



HAL
open science

StressID: a Multimodal Dataset for Stress Identification

Hava Chaptoukaev, Valeriya Strizhkova, Michele Panariello, Bianca D'alpaos, Aglind Reka, Valeria Manera, Susanne Thümmler, Esma Ismailova, Nicholas Evans, Francois F Bremond, et al.

► **To cite this version:**

Hava Chaptoukaev, Valeriya Strizhkova, Michele Panariello, Bianca D'alpaos, Aglind Reka, et al.. StressID: a Multimodal Dataset for Stress Identification. NeurIPS 2023 - 37th Conference on Neural Information Processing Systems, NIST, Dec 2023, New Orleans, United States. hal-04245507v1

HAL Id: hal-04245507

<https://hal.science/hal-04245507v1>

Submitted on 17 Oct 2023 (v1), last revised 8 Nov 2023 (v2)

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

StressID: a Multimodal Dataset for Stress Identification

Hava Chaptoukaev¹ Valeriya Strizhkova² Michele Panariello¹ Bianca D’Alpaos¹
Agbind Reka² Valeria Manera³ Susanne Thümmeler³
Esma Ismailova^{3,4} Nicholas Evans¹ François Bremond^{2,3}
Massimiliano Todisco¹ Maria A. Zuluaga¹ Laura M. Ferrari²
¹EURECOM, Sophia Antipolis, France
²Inria, Valbonne, France
³CoBTek, Université Cote d’Azur, Nice, France
⁴Mines Saint-Etienne, Centre CMP, Gardanne, France
{chaptouk,panariel,evans,todisco,zuluaga}@eurecom.fr
{vstrizhk,fbremond,lferrari}@zimbra.inria.fr

Abstract

1 StressID is a new dataset specifically designed for stress identification from
2 unimodal and multimodal data. It contains videos of facial expressions, audio
3 recordings, and physiological signals. The video and audio recordings are acquired
4 using an RGB camera with an integrated microphone. The physiological data
5 is composed of electrocardiography (ECG), electrodermal activity (EDA), and
6 respiration signals that are recorded and monitored using a wearable device. This
7 experimental setup ensures a synchronized and high-quality multimodal data col-
8 lection. Different stress-inducing stimuli, such as emotional video clips, cognitive
9 tasks including mathematical or comprehension exercises, and public speaking
10 scenarios, are designed to trigger a diverse range of emotional responses. The
11 final dataset consists of recordings from 65 participants that performed 11 tasks,
12 as well as their ratings of perceived relaxation, stress, arousal, and valence levels.
13 StressID is one of the largest datasets for stress identification that features three
14 different sources of data and varied classes of stimuli, representing more than
15 39 hours of annotated data in total. StressID offers baseline models for stress
16 classification including a cleaning, feature extraction, and classification phase for
17 each modality. Additionally, we provide multimodal predictive models combining
18 video, audio, and physiological inputs. The data and the code for the baselines are
19 available at <https://project.inria.fr/stressid/>.

20 1 Introduction

21 While a healthy amount of stress is necessary for functioning in daily life, it can rapidly begin to
22 negatively impact health and productivity when it exceeds an individual’s coping level. Negative
23 stress can be a triggering or aggravating factor for many diseases and pathological conditions [16],
24 and frequent and intense exposures to stress can cause structural changes in the brain with long-
25 term effects on the nervous system [10]. Monitoring of stress levels could play a major role in the
26 prevention of stress-related issues, and early stress detection is vital in patients exhibiting emotional
27 disorders, or in high-risk jobs such as surgeons, pilots or long-distance drivers.

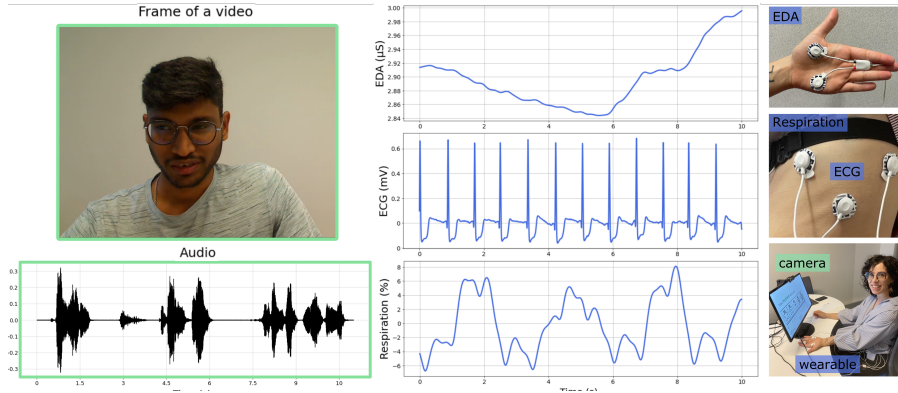


Figure 1: Data collection set-up of StressID.

