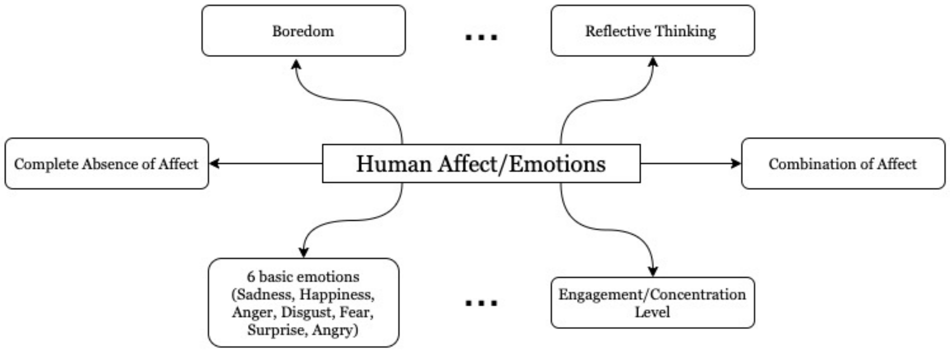
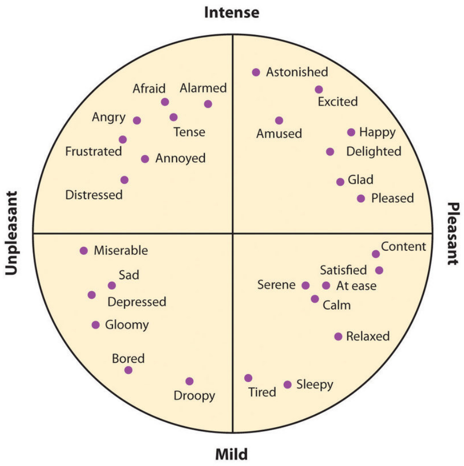
Structure of Presentation

- Defining Affect and its Application
- Task-based Classification of Reflective Thinking Using Mixture of Classifiers
- Key takeaways and filling the gap
- PhD Roadmap

Affective Computing

"Affective Computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects[1]"





Emotion as **Categorical**[2] set

Emotion as **Dimensional**[3] **set**

[1] *Affective computing - Wikipedia*.

[2] Ekman, Paul. "An argument for basic emotions." *Cognition & emotion* 6.3-4 (1992): 169-200.

[3] Russell, James A., and Albert Mehrabian. "Evidence for a three-factor theory of emotions." *Journal of research in Personality* 11.3 (1977): 273-294.

Application Areas

Automobiles
(Air traffic control, driver attentiveness)

Healthcare
(Patient monitoring, Depression analysis, ASD detection)

Entertainment
(Virtual Environment, Data synthesis, content preference)

Education
(Student engagement analysis, Reflective Thinking)

Security
(Face Recognition, Face Authentication)

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Leveraging ML/DL in Affective Computing

Application Areas

Automobiles
(Air traffic control, driver attentiveness)

Healthcare
(Patient monitoring, Depression analysis, ASD detection)

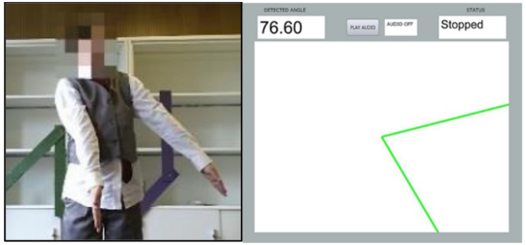
Entertainment
(Virtual Environment, Data synthesis, content preference)

Education
(Student engagement analysis, Reflective Thinking)

Security
(Face Recognition, Face Authentication)

Dataset and Task Description

WeDraw-1 Dataset[4]



Task 0

Forming Angles, where the child explored static representation of given angles using their arms

Task 1

Bodily Angles Sums and Differences, given two 3D object representing angles, the child had to represent the sum of angles using their arms.

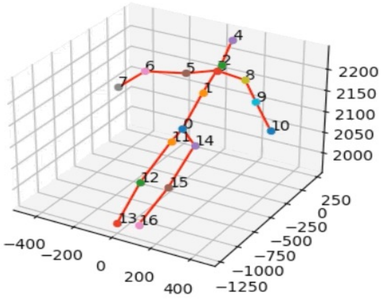
Rotating in Angles, represent the above sum of angles using full body rotation.

Task 2

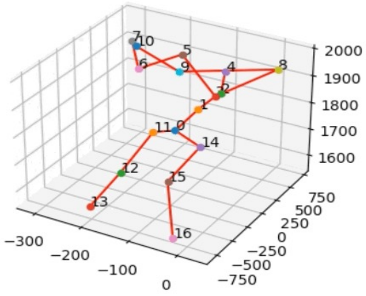
Making shape reflections, where the child explored symmetry and reflections of shapes using different shaped cutouts.

[4] Olugbade, Temitayo, et al. "Automatic detection of reflective thinking in mathematical problem solving based on unconstrained bodily exploration." *IEEE Transactions on Affective Computing* (2020)

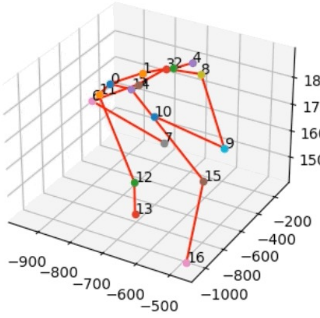
Reflective Thinking Detection



Task 0: Forming Static Angles



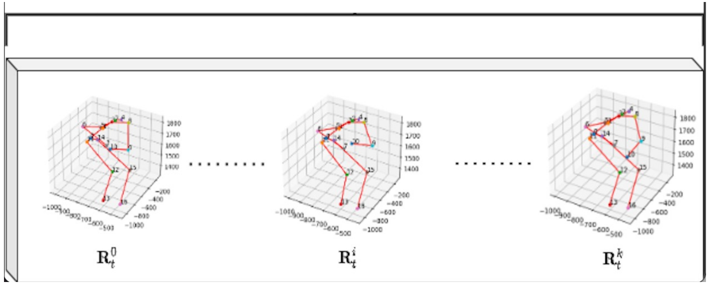
Task 1: Bodily Angles Sums and Differences, Rotating in Angles



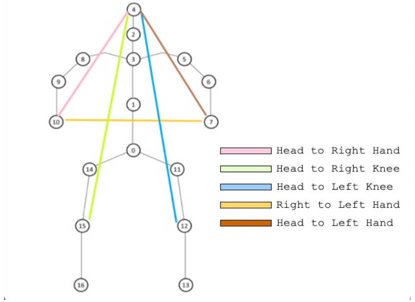
Task 2: Making shape reflections

Feature Space

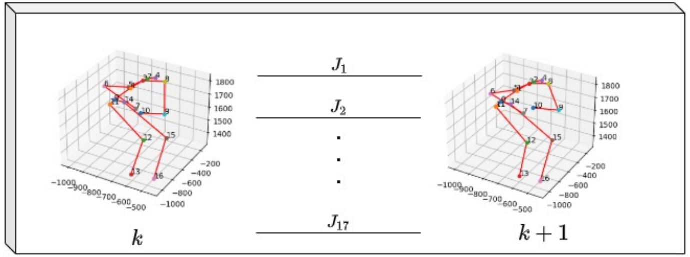
(a) Raw Features: $\mathcal{R} \in \mathbb{R}^{n \times 17 \times 3}$



