Digital Phenotype Profile: Data-driven tool to Evaluate Distress Experience in Healthcare Workers during COVID-19 Pandemic

Abstract

- We develop a digital phenotype profile (DPP) tool to automate and evaluate the distress of participants in the
- The dataset collected passive physiological signals and active mental health questionnaires.
- This paper focuses on correlating electrocardiogram, respiration, photoplethysmography and galvanic skin response with moral injury outcome scale (MIOS).
- The DPP tool uses data-driven techniques to create a robust evaluation of distress among participants.
- To accomplish this, we apply pre-processing techniques which involve normalization, data sanitation, segmentation, and windowing.
- During feature analysis, we extracted statistical and heart rate variability features, followed by feature selection techniques to rank the features. We conducted a literature review to support the ranking of the features.
- Prior to classification, we used k-means clustering to cluster the MIOS scores as there is not yet an established cut-off score.
- We then classified the separation of the MIOS scores using weighted support vector machine with leave-one-subject-out-cross-validation to achieve an accuracy of 98.67+/-0.87%
- The proposed DPP tool can be used as an automated tool to monitor mental health.

Hypothesis

- Signal analysis of the collected physiological signals from the VR experiment
- Create a data-driven tool that is able to classify user moral distress by evaluating
  - Physiological signals
  - Active data
- Offer interpretability and understanding to the analysis through
  - Feature analysis and ranking
  - Clustering of MIOS scores
  - Cross validation

METHODS

Dataset

- VR data set
    - Physiological data collected
        - The physiological signals collected include Respiration
        - (RESP), Electrocardiogram (ECG), Galvanic Skin Conductance (GSR), and Polyplethmography (PPG). In addition to the original signal, derivation of the signals were extracted, which include ECG pulse rate (PR), ECG RR interval, respiration rate elevated, and respiration rate. M
    - Active data collected
        - MIOS-10

Data sanitation

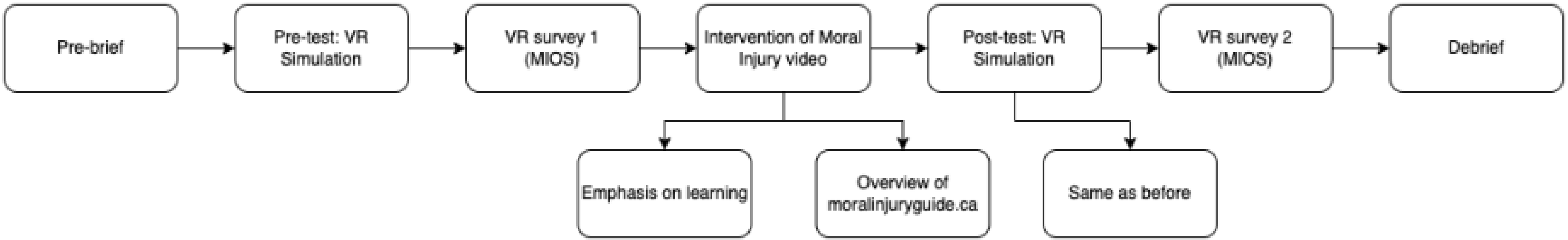
- Removal of bad data

Normalization

- Min-max normalization of the physiological signals

Segmentation

- Segmented the data according to when the participant took the data
  - Prebrief
  - Pre test (VR1)
  - Post test(VR2)
  - Debrief
- MIOS was collected during the Pre-brief, Pre-test: VR Scenario (VR1), Post-test: VR Scenario (VR2), and Debrief



Moving window

- The moving window is applied to each respective segment and it was determined that the optimum parameters of the moving window duration was 10 seconds with no-overlap, as it achieved the highest performance on training data.

Feature analysis

- Extracted 21 features from each signal [See next slide]
  - Mean and Variance from every signal (2 x 8 = 16)
  - HRV features (5)
  - Total = 5 + 16
- Used mRMR, Relieff, LASSO, and SHAPLEY to analyze the features extracted

