Detecting PTSD Using Neural and Physiological Signals: Recommendations from a Pilot Study

Manasa Kalanadhabhatta
University of Massachusetts Amherst
Amherst, MA, USA
manasak@cs.umass.edu

Shaily Roy
Syracuse University
Syracuse, NY, USA
sroy15@syr.edu

Trevor Grant
Independent Researcher
Syracuse, NY, USA
tgrant@syr.gov

Asif Salekin
Syracuse University
Syracuse, NY, USA
asalekin@syr.edu

Tauhidur Rahman
University of California San Diego
San Diego, CA, USA
trahman@ucsd.edu

Dessa Bergen-Cico
Syracuse University
Syracuse, NY, USA
dkbergen@syr.edu

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***Abstract*—Post-traumatic stress disorder (PTSD) is a serious condition that is characterized by negative mood and affect, hyperarousal, irritability, and reactivity, as well as deterioration of cognitive processes such as attention and memory. Timely identification and treatment of PTSD symptoms can significantly improve symptom management and recovery. However, accurate prediction of PTSD outside clinical settings is often challenging. In this work, we investigate whether deficits in cognitive performance can be used to classify individuals with and without PTSD. We further examine whether neural and physiological signals such as prefrontal cortex activity, heart rate, respiration, and electrodermal activity recorded in conjunction with cognitive task performance can be leveraged to improve PTSD classification. Our results indicate that working memory tasks can achieve an F1 score of 0.80 at classifying individuals with PTSD, which can be further improved to 0.91 by combining multimodal information from neurophysiological signals. Based on our findings, we provide recommendations for in-the-wild PTSD classification.**

***Index Terms*—post-traumatic stress disorder, PTSD, cognitive performance, neural activity, physiological signals, wearables**

I. Introduction

Post-traumatic stress disorder (PTSD) is a serious psychiatric condition that can develop when an individual is exposed to a traumatic experience that is beyond a regular stressor, including military combat, transportation accidents, natural disasters, sexual violence, personal assault etc. [1]. It is often characterized by recurring intrusive thoughts, flashbacks, nightmares, and avoidance of stimuli related to the traumatic experience [2]. The lifetime prevalence of PTSD among civilians in the United States ranges from 3 to 27%, with higher risk identified among females and younger populations [3].

Individuals with PTSD may experience emotional numbing, dysphoria, and psychosomatic symptoms, as well as significant negative affect and problems with emotional expression [4]. Additionally, PTSD may lead to irritability, hypervigilance, and trouble sleeping and concentrating [2]. Cognitive theories of PTSD further underscore the influence of emotional stress on cognitive functioning, having deleterious effects on memory, attention, planning, and problem-solving abilities [5]. Evidence-based treatment can significantly improve outcomes in individuals with PTSD – to this end, prior work has proposed several interventions ranging from clinical approaches such as psychoeducation, mindfulness training, or trauma-focused treatment [6] to digital tools such as game-based exposure therapy [7] or virtual reality-based stress inoculation [8].

However, for such interventions to be delivered effectively, it is imperative to be able to accurately diagnose and monitor an individual's PTSD symptoms over time [2]. A characterization of PTSD symptoms, and the associated changes in mood and affect, is also beneficial for the development of context-aware affective computing tools [9]. Nonetheless, there is a lack of prior work on detecting PTSD in the wild, especially in a non-military population.

This work therefore focuses on furthering the affective computing community's knowledge of multimodal PTSD prediction in real-world settings. Specifically, we investigate whether performance as well as physiological and neural signals measured during cognitive tasks can be leveraged to identify individuals with PTSD. To this end, we aim to answer the following research questions:

- *RQ1:* Are PTSD symptoms associated with self-reported affect and/or objective cognitive performance in a civilian population?
- *RQ2:* Can performance on cognitive tasks involving attentional control, emotion regulation, or working memory demands predict PTSD? If so, which tasks have the best predictive performance?
- *RQ3:* Can multimodal models leveraging neural and/or physiological signals during cognitive tasks improve PTSD classification? If so, which multimodal features are most informative for prediction?