28 In the last few years, machine and deep learning have been playing major roles in stress recognition.
 29 An essential element in building robust and reliable frameworks for stress recognition is high-
 30 quality datasets. However, existing datasets suffer from multiple limitations. They are generally
 31 restricted in size (i.e. a few dozen of participants) and a majority is focused on a single source of
 32 data (i.e. physiological signals, video or audio) – although multimodal datasets have considerable
 33 advantages [24, 27]. Moreover, existing datasets often provide imbalanced subject responses, due
 34 to both an inability of the recording protocol to elicit strong reactions and a lack of diversity in the
 35 stimuli – making it difficult to deploy deriving analyses to real-life applications.

36 To address these limitations, we propose StressID, a novel multimodal dataset with facial video,
 37 audio, and physiological data. To the best of our knowledge, StressID is one of the largest available
 38 multimodal dataset in the field that includes varied stimuli. It is composed of 65 subjects and more
 39 than 39 hours of annotated data in total. StressID is designed specifically for the identification of
 40 stress from different triggers, by using a guided breathing task, 2 video clips, 7 different interactive
 41 *stressors*, and a relaxation task. As illustrated in Fig 1, StressID uses a collection of wearable
 42 sensors to record the physiological responses of the participants, namely, an Electrocardiogram
 43 (ECG), an Electrodermal Activity (EDA) sensor, and a respiration sensor. The data is coupled with
 44 synchronized facial video and audio recordings. Each task is associated with 6 different annotations:
 45 4 scores from a self-assessment rating perceived stress and relaxation, along with valence and
 46 arousal based on the Self-Assessment Manikin (SAM) [9]; and 2 discrete labels derived from the 4
 47 self-assessments. These data annotations serve to train supervised models.

48 We summarize our main contributions as follows:

- 49 • A novel multimodal dataset focused on stress-inducing tasks, composed of ECG, EDA,
 50 respiration, facial video, and audio recordings. The modalities are synchronized and anno-
 51 tated with self-assessments from the participants evaluating their levels of relaxation, stress,
 52 valence, and arousal.
- 53 • An easy to reproduce experimental protocol for recording behavioral and physiological
 54 responses to diverse triggers, using wearable and global sensors.
- 55 • Instructions for using the presented dataset and an open-source implementation of sev-
 56 eral baseline models for stress recognition from video, audio, and physiological signals
 57 respectively, as well as multimodal models combining the three inputs.

58 The remainder of this paper is organized as follows. Section 2 provides an overview of the existing
 59 datasets for stress recognition. Section 3 describes the dataset design and its contents. In Section 4
 60 we present multiple baselines for stress detection using machine learning. In Section 5 and 6, we
 61 discuss the limitations and ethical considerations of our work. Finally, we summarize our work and
 62 discuss future directions.

63 2 Related work

64 Table 1 places *StressID* in the context of related stress recognition datasets. The SUS datasets [49]
 65 gather the recordings of 35 subjects collected during aircraft communication training. This unimodal
 66 collection of datasets only features audio recordings without self-assessments or external annotation
 67 and employs an uncommon elicitation task. SADVAW [52] is a dataset composed of 1236 video clips
 68 from 41 Korean movies, making the setting closer to the real world and including a broader range
 69 of responses. However, it features video recordings exclusively, restricting deriving applications to
 70 computer vision systems only. Among the works investigating the physiological aspect of stress,
 71 DriveDB [23] collects physiological data from 9 subjects exposed to driving-related tasks. The lack
 72 of self-assessment or external annotations significantly limits the accuracy of measuring stress. In
 73 addition, the dataset is collected in the very specific setting of driving, with a narrow range of stressors
 74 – considerably restricting its usage. WeSAD [45] and CLAS [34], two of the most widely explored
 75 datasets for stress recognition, contain physiological data from 15 and 62 subjects respectively,
 76 collected using wearable devices. The participants partake in various tasks, combining perceptive
 77 stressors in the form of audiovisual stimuli, with several variations of the Trier Social Stress Test
 78 (TSST) [3]. However, they do not include any behavioral modalities.