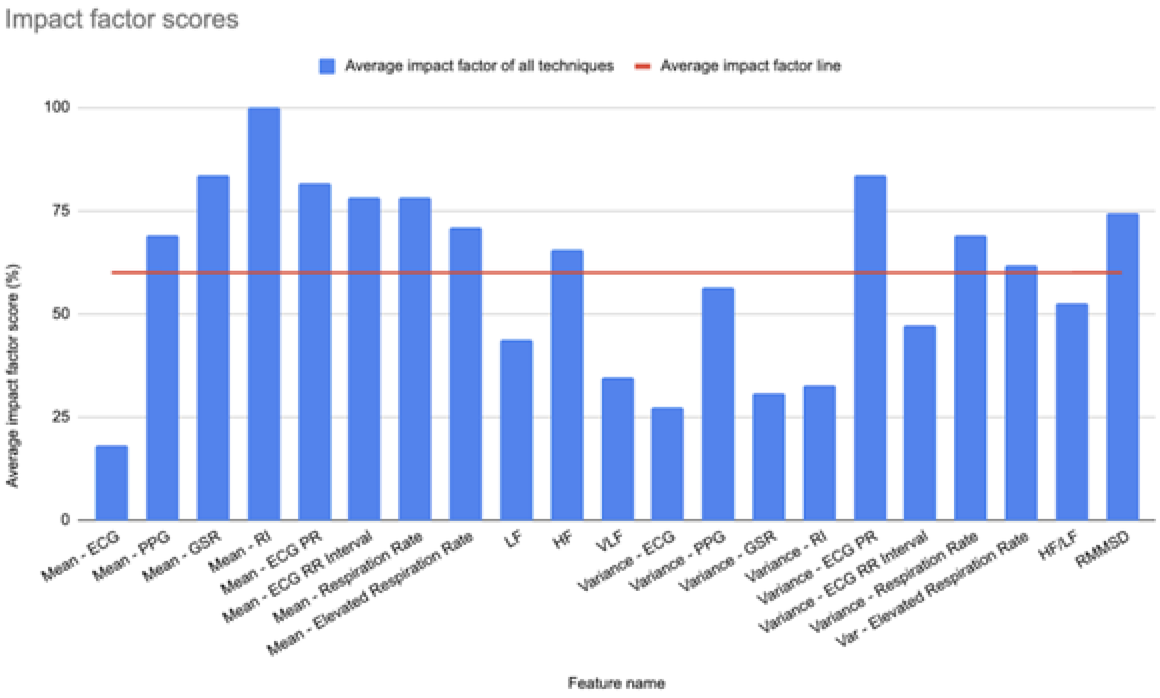
Feature	Description
Mean	Average value of the window
Variance	Variance value of the window
LF	Relative power of low frequency band of HRV (0.04–0.15 Hz)
HF	Relative power of low frequency band of HRV (0.15–0.4 Hz)
VLF	Relative power of low frequency band of HRV (0.0033–0.04 Hz)
LF/HF	Ratio of Low and High frequency
RMSSD	Root mean square of successive RR interval differences

Classification

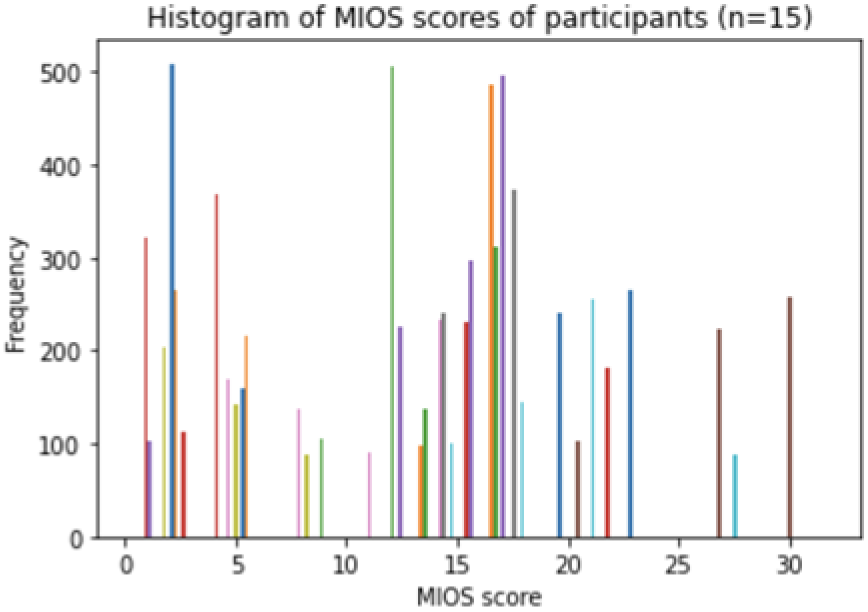
- Clustering using k-means to determine the cluster separations of MIOS
- Predictive models
    - SVM and DT
- Cross validation
    - Leave on out cross validation
    - Ablation