These questions have important research and real-world

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implications in terms of informing the development of affective technologies that account for a user's underlying trauma context. Our findings indicate that (i) PTSD symptom severity is associated with dimensions of negative affect as well as deficits in attention and working memory, (ii) these working memory deficits can be used to identify individuals with PTSD, and (iii) multimodal physiological and neural signals recorded in conjunction with working memory tasks can improve PTSD classification performance. Based on these results, we provide recommendations on the cognitive tasks and neurophysiological signals that can be used to accurately predict PTSD in civilian populations.

II. Related Work

A. Effect of PTSD on Affect and Cognition

PTSD is a psychiatric disorder characterized by recurring intrusive thoughts, flashbacks, nightmares, and avoidance of stimuli related to the traumatic experience [2]. Research has demonstrated that individuals with PTSD exhibit atypical levels of stress hormones, which can contribute to negative affect, emotional numbing, hyperarousal symptoms, and mood and anxiety disorders [4]. Characterizing PTSD symptoms can therefore help contextualize an individual's affective states.

In addition to impacting emotions, cognitive models of PTSD also suggest that it can alter functional brain activity and lead to alterations in cognitive processes such as memory, attention, and planning [5], [10]. Individuals with PTSD exhibit performance deficits in motor reaction and interference control [11], affective working memory [12], as well as attentional bias tasks [13]. This association between PTSD and cognitive performance motivates our investigation into using task performance as a potential predictor of PTSD.

B. Neural and Physiological Correlates of PTSD

Neuroimaging research over the years has discovered altered activity in several brain regions among individuals with PTSD. For instance, Henigsberg et al. reported stronger amygdala activation in response to emotional stimuli compared to non-emotional stimuli, smaller hippocampus size and activity during memory tasks, and lower prefrontal cortex (PFC) activity during cognitive control among individuals with PTSD as compared to healthy controls [14]. Individuals with PTSD have also been observed to exhibit higher event-related potential latencies during response inhibition and higher frontal activity in response to irrelevant stimuli [15], as well as significantly higher oxyhemoglobin changes in the lateral PFC during response inhibition [16].

Additionally, PTSD is associated with a range of physiological changes such as higher heart rates and lower high-frequency heart rate variability (HRV) during stress [17]. Individuals with PTSD also exhibit decreased parasympathetic activity in the autonomic nervous system and reduced HRV in response to affective stimuli [18]. Decreased parasympathetic and increased sympathetic control were also evidenced by low baseline respiratory sinus arrhythmia and high baseline electrodermal activity (EDA) among individuals with PTSD [19]. PTSD is also associated with a higher number of EDA responses during threatening stimuli [20]. These observations set the stage for investigating whether neural or physiological activity during cognitive tasks can differentiate between individuals with and without PTSD.

C. Detecting PTSD in the Wild

Early detection and intervention are crucial for improving long-term outcomes among individuals with PTSD [2]. To this end, wearable devices have emerged as a potential tool for in-the-wild PTSD detection, with several studies exploring their predictive utility. For example, Sadeghi et al. utilized a smartwatch to predict PTSD hyperarousal events among veterans using heart rate and body acceleration features, achieving an accuracy of over 81% using an XGBoost classifier [21]. Fletcher et al. used an ankle-worn EDA, motion, and skin temperature sensor to detect arousal events and initiate cognitive-behavioral interventions [22]. However, these studies are limited by the subjective nature of self-reported arousal *events* and do not test for overall PTSD symptom severity.

Webb et al. attempted to fill this gap and used heart rate and skin conductance signals while participants watched emotionally evocative videos via virtual reality to identify individuals with PTSD vs those without trauma/PTSD, achieving a classification accuracy of 90% [23]. Similarly, Liu et al. used brain activity measured via functional Magnetic Resonance Imaging (fMRI) to distinguish individuals with PTSD from healthy controls with an accuracy of 92.5% [24]. Nevertheless, the use of neural data for PTSD detection in the wild has been very limited due to practical considerations.