(b) Handcrafted Features: $\mathcal{H}_{seg} \in \mathbb{R}^{n \times 5}$



(c) Temporal Features: $D \in \mathbb{R}^{n \times 17}$



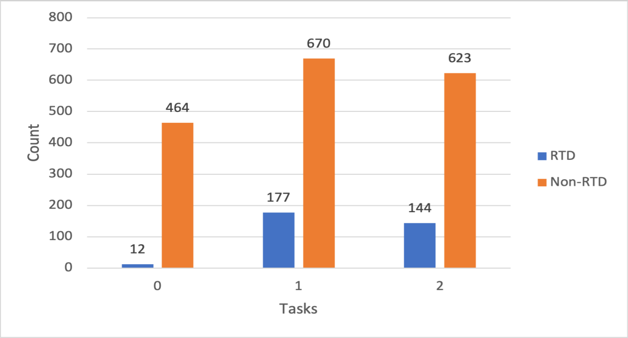
(d) Extended Handcrafted Features: $\mathcal{H}_{ext} \in \mathbb{R}^{n \times 29}$

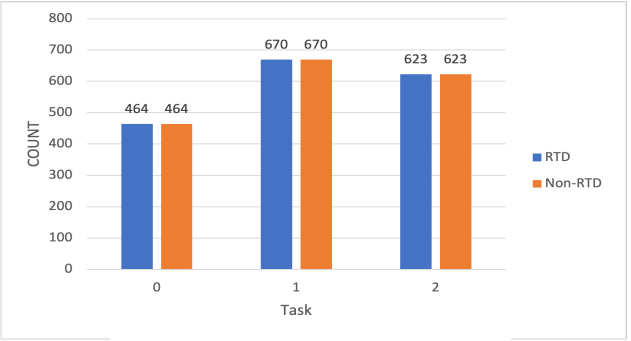
- Extended Handcrafted features inspired by the baseline [5].
- 29 features evaluated on different energy functions.

[5] Olugbade, Temitayo, et al. "Automatic detection of reflective thinking in mathematical problem solving based on unconstrained bodily exploration." *IEEE Transactions*

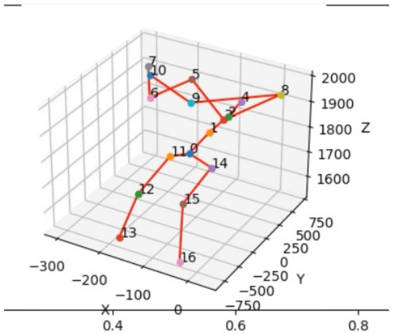
Augmentation Techniques

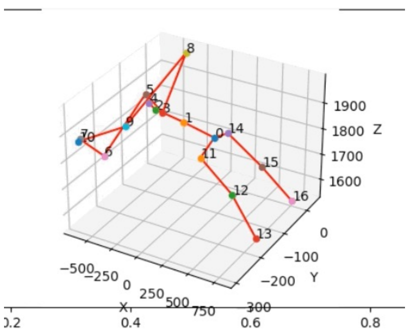
Synthetic Minority Oversampling Technique (SMOTE)[6]





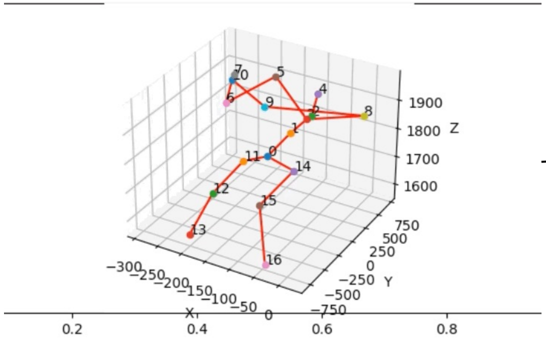
Reflection



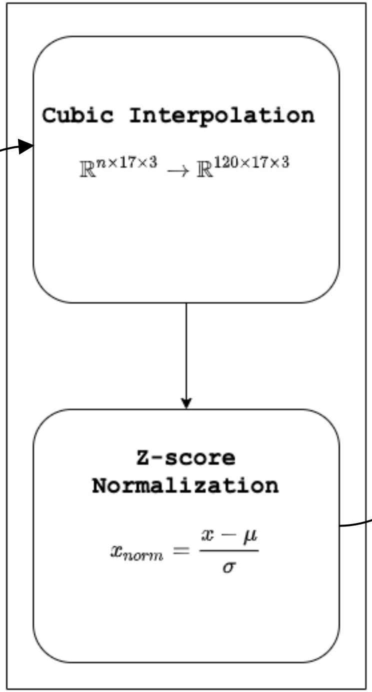


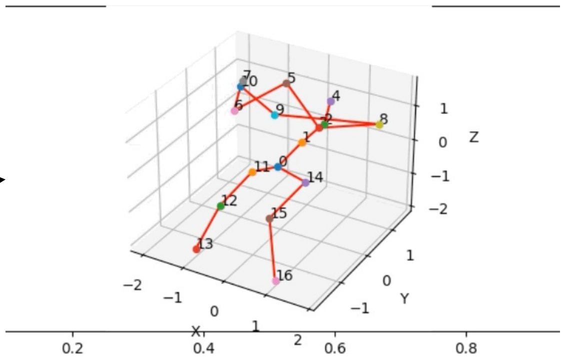
[6] Chawla, Nitesh V., et al. "SMOTE: synthetic minority over-sampling technique." *Journal of artificial intelligence research* 16 (2002): 321-357.

Data Preprocessing



$\mathcal{R} \in \mathbb{R}^{n\times17\times3}$





$\mathcal{R} \in \mathbb{R}^{120\times17\times3}$

Task-based classification

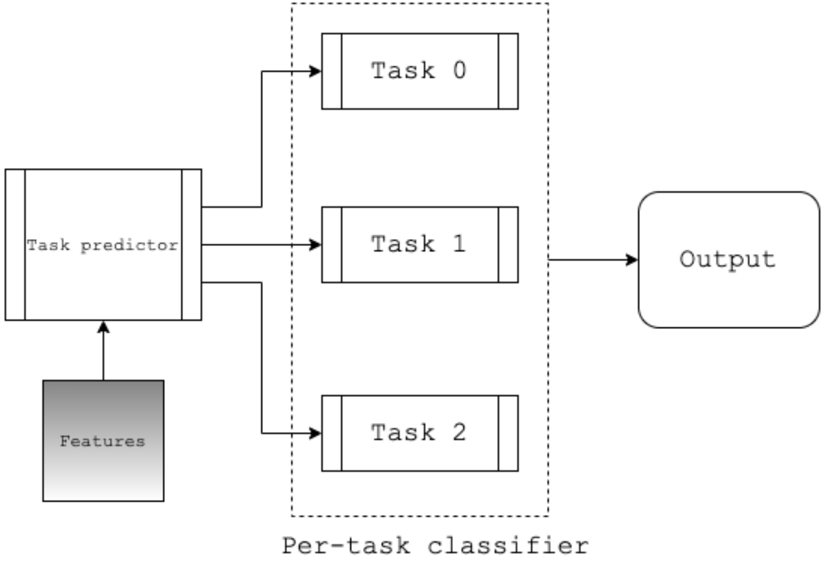


Fig 7: Task-based framework

Features
Raw Features
Handcrafted Features
Extended HF
Temporal Features

Augmentation
SMOTE
Reflection

Classifier
Random Forest
Gradient Boosting
LSTM

Table I: Bag of Features, Augmentations, and Classifiers

Data Visualization using UMAP[7]