79 There exists a few multimodal datasets for stress recognition, such as MuSE [25] and SWELL-
 80 KW [31]. They feature a broader set of modalities and are collected in laboratory environments
 81 imitating real-life activities. MuSE participants are elicited through audiovisual and public speaking
 82 tasks. SWELL-KW participants perform office work on several topics designed to elicit different
 83 emotions. These datasets are limited in size with recordings of respectively 28 and 25 subjects.
 84 Finally, the distracted driving dataset [51] gathers recordings of 68 subjects in the setting of simulated
 85 driving with stress-inducing distractions. The lack of diversity in the stimuli restricts subsequent
 86 applications to the setting of driving. Moreover, cardiac activity is acquired in terms of heart rate,
 87 which does not allow the extraction of heart rate variability (HRV) measures, a key measure in the
 88 identification of stress [28].

89 **Comparison with the state-of-the-art.** *StressID* aims to fill the gap in the existing related work. It
 90 features both physiological and behavioral modalities, includes a large number of participants, and ex-
 91 ploits varied stimuli. Indeed, *StressID* employs diverse and carefully selected tasks, and rather than
 92 relying on task-based ground truths, the subjects of *StressID* reply to 4 self-assessment questions
 93 after each task, thus providing insights on the subject’s emotional state. Although CLAS [34] and
 94 WeSAD [45] present similar experimental set-ups, they focus on physiological modalities and do not
 95 include behavioral data. Instead, *StressID* features three types of modalities: video, audio, and phys-
 96 iological signals capturing complementary information. While MUSE [25] and SWELL-KW [31] are
 97 also multimodal datasets recorded in similar conditions, they are very limited in size. On the contrary,
 98 with 65 subjects recorded *StressID* is one of the largest datasets designed for stress identification.
 99 Finally, although the size and modalities of the distracted driving dataset [51] are comparable to
 100 *StressID*, it relies on very environment-specific stressors, whereas *StressID* includes emotional
 101 video-clips, cognitive tasks, and social stressors based on public speaking, which represents a key

Table 1: Comparison of *StressID* to related datasets.

Dataset	#Subjects	Modalities	Stressors	Data annotations
SUS	35	Speech	Aircraft communication training	Stressor-based
SADVAW	-	Video	-	External annotations
DriveDB	9	EMG, EDA, ECG, HR, Respiration	Driving tasks	Stressor-based
WeSAD	15	ECG, EDA, EMG, BVP, Respiration, Temperature, Acceleration	TSST, Audiovisual	Stressor-based, PANAS [53], STAI [48], SAM [9]
CLAS	62	ECG, PPG, EDA, Acceleration	Cognitive load, Audiovisual	SAM
MuSE	28	EDA, HR, Breath rate, Temperature, Face and upper body video, Audio	Public speaking, Audiovisual	PSS [32], SAM, External annotations
SWELL-KW	25	ECG, EDA, Face and upper body video, Posture, Computer logging	Office work with interruptions and time pressure	NASA task load [22], SAM, Stress assessment
Distracted Driving dataset	68	EDA, HR signal, Respiration, Face video, Driving performances	Simulated driving with distractions	Stressor-based, NASA task load, SAM
<i>StressID</i>	65	EDA, ECG, Respiration, Face video, Speech	Cognitive load, Public speaking, Audiovisual	SAM, Stress assessment

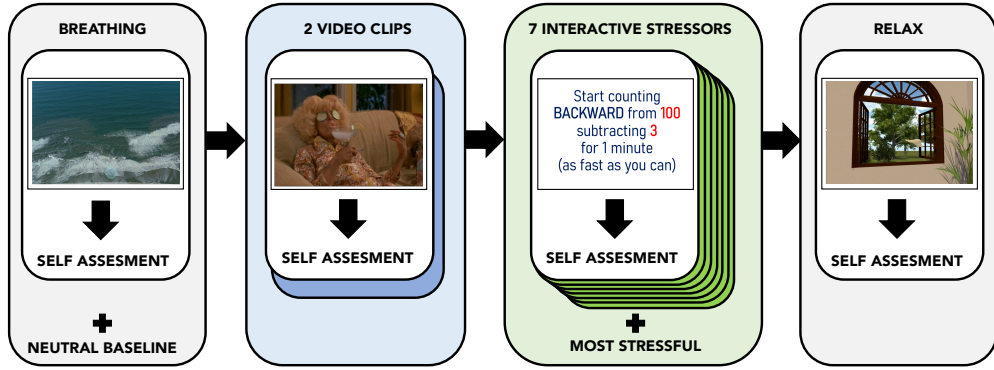


Figure 2: Overview of the experimental protocol. The experiment consists of 11 tasks divided into four blocks: a guided breathing task, 2 emotional video clips, 7 interactive stressors, and a relaxation task.