The emergence of functional Near-Infrared Spectroscopy (fNIRS) as a relatively non-invasive, safe, portable, and cost-effective means of monitoring brain activity as compared to traditional neuroimaging technologies has created opportunities for investigating the neural basis of psychiatric and neurological disorders and utilizing these for diagnoses more widely [25]. Balters et al. utilized a portable fNIRS system to investigate the cortical activation patterns associated with emotional face processing and predict PTSD in youth with post-traumatic stress symptoms (PTSS) [26]. They observed increased activation in the dorsolateral prefrontal cortex (DLPFC) in response to both fearful and neutral faces compared to baseline, and demonstrated a strong correlation between cortical responses in eight frontocortical channels and PTSS scores. Our work builds on prior research to investigate the feasibility of using fNIRS and physiological signals for in-the-wild PTSD classification.

III. Methods

A. Participants

As part of a larger study on the effect of mindfulness-based interventions on PTSD symptom severity, 31 participants were recruited to complete a baseline and a six-week follow-up session post intervention [27]. The present study reports only on the baseline sessions, focusing on the detection of PTSD symptom severity at this stage. Therefore, none of the participants were exposed to any mindfulness strategies or other PTSD interventions. The study was approved by the Institutional Review Board at Syracuse University and was advertised as a study on college student stress and trauma; the presence of PTSD was not an inclusion/exclusion criterion. All participants completed written informed consent at the start of the study. All participants were female (recruitment was open to all genders but only female participants volunteered). The mean age of the participants was 22.4 years (SD: 4.52 years). 19 participants identified as White, 8 as Black, and 1 each as Asian, Hispanic, and Native American.

B. PTSD, Stress, and Affect Measures

The PTSD Checklist - Civilian Version (PCL-C; [28]) was used to measure participants' traumatic stress. The PCL-C is a 17-item self-report questionnaire in which civilian respondents rate how bothered they have been by DSM-IV posttraumatic stress symptoms in the past month on a 5-point Likert scale from "not at all" (1) to "extremely" (5). The PCL-C is used to screen for PTSD and monitor symptom changes, with scores above 30 indicating sub-threshold PTSD. Accordingly, we categorize all participants scoring above 30 as those with PTSD ($N = 19$) and the rest as non-PTSD ($N = 12$).

Participants' positive and negative affect over the past week were measured using the Positive and Negative Affect Schedule (PANAS-SF; [29]). Additionally, somatic symptoms of anxiety over the past seven days were measured using the Somatic Arousal – Fear questionnaire [30]. Lastly, the 10-item Perceived Stress Scale (PSS) was used to assess how unpredictable, uncontrollable, and overloaded participants found their lives to be in the past month [31].

C. Cognitive Tasks

Participants completed six cognitive tasks that involved attentional control (AC), emotion regulation (ER), or working memory (WM) demands. These tasks were selected in order to engage cognitive resources known to be impaired by stress and PTSD [12], [15], [32]. Tasks were presented using a Latin Square design with controlled rest periods between each task via an experiment developed using the PsychoPy toolkit [33]. Participants read the on-screen instructions and completed a set of practice trials for each task before the beginning of the testing session.

The AC tasks included a *Reaction Time* task [34], where participants were required to respond as quickly as possible to a large "X" stimulus that appeared on the screen in each trial. Additionally, a *Go/No-Go* task [35] was used to test response inhibition – in each trial, participants were presented either with the target stimulus (a red rectangle) or a distractor (a blue oval). Participants were required to respond as quickly as possible when a target stimulus appeared and withhold their response when the distractor stimulus appeared.

Participants also completed two ER tasks – the emotional Stroop task and an emotional delayed recall/working memory task. The *Emotional Stroop* task [13] is a variant of the classic Stroop task, where participants are asked to respond with the color a word is presented in rather than reading aloud the color the word spells. In this variant, participants are asked to respond to words that represent neutral valence (e.g. "pencil", "fruit") or negative valence or physical threat (e.g., "weapon", "fight"). The words are presented in one of four colors (red, yellow, green, or blue) and the participants are asked to respond with the letter corresponding to the first letter of the color (e.g., "r" for "red"). In the *Emotional Working Memory* task [12], participants are shown a sequence of six letters to memorize and are asked to recall them after a delay period. During the delay, they are presented with an image that has either a neutral or a high negative valence.

Finally, the WM tasks included an *N-Back* task [36] where participants were presented with a stream of letters on the screen and asked to recall whether the current letter was the same as the one displayed N stimuli previously. In addition to this visual task, we used an auditory variant, the *Audio N-Back* task, that followed the same protocol but used auditory cues instead. We used N=2 for both variants of the task.