RESULTS

Imapct factor of the features



Histogram of MIOS score before clustering

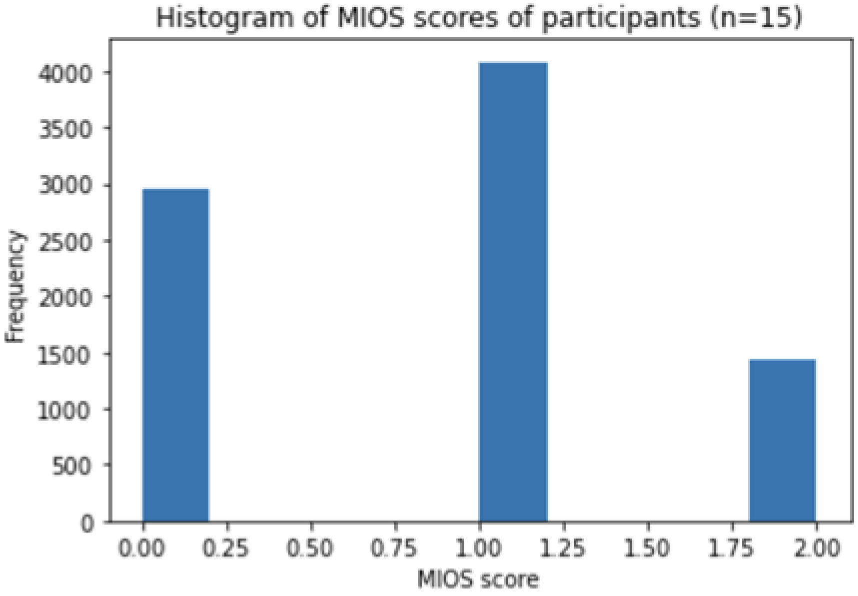


MIOS Histogram after clustering

Class 0 - Low moral distress

Class 1 - Moderate moral distress

Class 2 - High moral distress



SVM and DT

- Leave one subject out cross validation (LOSOCV)
  - LOSOCV achieved an overall accuracy of 96.78±3.76% 320 and 98.67±0.87% for DT and SVM, respectively.

Robustness tests

1. In addition, we conducted an ablation test to remove the key features as identified in the feature analysis. We removed the top four features (Mean - RI, Mean - GSR, Mean - Variance PR, and Mean - ECG RR Interval). We employed DT and SVM and achieved an accuracy of 79.76% and 66.44%, respectively.
2. Lastly, we evaluated a downsampled dataset. There was a slight imbalance in the dataset as seen in Figure 6. When downsampling, we reduced the number of samples to be equal in all clusters. In result, each cluster contained samples. We employed a DT and SVM model and achieved an accuracy of 98.34% and 99.32%, respectively.

DISCUSSION

Single Subject Analysis

- Applied the technique to each individuals to create a digital phenotype profile
- DPP is an automated reasoning and meta-reasoning tool to monitor mental health in participants. The tool analyzes passive physiological signals to evaluate and suggest user distress experience.

Digital phenotype profile

- We adopted data science techniques and we proposed a novel pipeline to evaluate user distress experience. Data science in mental health is a set of techniques that include data privacy, data quality, literature support, data-driven analysis, and visualizations

Robustness

- Robustness is the effectiveness of an algorithm to be tested on new independent but similar data to the trained dataset.
- The DPP takes an approach to create a robust predictive model through the use of systematic techniques
- We focused on interpretability and explainability of the analysis, which were highlighted in the methods discussion above.
- The purpose of the DPP tool is to be a data-driven decision support for healthcare workers to manage stress levels during the COVID-19 pandemic. The tool is used to track and correlate user mental health and physiological signals, allowing users to improve their lifestyle.

Drawbacks

- The model may have overfitted
- Class 1, representing moderate distress, has the highest number of samples, whereas class 2, representing severe distress, has the lowest number of samples. The pipeline may have oversampled 420 class 1 labels, causing an overfitted model. In an ideal scenario, the three class labels would have equal samples.
- Unfortunately, to elicit severe levels of distress within the VR scenario is ethically wrong and it is not possible.

Future work

- Future applications can evaluate our tool using wearables that collect the same physiological data. This will allow for continuous data collection of physiological signals for long-term analysis. This also offers scalability as we can increase the number of participants to validate our tool. This can be done through passive data collection through wearables, which can be scaled and offered to many more participants and it can collect data without the obstruction of their daily lives

Clinical Impact

- Wearable devices can be substitute the devices used in the VR experiment, allowing for continuous and unobtrusive physiological monitoring
- In doing so, we can monitor user mental health and offer appropriate interventions accordingly. Interventions may include mental health resources, Internet-based cognitive-behavioral therapy (iCBT), mindfulness, exercise, and improving sleep habits. This will offer psychiatrists a continuous and deeper understanding of one’s mental health to offer the appropriate care.
- The proposed tools can have a real-world application in the medical domain as it can be used by clinicians to expedite and validate their treatments. The tool would be used to simplify and objectively offer the right treatment to the user through evaluating the user’s psychosis