Feature selection for task-predictor

Raw Features $\mathcal{R}$ shows distinct segregation in low-dimensional space per task

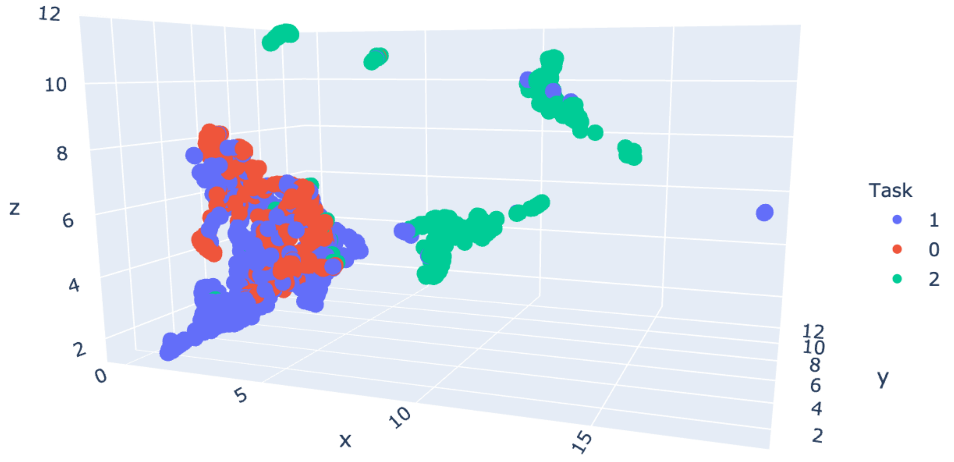


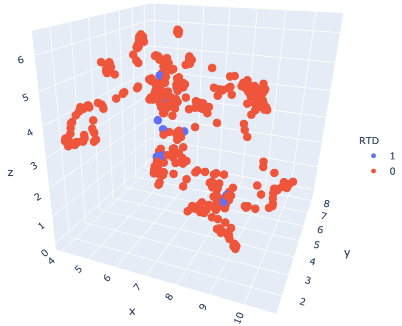
Fig 8: UMAP embeddings of Raw features based on tasks

[7] McInnes, Leland, John Healy, and James Melville. "Umap: Uniform manifold approximation and projection for dimension reduction." *arXiv preprint arXiv:1802.03426* (2018).

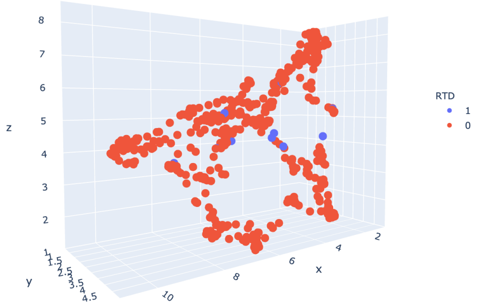
Data Visualization (Task 0)

Fig 9: UMAP embeddings for feature elimination for Task 0 on RTD labels.

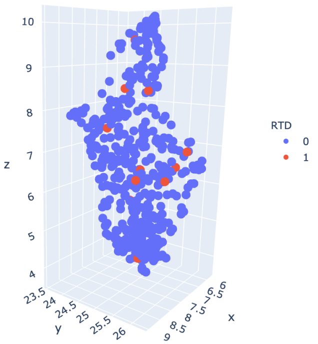
(a) Raw Features



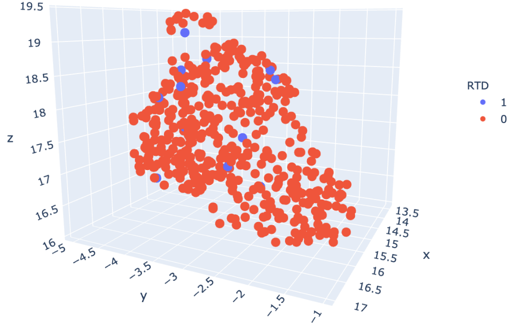
(b) Handcrafted Features



(c) Extended HF



(d) Temporal Features



Data Visualization (Task 1)

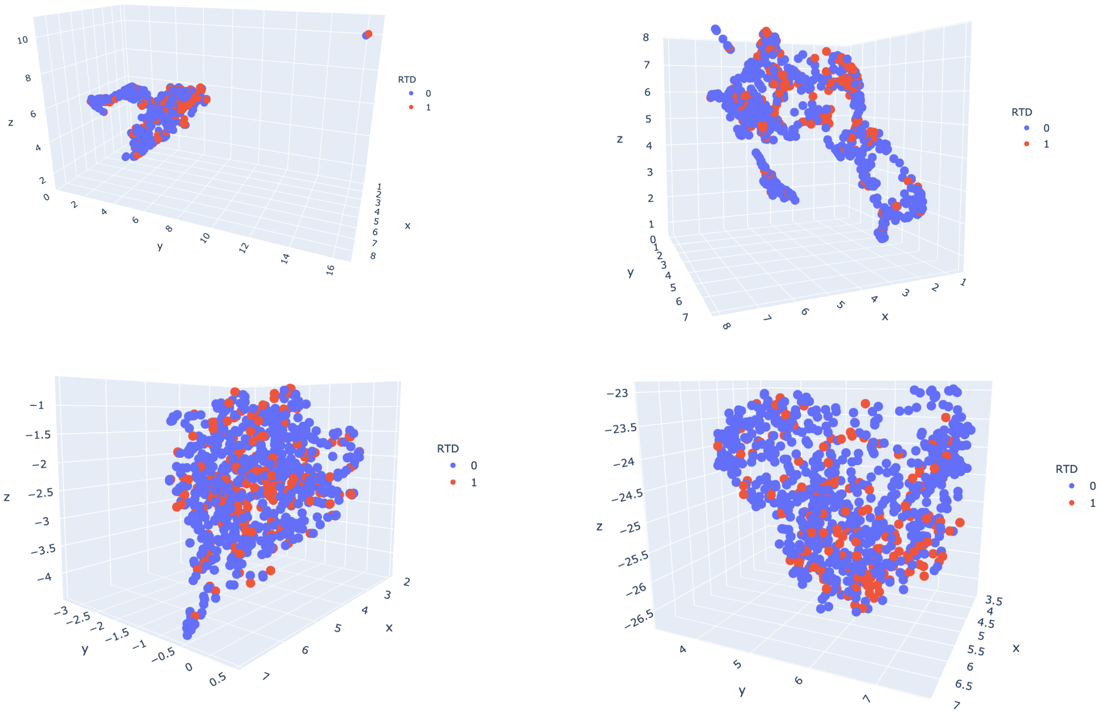
Fig 10: UMAP embeddings for feature elimination for Task 1 on RTD labels.