The performance on each of the cognitive tasks was measured in terms of the average response times and the average accuracy across all trials.

D. Measuring Prefrontal Cortex Neural Activation

Participants' neural activation levels in the dorsolateral prefrontal cortex (DLPFC) during the cognitive tasks were recorded using functional Near Infrared Spectroscopy (fNIRS). We used the Hitachi ETG-4000 fNIRS device with a 3x11 probe covering the frontal cortex region and resulting in 52 channels of data. The position of the optode array was consistent across all participants, with the central channel positioned over the nasion and the middle bottom probe over the Fpz location as per the international 10-20 coordinate system [37]. Data were recorded at 10 Hz and a bandpass filter of 0.01 to 0.5 Hz was applied to remove physiological noise and isolate cognitive activation. The data were downsampled to 4 Hz and converted to changes in optical density per channel. The relative changes in oxyhemoglobin (ΔHbO) and deoxyhemoglobin (ΔHbR) were computed using the modified Beer-Lambert law [38].

The ΔHbO data was modeled as a generalized linear model (GLM) for each cognitive task completed by the participant as well as for the rest periods in order to obtain the per-channel coefficients that indicate the magnitude of neural activation. The GLM was fit using the autoregressive iteratively reweighted least squares approach based on the canonical hemodynamic response function [39]. The per-channel coefficients were condensed into activation levels across particular regions of interest (ROIs) by mapping them to functional brain regions. Data were averaged across three ROIs – the frontopolar area (FPA), the orbitofrontal cortex (OFC), and the premotor cortex (PMC) – on each hemisphere (left/right). Additionally, the average activation levels across the entire left and right DLPFC were also computed. This resulted in eight ROI-based activation level values for each cognitive task. The values for each task were normalized for each participant by subtracting the activation levels of the controlled rest period.

E. Measuring Physiological Responses

In addition to neural activation, we recorded participants' physiological data including electrocardiogram (ECG), electrodermal activity (EDA), and respiration rate using the Biopac MP-150 receiver device. ECG data were obtained using 3 electrodes, each placed on the right and left arm and the left leg. Respiration data was collected using the BIOPAC respiratory effort transducer band and EDA was measured at the palm of the participant. The raw data was processed to extract five aggregated physiological measures during each cognitive task as well as the rest periods – mean heart rate, mean ECG peak distance, respiration rate, mean EDA amplitude, and mean EDA rise time. The values for the rest periods were subtracted from the values for each task for each participant. The five physiological measures are together referred to henceforth as the Biopac signals.

F. Analysis

We now describe the analysis methods used to answer the research questions previously described in Section I. First, we attempted to determine whether PTSD severity is associated with weekly or monthly affect ratings as well as with performance on each cognitive task described in Section III-C. We computed the Spearman correlation between the PTSD scores and self-reported measures of positive and negative affect, somatic arousal, and perceived stress. Similarly, we also computed the Spearman correlation between PTSD severity and the average reaction time on each task to validate prior work that shows attention, emotion regulation, and memory deficits among individuals with PTSD [12], [13], [32].

Further, we examined whether cognitive task performance can be leveraged to predict PTSD status. To this end, we trained machine learning models that use the response time and accuracy on each task as features to predict whether a person's PTSD score is above the clinical threshold.

We used a stratified 3-fold cross-validation scheme to evaluate model performance and report the mean F1 scores and accuracies across all folds. Within each fold, missing feature values were first imputed using the mean value over the train set in that fold, and synthetic minority oversampling (SMOTE) was used to handle class imbalance [40]. SMOTE uses the training data to create synthetic samples of the minority class from the neighborhood of existing samples to improve training. The features were then scaled and principal component analysis (PCA) was applied [41]. We chose PCA for dimensionality reduction and regularization instead of using feature selection based on training data in order to maintain consistent feature sets across training folds. We trained and evaluated five different machine learning models – logistic regression, random forest, gradient boosting, K-nearest neighbors, and support vector classifiers – and selected optimal hyperparameters via grid search. These models were chosen due to their amenability to datasets of sizes similar to ours as well as their relatively higher explainability in comparison to deep learning models. In addition to training PTSD prediction models individually on the features from *each* cognitive task, we followed the same strategy to train a classifier on the concatenated features from *all* cognitive tasks to investigate whether multiple tasks can achieve better classification performance.