102 aspect to guarantee the collection of a wide range of responses. To summarize, *StressID* is the first
 103 multimodal dataset for stress identification that is recorded on a large number of participants but also
 104 features a wide range of stimuli ensuring more versatility of deriving applications.

105 3 StressID Dataset

106 In this section, we first describe our dataset design in 3.1. We then introduce the resulting dataset
 107 in 3.2, and outline our data annotation process in 3.3.

108 3.1 Dataset Design

109 3.1.1 Experimental Protocol

110 Figure 2 illustrates the experimental protocol used to collect *StressID*. It consists of 11 tasks
 111 separated by self-assessments and grouped into 4 blocks: guided breathing, watching emotional video
 112 clips, a sequence of interactive tasks, and a relaxation phase. Tasks have been designed to elicit 3
 113 different categories of responses; 1) stimulate the audiovisual cortex of the participants, 2) increase
 114 the cognitive load by soliciting attention, comprehension, mental arithmetic or multi-tasking abilities,
 115 and 3) elicit psycho-social stress leveraging on public speaking as a stressor. All stimuli are easy to
 116 implement and do not require any special setup [5]. The full instructions given to participants are
 117 provided in the supplementary material.

118 **Guided breathing.** The first block of the protocol consists of the single task of *Breathing*. The
 119 participants watch a guided breathing video of 3 minutes. It aims to relax and reset to neutral the
 120 emotional state of the subjects. This recording is used as a baseline for the non-verbal neutral state of
 121 each participant. After the breathing task, the participants count forward for 1 minute.

122 **Emotional video-clips.** This block consists in watching 2 emotional videos clips, retrieved from the
 123 FilmStim database [44]. These videos have been selected to elicit specific emotional responses.

- 124 • *Video1* : an extract from the movie *There’s something about Mary*, selected to elicit low
 125 arousal and positive valence in the participants.
- 126 • *Video2* : an extract from the movie *Indiana Jones and the Last Crusade*, selected to elicit
 127 high arousal and negative valence.

128 **Interactive tasks.** This block consists of a sequence of 7 interactive stressors based on well-
 129 established clinical methods to induce stress [7]. All the tasks have a strict requirement for response
 130 in 1 minute and the order of the stressors is designed to be unexpected to the participants.

- 131 • *Counting1* : a Mental Arithmetic Task (MAT) designed to increase the participants' cognitive
132 load through arithmetic operations with a varying range of difficulty. In this task, the
133 participants receive the instructions to count backwards from 100 subtracting 3 as fast as
134 they can.
- 135 • *Counting2* : another MAT of increased difficulty. Participants are asked to count backward
136 from 1011 subtracting 7 as fast as they can.
- 137 • *Stroop* : a variant of the Stroop Color-Word Test [50], selected to increase the cognitive load
138 by soliciting the attention and reactivity of the participants.
- 139 • *Speaking* : a Social Evaluative Task (SET), leveraging public speaking as a social stressor.
140 The subjects are instructed to explain their strengths and weaknesses, emulating stressful
141 job interview conditions.
- 142 • *Math* : a task designed to increase the mental workload. The participants are asked to
143 resolve 20 mathematical problems in one minute.
- 144 • *Reading* : a task composed of 2 phases and designed as a TSST variation. Participants
145 have to read a text, in the first step, and then explain what they read, in the next step, thus
146 simultaneously soliciting comprehension abilities and using speaking as a stressor.
- 147 • *Counting3* : a MAT with added difficulty. Participants are instructed to count backwards
148 from 1152 subtracting 3, as fast as they can, while repeating an independent hand movement.
149 This task is designed to increase the mental workload by soliciting participants' multi-tasking
150 abilities.

151 At the end of the third block, the participants are asked to designate the task perceived as most
152 stressful.

153 **Relaxation.** The last block of the experimental protocol is solely composed of the *Relax* task. It
154 consists of a 2 minute and 30 seconds long relaxation, where participants are instructed to watch a
155 relaxing video [21].