(a) Raw Features

(b) Handcrafted Features

(c) Extended HF

(d) Temporal Features

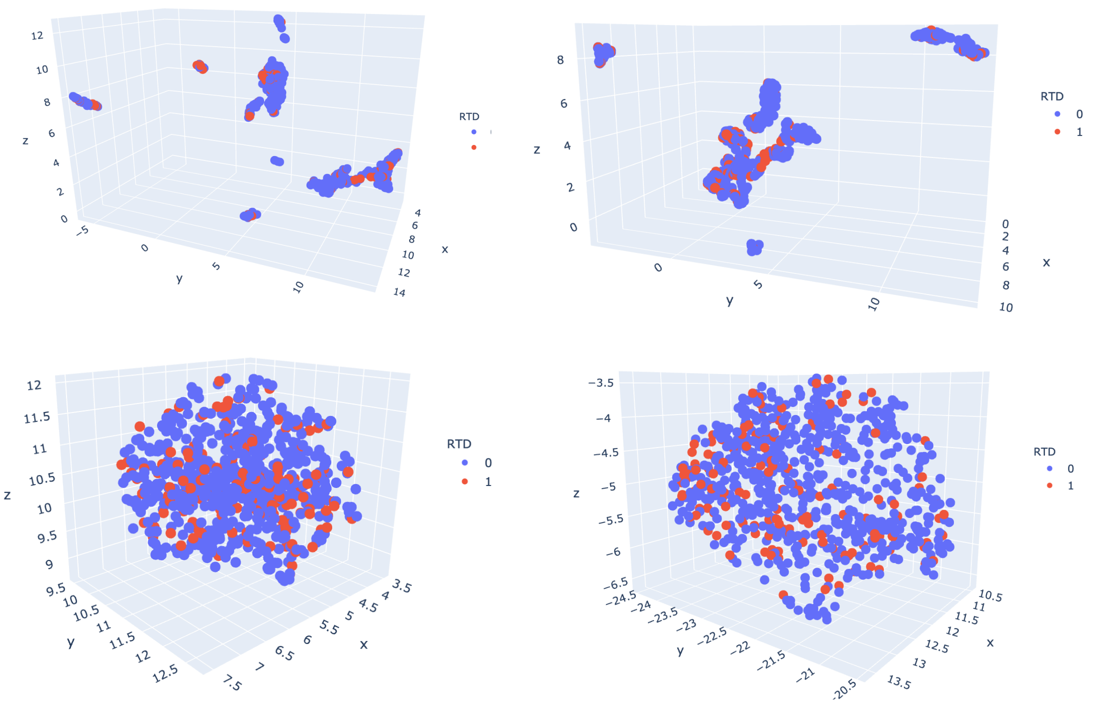


Data Visualization (Task 2)

Fig 11: UMAP embeddings for feature elimination for Task 2 on RTD labels.

(a) Raw Features

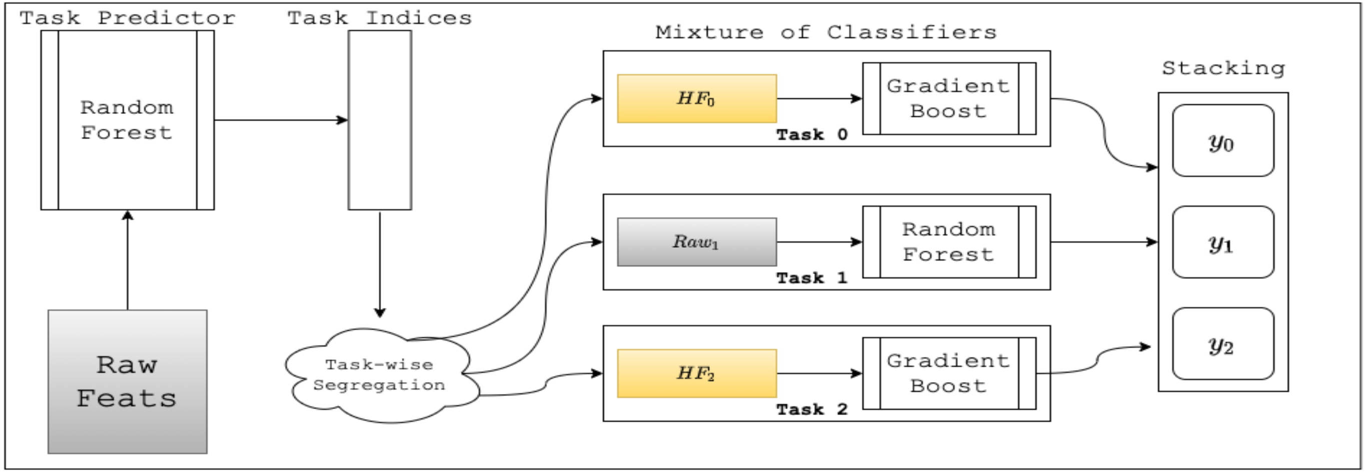
(b) Handcrafted Features



(c) Extended HF

(d) Temporal Features

Architecture



Classification Type		Method	Feature
Task Prediction		Random Forest	Raw Feature
RTD	Task 0	Gradient Boosting	Handcrafted Feature
	Task 1	Random Forest	Raw Feature
	Task 2	Gradient Boosting	Handcrafted Feature

Results – Phase I | Task Prediction

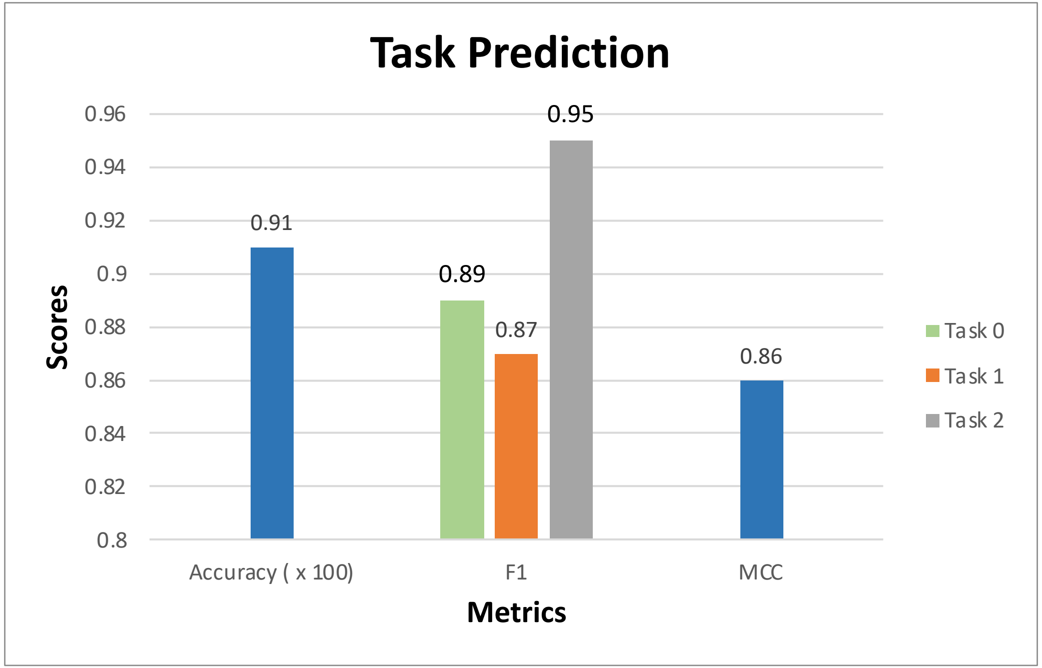
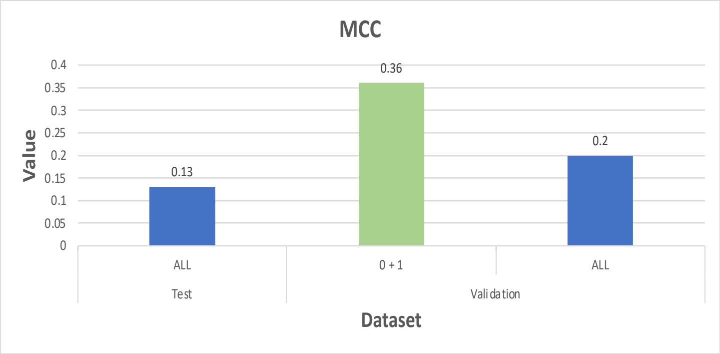
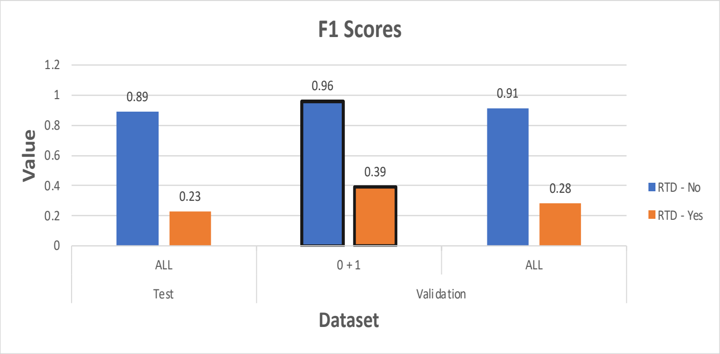