After examining the predictive accuracy of task performance-based models, we used the physiological and neural data described in the previous subsections to train and evaluate multimodal PTSD prediction models. Specifically, we employed the same pipelines and evaluation strategy that was used for task performance-based models to train models with three additional feature sets during each cognitive task: (i) task performance + Biopac (physiological) features, (ii) task performance + fNIRS (neural) features, and (iii) task performance + Biopac + fNIRS features. The Biopac features included mean heart rate, mean ECG peak distance, respiration rate, mean EDA amplitude, and mean EDA rise time. The fNIRS features included activation levels in the left and right DLPFC, FPA, OFC, and PMC. We tested whether these additional features improve predictive performance over using only task performance for classification. In addition to evaluating this for each cognitive task, we also investigated whether these feature sets improve PTSD prediction when utilizing all cognitive tasks.

Finally, we scrutinized the interpretability of the best-performing PTSD classifier by computing the SHapley Additive exPlanations (or SHAP values; [42]) for the model. SHAP uses a game theoretic approach to explain the predictions of a machine learning model by computing the contribution of each feature to the prediction in an additive fashion. We report the importance of each feature in terms of the mean absolute SHAP value as well as examine the dependence of SHAP values on the magnitude of input features in order to determine how they impact the predicted PTSD probabilities. We compared our findings to the existing literature on the effect of PTSD on physiology and neural activation to critically evaluate the features that influence our model's predictions.

IV. Results

A. Association Between PTSD and Affect/Cognition

Table I shows the Spearman correlation (and p value) between each affect/cognitive performance score and PTSD symptom severity. We observe that

- Positive affect does not show a significant association with PTSD severity. However, negative affect, somatic arousal, and perceived stress all exhibit a significant ($p < 0.01$) positive correlation with PTSD scores.
- PTSD scores show a significant negative correlation with response times on the Reaction Time and Audio N-Back tasks.

Our findings are in line with prior research showing that PTSD severity is strongly associated with negative emotional states [4] as well as attention [11] and working memory

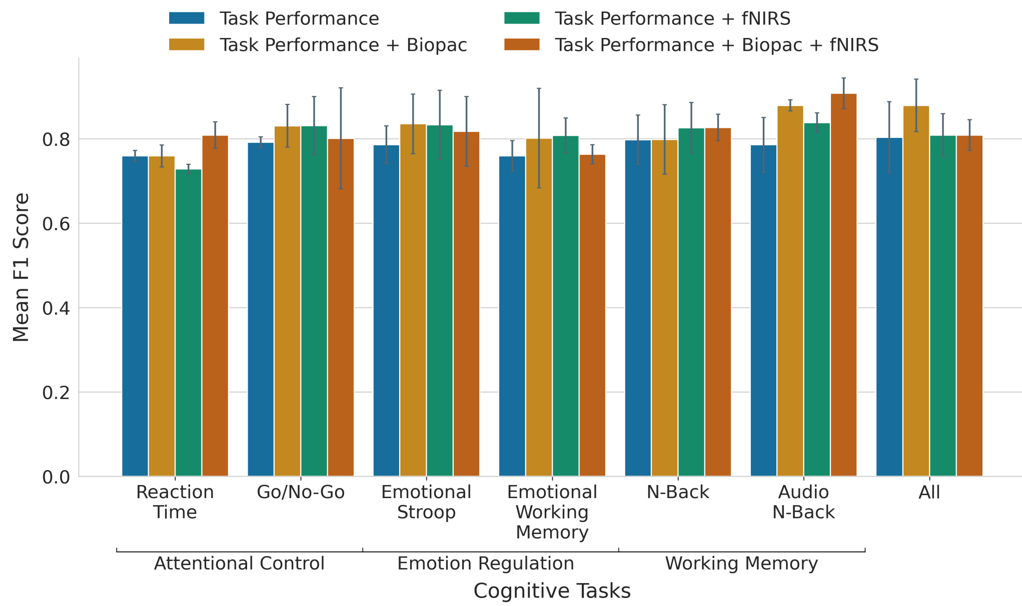

Fig. 1: Mean and standard deviations of F1 scores of the best-performing models for each feature set and cognitive task.