156 3.1.2 Sensors

157 Three different physiological signals are collected in *StressID*: electrocardiogram (ECG), electro-
158 dermal activity (EDA), and respiration signal. They are recorded using the *BioSignalsPlux* acquisition
159 system¹. The *BioSignalPlux* kit consists of a 4-channel hub communicating via Bluetooth with the
160 *OpenSignals (R)evolution* platform for data visualization and acquisition, connected to an ECG,
161 EDA, and a respiration sensor. The hub ensures the synchronized recording of up to 4 sensors
162 simultaneously. The ECG is acquired with 3 Ag/AgCl electrodes located on the ribs of the non-
163 dominant side of the subjects. The EDA is measured with 2 Ag/AgCl electrodes attached to the
164 palm of the non-dominant hand. The respiration is measured through a chest belt with an integrated
165 piezoelectric sensing element. The selected devices have a high signal-to-noise ratio [39, 40, 41], and
166 all physiological signals are acquired with a sampling rate of 500 Hz and resolution of 16 bits per
167 sample.

168 The video and audio are acquired using a Logitech QuickCam Pro 9000 RGB camera with an
169 integrated microphone. The video is acquired with a 720p resolution and a rate of 15 frames per
170 second. The audio is recorded at a sampling rate of 32kHz and a resolution of 16 bits per sample.

171 3.2 Dataset Description

172 3.2.1 Recruitment and Recording

173 In total, 65 healthy participants were recruited on a voluntary basis, without any compensation. They
174 included 18 women and 47 men of ages ranging between 21 and 55 years old (29y.o. \pm 7). Among
175 the participants, 32% were master students and interns, 20% PhD students, and the remaining 48%

¹biosignalsplux, PLUX wireless biosignals S.A. (Lisbon, Portugal)

176 represented diverse tertiary professions. All subjects were required to have sufficient proficiency in
177 English and they were requested to sign a consent form to participate.

178 The participants could either consent to, **Option A:** research use and public release of all their
179 recorded data, including identifying data (i.e. physiological, audio, and video). **Option B:** research
180 use of all their recorded data, but no public release of identifying data (i.e. only physiological and
181 audio data, but no video). Among the 65 participants, 62 opted for option A and 3 opted for option B
182 (2 women and 1 man).

183 Each participant was recorded in a single session, lasting approximately 35 minutes. They were
184 instructed not to smoke, intake caffeine, or exercise 3 hours before the experiment. At the beginning
185 of each session, they were introduced to the purpose and content of the study. The experiments are
186 conducted entirely in English. The experimental protocol was identical for all participants, and the
187 experimenter was always present in the room during the recording.

188 3.2.2 Dataset Composition

189 Following data collection, we split each recorded session into individual tasks: one 3 minutes
190 breathing recording (block 1), 2 recordings corresponding to the watching of the video clips of
191 respectively 2 and 3 minutes (block 2), 7 separate 1-minute recordings of the interactive tasks (block
192 3), and a 2 minute and 30 seconds long relaxation recording (block 4). As the guided breathing,
193 the video clips and the relaxation parts do not carry meaningful audio, the audio part of the dataset
194 consists of the 7 talking tasks only. During the acquisitions, due to camera malfunctions, 8 video
195 and audio recordings were damaged. More information about the available modalities for each
196 subject can be found in the supplementary material. After splitting, `StressID` is composed of
197 711 distinct annotated recordings of the physiological modalities, 587 annotated videos, and 385
198 annotated audio recordings. In total, the final task-split dataset amounts to approximately 19 hours
199 of annotated physiological data, 15 hours of annotated video data, and 6 hours of annotated audio
200 data, thus amounting to more than 39 hours of data in total. Each task is identified in the dataset
201 by `subjectname_task`, where the task names are as described in Section 3.1.1. This convention
202 facilitates different types of analyses, whether subject-specific or task-specific.

203 3.3 Data Annotation

204 Each task is annotated using the answers to self-assessment questions. The first 2 questions establish
205 the participants' perceived stress and relaxation levels on a 0-10 scale. Additionally, they answer the
206 SAM [9] to assess their valence and arousal on a 0-10 scale. Research suggests relaxation and stress
207 conditions can be described in different quadrants of the arousal-valence space. For instance, high
208 arousal and negative valence are characteristics of emotional stress induced by threatening stimuli [15],
209 while low arousal and positive valence are characteristics of a calm and relaxed state [35].