Fig 12: Task prediction on validation set

Results – Phase II | RTD Classification





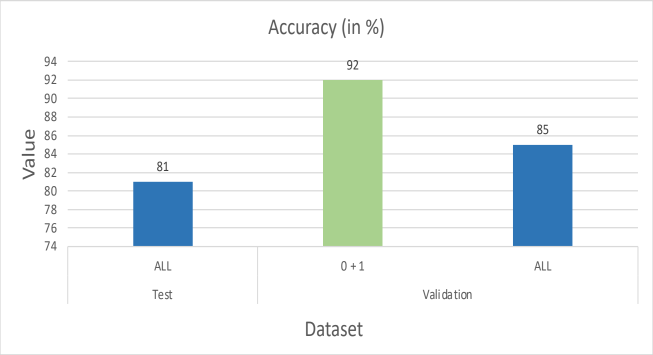
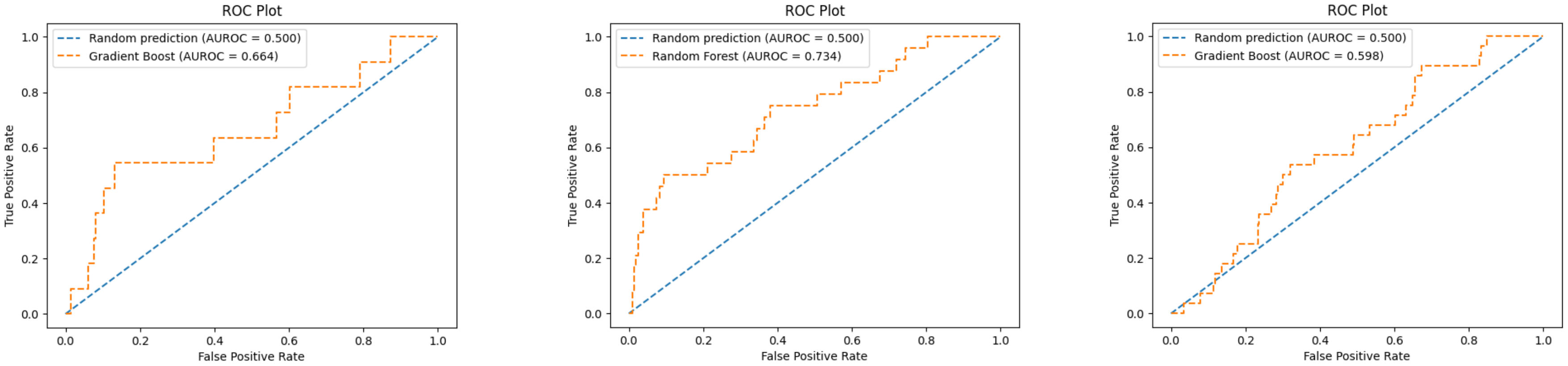


Fig 13: RTD results across validation and test sets

Results – Better than Random Prediction



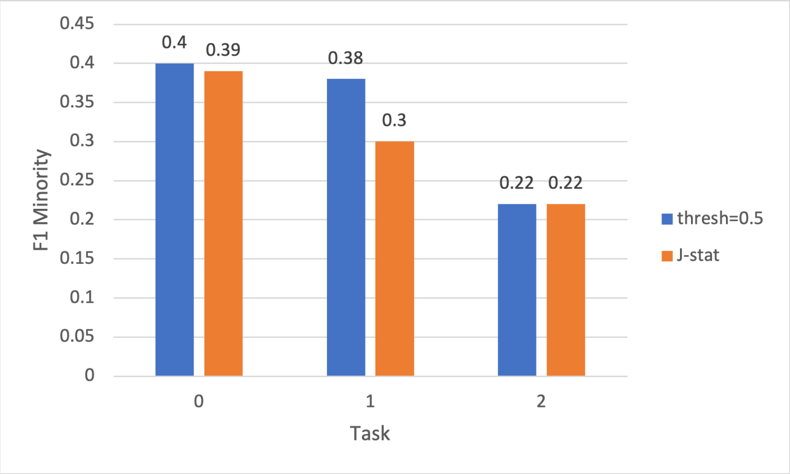
Handcrafted Feat → GB
(a): Task 0

Raw Feat → RF
(b): Task 1

Handcrafted Feat → GB
(c): Task 2

Fig 14: Task-wise ROC curves

Results – Optimal Threshold for improved RTD classification



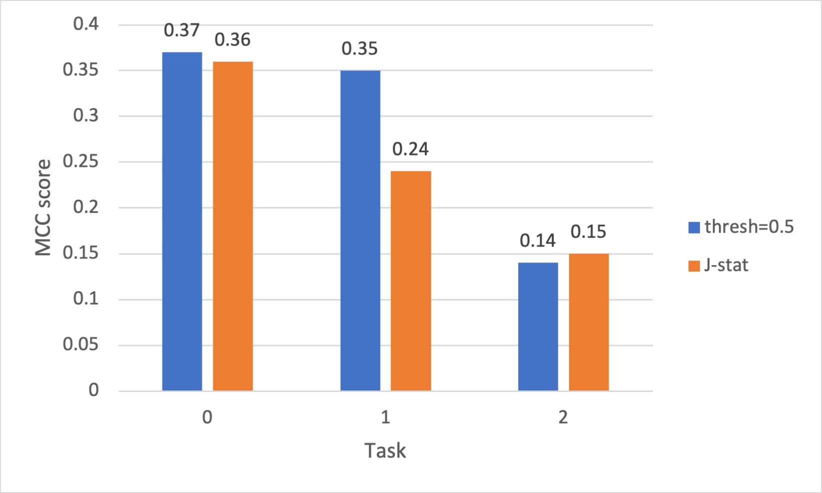
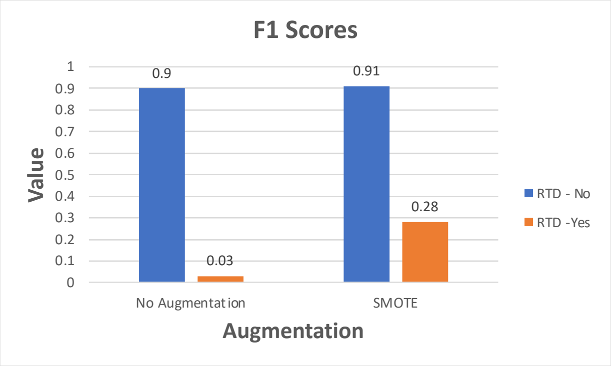