TABLE I: Correlation between PTSD symptom severity and affect scores/cognitive performance ($^* \implies p < 0.05$).

	Spearman r	**p value**
Affect (self report)		
Positive Affect	-0.06	0.75
Negative Affect	0.71	$< 0.001^*$
Somatic Arousal	0.42	0.02^*
Perceived Stress	0.62	$< 0.001^*$
Cognitive Performance (response time)		
Reaction Time	-0.37	0.04^*
Go/No-Go	-0.30	0.11
Emotional Stroop	-0.21	0.26
Emotional Working Memory	0.10	0.58
N-Back	-0.33	0.07
Audio N-Back	-0.51	0.03^*

deficits [32]. Knowing whether an individual has PTSD may provide important context about their affective and cognitive states, helping intervene more effectively.

B. Predicting PTSD Using Cognitive Task Performance

PTSD prediction models were trained using features from cognitive task performance as described in Section III-F. Specifically, the average reaction time and performance accuracies from each task were used as features to train task-specific models. We found that logistic regression models outperformed others for all task-specific models. The average F1 score and accuracy for the best task-specific models are reported in Table II. The model trained on the N-Back task features outperformed other tasks, with an average F1 score of 0.80 and an average accuracy of 0.74 at detecting PTSD.

When training machine learning models to predict PTSD using features from all cognitive tasks, a support vector classifier achieved the best classification performance, with an F1 score of 0.80 and an accuracy of 0.71 (see Table II).

TABLE II: PTSD classification based on task performance – mean F1 Score and accuracy of best-performing models for each cognitive task (LR: Logistic Regression, SVC: Support Vector Classifier).

Task	**Best Model**	**F1 Score Mean $\pm$ SD**	**Accuracy Mean $\pm$ SD**
Reaction Time	LR	0.76 ± 0.01	0.61 ± 0.02
Go/No-Go	LR	0.79 ± 0.06	0.67 ± 0.10
Emotional Stroop	LR	0.79 ± 0.05	0.67 ± 0.01
Emotional Working Memory	LR	0.76 ± 0.01	0.61 ± 0.02
N-Back	LR	$\mathbf{0.80 \pm 0.09}$	$\mathbf{0.74 \pm 0.12}$
Audio N-Back	LR	0.79 ± 0.05	0.68 ± 0.09
All	SVC	0.80 ± 0.02	0.71 ± 0.07

To summarize, our results indicate that

- The N-Back working memory task is best at classifying individuals with and without PTSD based solely on reaction time and performance accuracy.
- A combination of all six cognitive tasks fails to significantly improve classification performance over using only the N-Back task.

Prior research has also demonstrated the utility of the N-Back task towards probing working memory deficits as well as delivering working memory training interventions among individuals with PTSD [43].

C. Multimodal Prediction of PTSD

In addition to predicting PTSD based on cognitive performance, we evaluated whether DLPFC neural activity or physiological signals such as heart rate, respiration, or EDA recorded during cognitive tasks could improve classification

TABLE III: Multimodal PTSD classification – mean F1 score and accuracy of best-performing task/model combinations for each multimodal feature set (ANB: Audio N-Back, GB: Gradient Boosting classifier).

Feature Set	Best Task	Best Model	F1 Score Mean $\pm$ SD	Accuracy Mean $\pm$ SD
Task+Biopac	ANB	GB	0.88 ± 0.03	0.84 ± 0.04
Task+fNIRS	ANB	GB	0.84 ± 0.12	0.81 ± 0.12
Task+Biopac+fNIRS	ANB	GB	0.91 ± 0.08	0.88 ± 0.11

performance. To this end, we evaluated models trained with Task Performance + Biopac, Task Performance + fNIRS, and Task Performance + Biopac + fNIRS features.

Figure 1 shows the mean F1 scores of these models in comparison to those using only Task Performance markers as features. Specifically, we plot the mean and standard deviation of the best-performing model across 3-fold cross-validation for each feature set and cognitive task. We find that

- The addition of Biopac features improves prediction performance over solely using performance features under the Go/No-Go, Emotional Stroop, Emotional Working Memory, and Audio N-Back tasks.
- The addition of fNIRS features improves prediction performance over solely using performance features under the Go/No-Go, Emotional Stroop, Emotional Working Memory, N-Back, and Audio N-Back tasks.
- When using the Reaction Time or Audio N-Back tasks for classification, adding both Biopac and fNIRS features provides better classification performance than using only one of these modalities.