Fig 15: Comparison of F1 minority and MCC scores after finding best threshold score

Experiments

(a)



(b)

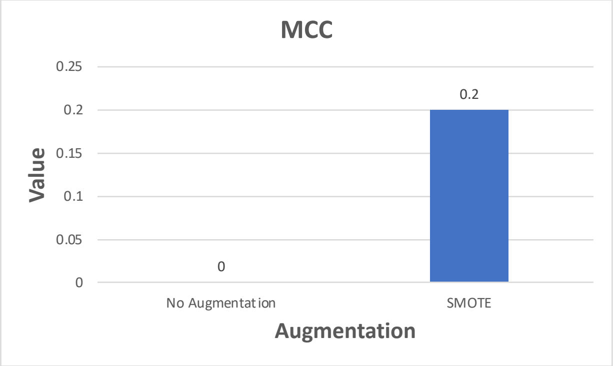
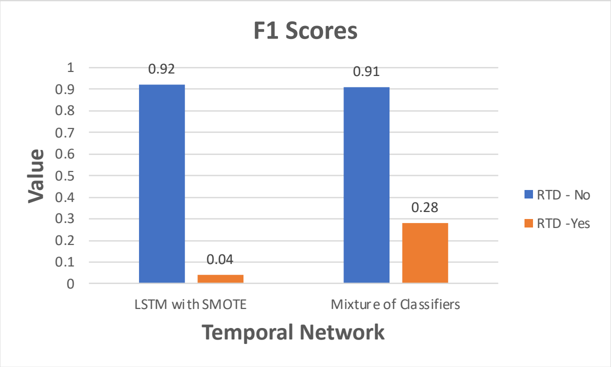


Fig 16: Effect of SMOTE as data augmentation

(a)



(b)

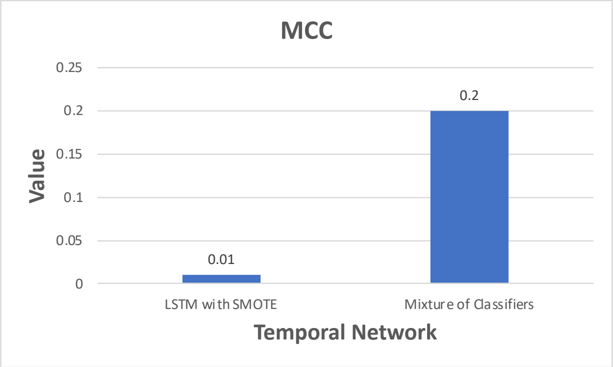
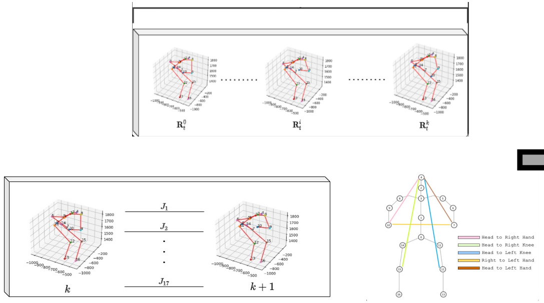
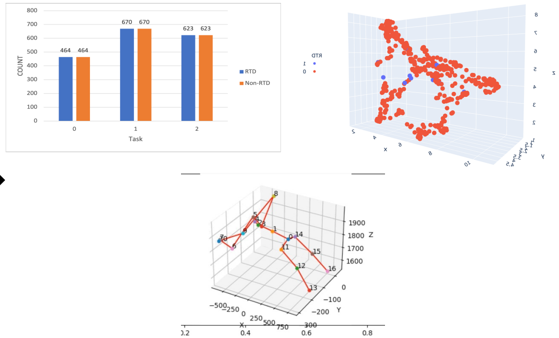


Fig 17: Using Temporal Networks with SMOTE

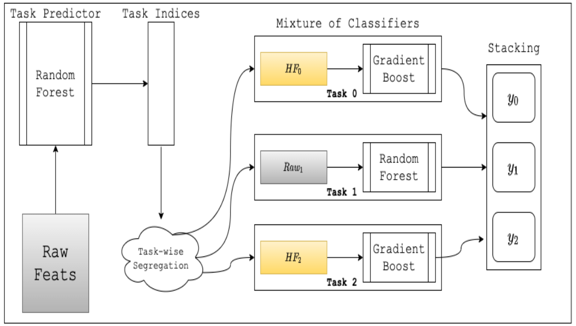
Summary



Feature Space



Augmentation & UMAP



Pipeline

Class	RTD No	RTD Yes
RTD No	648	81
RTD Yes	40	23

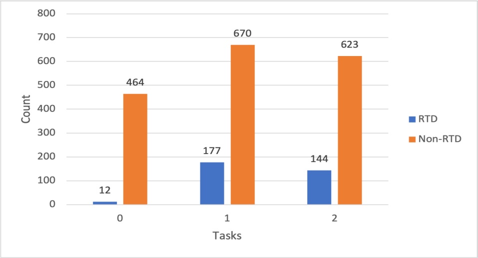
Confusion Matrix

Dataset	Accuracy (in %)	F1	MCC
Validation	85	[0.91, **0.28**]	**0.2**
Test	81	[0.89, **0.23**]	**0.13**

Results

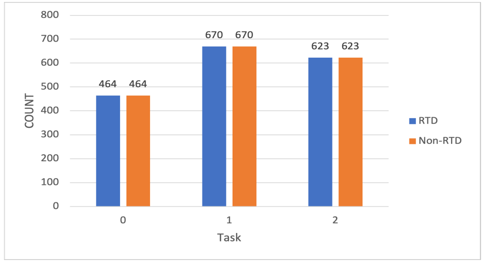
Limitations and Future Work

- *Minority class performance is limited.*

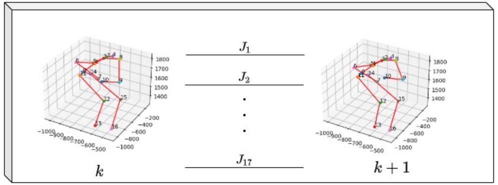


SMOTE

Not Enough?

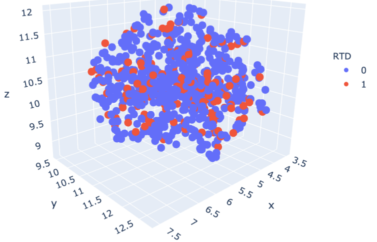


- *Dimensionality reduction using UMAP did not provide concrete class separation*



UMAP

Is it Useful?



Addressing the Limitations

Flow-based Generative Models[7]

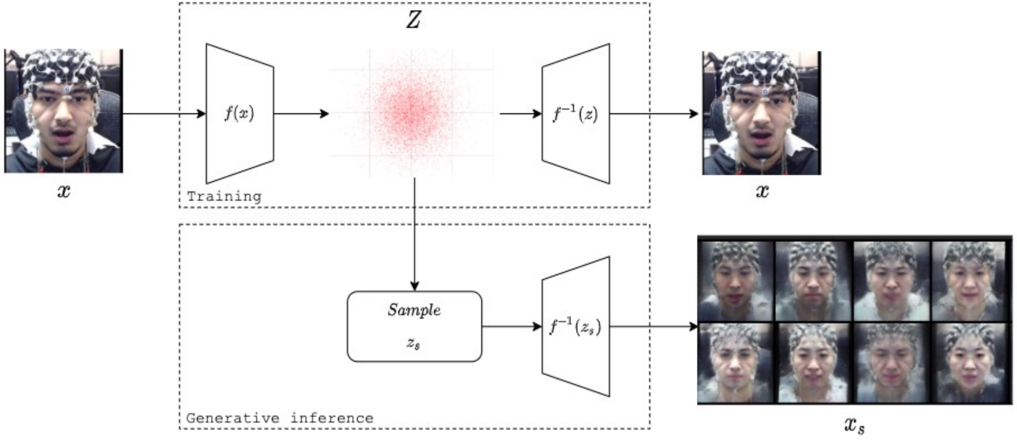


Fig 18: Normalizing Flow Architecture

Self-attention models (Transformers)[8]

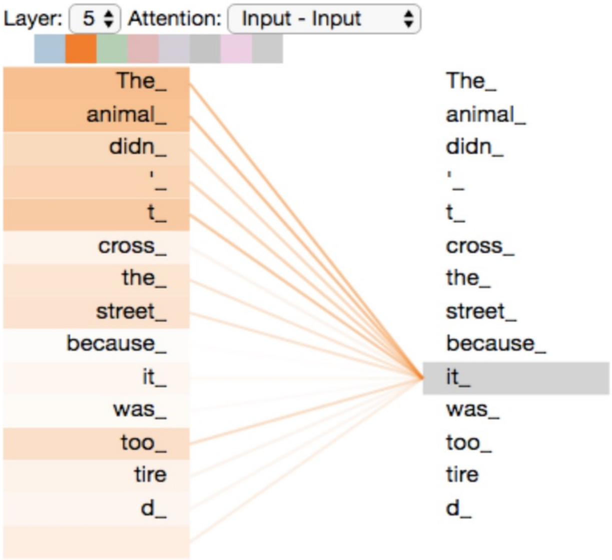


Fig 19: Transformer visualization

[7] Rezende, Danilo, and Shakir Mohamed. "Variational inference with normalizing flows." *International conference on machine learning*. PMLR, 2015.
[8] Vaswani, Ashish, et al. "Attention Is All You Need.(Nips), 2017." *URL http://arxiv. org/abs/1706.03762* (2021).

PhD Roadmap (Publications)

- **Task-based Classification of Reflective Thinking Using Mixture of Classifiers (ACII 2021)**
  S. Aathreya, L. Jivnani, S. Srivastava, S. Hinduja and S. Canavan. Task-based Classification of Reflective Thinking Using Mixture of Classifiers. *Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*, 2021.

- **Recognizing Emotion in the Wild using Multimodal Data (ICMI 2020)**
  S. Srivastava, S. Aathreya, S. Hinduja, Sk R. Jannat, H. Elhamdadi, and S. Canavan. Recognizing Emotion in the Wild using Multimodal Data. *International Conference on Multimodal Interaction, 2020*.

- **Three-level Training of Multi-Head Architecture for Pain Detection (FG 2020)**
  S. A. S. Lakshminara, S. Hinduja and S. Canavan. Three-level Training of Multi-Head Architecture for Pain Detection. *Face and Gesture Recognition*, 2020.

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PhD Roadmap (Current Work)

Effect of Conditional Affect Modality Synthesis using Tractable Generative Models

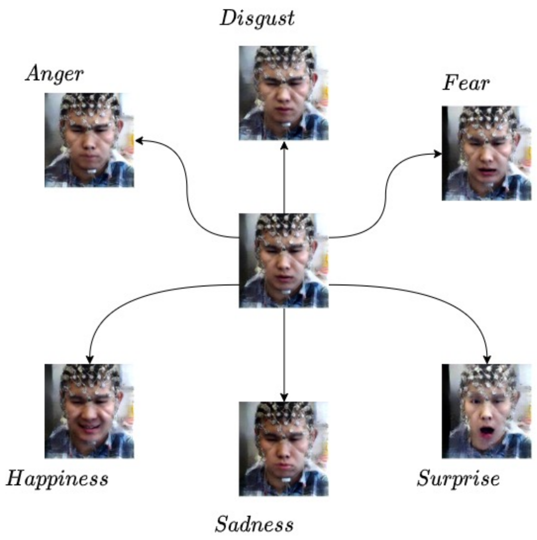

Fig 20: Under preparation for **ACII 2022**

PTSD Analysis using Self-attention Models

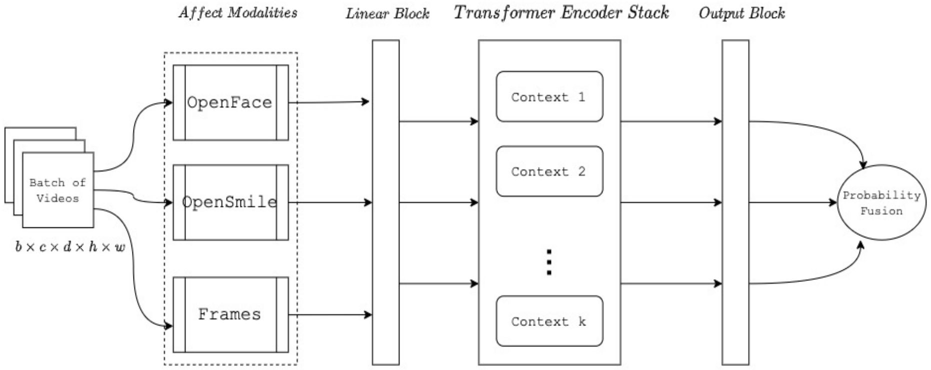

Fig 21: Under preparation for **WACV 2023**

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PhD Roadmap (Future Work)

Flow-based Supervised Learning using Contrastive Bhattacharyya Loss

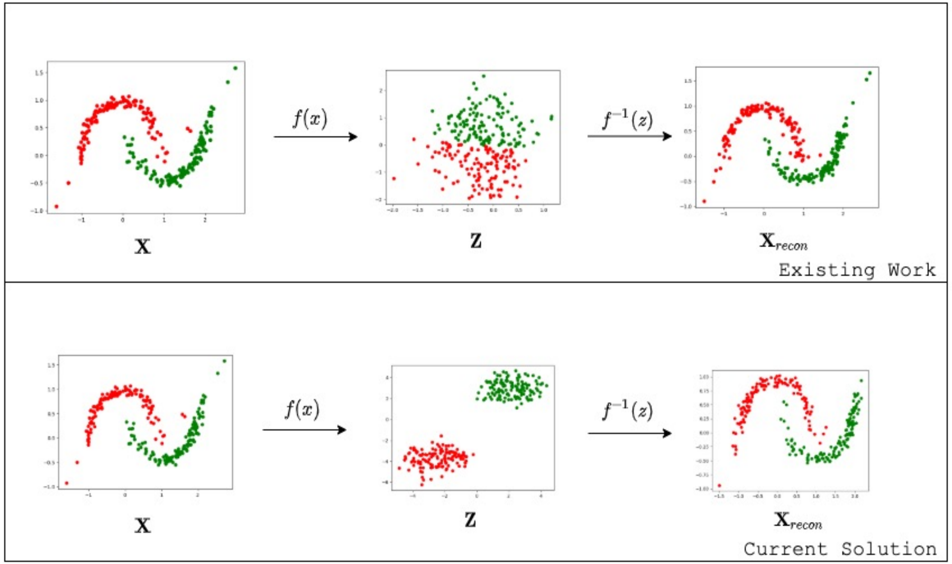


Fig 22: Progress till now includes low dimensional output. Need to scale it to higher dimensions.