In terms of overall multimodal classification performance, Table III shows the mean F1 scores and accuracy for the best-performing classifiers for each multimodal feature set (i.e., task performance + Biopac, task performance + fNIRS, and task performance + Biopac + fNIRS features). We observe that

- Gradient boosting classifiers trained on features from the Audio N-Back task provide the best multimodal classification performance when using a single cognitive task.
- The addition of Biopac features achieves an average F1 score of 0.88, outperforming fNIRS features that achieve an F1 score of 0.84. However, the addition of both Biopac and fNIRS can further improve classification, with an F1 score of 0.91 and an accuracy of 0.88.

Further, Figure 1 also shows that using multimodal features from *all* cognitive tasks does not improve PTSD classification F1 scores over using *only* the Audio N-Back task.

The better performance of multimodal classifiers trained on the Audio N-Back task, compared to those trained on other cognitive tasks, is supported by prior findings on neural and physiological correlates of working memory in individuals with PTSD [44]. PTSD is also known to mediate the relationship between HRV and working memory performance [45]. As seen in the previous subsection, the N-back and Audio

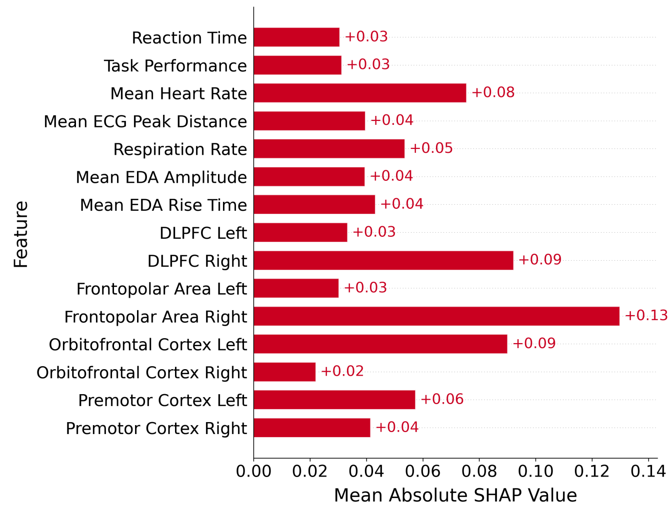

Fig. 2: SHAP Feature Importances for the Multimodal PTSD Prediction Model

N-Back WM tasks also achieve the two highest accuracies at classifying PTSD among all cognitive tasks based solely on task performance measures.

D. Model Interpretability and Feature Importance

After identifying the best-performing multimodal model for PTSD classification, we examine the impact of each task performance, physiological, and neural feature on the model's predictions. We do so by computing the mean absolute SHAP value of each feature in the multimodal (task performance + Biopac + fNIRS) Audio N-Back model.

As observed in Figure 2:

- The right FPA activation level emerged as the most important feature, changing the predicted probability of PTSD by 0.13. Activation levels in the right DLPFC and the left OFC were the next most important features, each with a SHAP value of 0.09.
- Mean heart rate was the most important physiological feature with a SHAP value of 0.09, followed by respiration rate and mean EDA rise time.

In order to better understand the contribution of each feature to the model's PTSD predictions, we also examine the SHAP summary plot showing feature magnitudes along with their effects and overall importance (Figure 3). This plot demonstrates that:

- Higher activation values in the right DLPFC, left OFC, and right PMC are associated with high negative SHAP values (or a lower predicted PTSD probability).
- Higher activation values in the right FPA and left PMC are associated with high positive SHAP values (or a higher predicted PTSD probability).
- A higher heart rate and EDA amplitude decrease the predicted PTSD probability, whereas a higher ECG peak distance, respiration, or EDA rise time increases the predicted probability.