Cross-Modal Data Synthesis

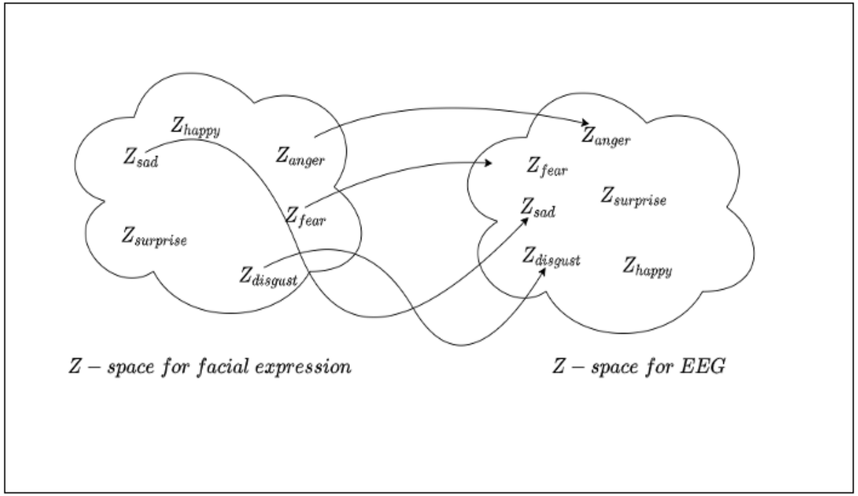
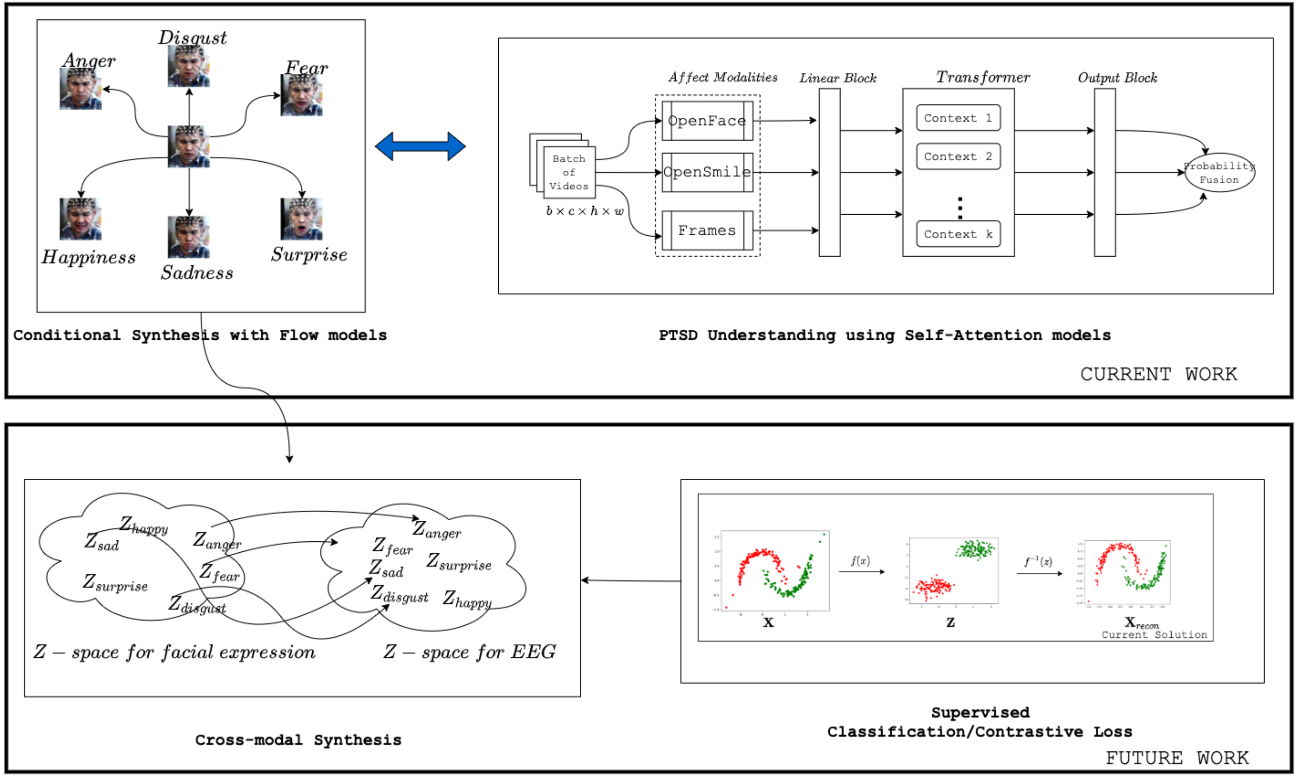


Fig 23: Cross Modality Synthesis by combining Data Augmentation and Supervised Classification.

PhD Roadmap (Putting It Together)



PhD Roadmap (Timeline)

Tasks	Timeline						
	Spring 2022	Summer 2022	Fall 2022	Spring 2023	Summer 2023	Fall 2023	Spring 2024
Conditional Synthesis of Affect Modality using Flow-based generative models							
Affective Computing & Intelligent Interaction (ACII) 2022 Submission							
PTSD understanding using self-attention models							
Winter Applications of Computer Vision (WACV) 2023 Submission							
Flow-based Classification using Contrastive Bhattacharyya Loss							
Computer Vision and Pattern Recognition (CVPR) 2023							
Cross-modal Synthesis of Affect Modalities (Face, physiological, audio)							
IEEE Transactions on Affective Computing (TAC) Submission							
Dissertation Defense							

PhD Timeline: Fall 2019 – Spring 2024
Thesis Defense: April 2024

PhD Highlights so far…

- Collaborating with Dr. Shaun Canavan and Dr. Alison Salloum for PTSD understanding
- Collaborating with Dr. Tempest Neal and Dr. Shaun Canavan (NSF award no. 2039373)
    - Multimodal Continuous Authentication
- ICPR 2022 Reviewer
- Joining as AI research Intern at Zippin for Summer 2022
- Best paper award (ACIIW 2021)
    - *Task-based Classification of Reflective Thinking Using Mixture of Classifiers*

Summary

- *Application areas of Affective Computing*
  - Better augmentation technique
    - Capture the underlying distribution of the dataset
  - Comprehensible latent space representation
- *Addressing Limitations*
  - Conditional generative models (Glow[8])
    - Synthesize and manipulate likelihood-based data.
  - Supervised classification
    - Flow-based models
    - Contrastive Bhattacharyya loss

[9] Kingma, Durk P., and Prafulla Dhariwal. "Glow: Generative flow with invertible 1x1 convolutions." *Advances in neural information processing systems* 31 (2018).