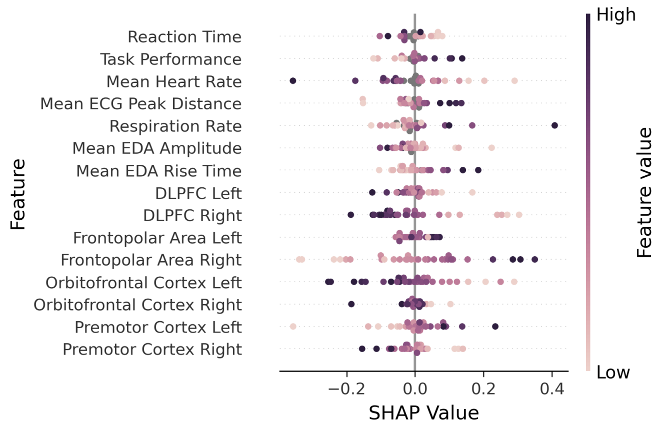

Fig. 3: SHAP Summary Plot for the Multimodal PTSD Prediction Model

Comparing the feature dependencies learned by our model with existing work on neurophysiological responses among individuals with PTSD, we note that previous work that has observed reduced activity in the right hemisphere [46] as well as generally in the LPFC [47] among participants with PTSD during WM tasks. However, there is limited research on physiological responses during WM tasks among individuals with PTSD, and future work should validate whether the same relationships as described above would hold in a broader population.

V. Discussion

This work presents results from an exploratory study on PTSD classification using multimodal signals during the completion of cognitive tasks. We collect pilot data involving various cognitive tasks and multiple sensing modalities in order to train baseline machine learning models and benchmark classification performance under a variety of settings. Our findings have important implications for choosing the task settings and the auxiliary signals to be recorded for optimal PTSD classification in civilian populations. Informed by these, we make the following specific recommendations for future studies and in-the-wild deployments:

- For in-the-wild PTSD classification where additional sensing capabilities are unavailable, reaction times and response accuracy on the **N-Back task** may be used to achieve reasonably high classification performance.
- For in-the-wild PTSD classification where it is possible to include other sensing modalities (e.g., wearables), practitioners should consider using the **Audio N-Back task** and collect physiological signals such as heart rate/HRV, EDA, and respiration rate for improved prediction performance.
- Within lab settings or when portable fNIRS devices may be used, DLPFC activation may be recorded in addition to task performance and physiological signals corresponding to the **Audio N-Back task** in order to further improve PTSD classification.

Posthoc analysis of our models also reveals that single-task models perform as well as, or better than, models trained on features from all cognitive tasks. The emergence of WM tasks as the best predictors of PTSD is also in line with prior literature – attention and memory deficits are commonly observed in PTSD populations [32] and cognitive training tasks for PTSD also often target WM or emotional WM [43]. Similarly, our analysis of SHAP values of multimodal features also indicates that the model learns some known associations – prior work has established that individuals with PTSD may engage fewer cognitive resources and exhibit lower PFC activation during WM tasks [47].

As a pilot study, our work has certain limitations that should be addressed in future research. Our study was conducted with an entirely female participant pool, and further investigations are needed to replicate these findings with larger sample sizes that include male participants to examine if there are similar or different predictors of PTSD for the biomarkers measured in this study. The study relies on self-reported measures of affect and PTSD symptoms, which may be subject to bias and measurement error. Moreover, this was a volunteer non-clinical sample and further research may be needed to affirm these findings with clinical samples that score above the subthreshold score of 30 for PTSD.

VI. Conclusion

This work aims to expand the understanding of how performance differences, physiological signals, and neural correlates during cognitive tasks can be used to identify individuals with PTSD. We show that neurophysiological features collected in conjunction with the Audio N-Back task can be used to develop a brief, accurate screening tool for PTSD, enabling the identification of at-risk individuals in a non-invasive manner and helping intervene effectively. Our findings provide valuable insights for the development of affective technologies that account for an individual's underlying trauma context.

Ethical Impact Statement

Since our work involves predicting highly sensitive outcomes such as PTSD symptom severity, it is important to take several measures to ensure ethical and responsible deployments of any models that may be developed based on these recommendations. Our findings as well as future models should be validated on larger samples and evaluated on different demographic groups to ensure fairness and reliability. The screening outcomes should be handled in a privacy-sensitive manner and individuals identified as experiencing PTSD should be provided effective interventions.

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