210 The distributions of the `StressID` self-assessments are reported in Figure 3. The analysis of the
211 distributions highlights a positive correlation between stress and arousal, as well as relax and valence.
212 This suggests that across subjects and tasks, a high arousal is associated with a higher level of
213 stress, and a positive valence corresponds to a higher level of relaxation. In addition, the marginal
214 distributions of stress and relax ratings (Figure 3) highlight a balance in the perceived stress and
215 relaxation levels of the participants across the whole experiment, suggesting that the experimental
216 protocol of `StressID` can arouse proportional instances of stress and relaxation. Furthermore, the
217 distribution of arousal is significantly skewed towards a high rating across the dataset, while valence is
218 centered around a neutral value, highlighting the ability of the protocol to create a high involvement in
219 the participants and elicit strong responses. An extended analysis of the self-assessment distributions
220 analyses can be found in the supplementary material.

221 We propose 2 discrete labels that can be used to train supervised models: a 2-class label and a 3-class
222 one. The 2-class label is computed using the stress self-assessment of each task by splitting the 0-10
223 scale at 5. Precisely, tasks with self-assessment of stress below 5 are considered **not stressed** (0)
224 while tasks with self-assessment equal or above 5 are **stressed** (1). The 3-class label is based on the

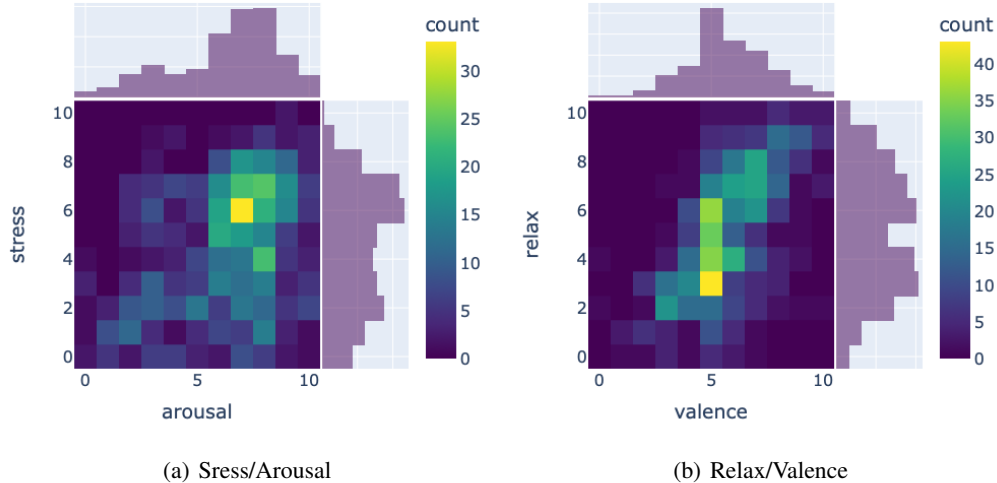


Figure 3: Distribution of the self-assessment answers. (left) Joint and marginal distributions of stress and arousal. (right) Joint and marginal distributions of the relax and valence ratings.

225 results outlined by [15, 35], which are in line with the observations drawn from Figure 3. It allows
 226 the prediction of **relaxed** vs. **neutral** vs. **stressed**. We considered a subject to be **relaxed** (0) for a
 227 task where they reported a valence rating above 5, arousal rating below 5, and perceived relaxation
 228 rating above 5. Similarly, we label tasks with arousal levels above 5, valence levels below 5, and
 229 perceived stress levels above 5 as **stressed** (2), and **neutral** (1) otherwise.

230 4 Baselines

231 We implement several unimodal and multimodal baselines combining features extracted from video,
 232 audio, and physiological inputs. We train the models to perform 2-class classification, i.e. binary
 233 discrimination between stressed and not stressed, as well as 3-class classification. In all the experi-
 234 ments, we generate 10 random splits, using 80% of the tasks for training, and 20% for testing for each
 235 split. The results are averaged over the 10 repetitions. To ensure robustness to potential imbalance
 236 resulting from the train-test splits, the results are assessed using the weighted F1-score and the
 237 balanced accuracy on the test data. The full list of extracted features, additional experiments, model
 238 hyperparameters, and training details are reported in the supplementary material. The implementation
 239 of all the baselines can be found at <https://github.com/robustml-eurecom/stressID>.

240 4.1 Unimodal Baselines

241 Each unimodal baseline is trained and tested on all available tasks of the corresponding modality, i.e.
 242 715, 587, and 385 tasks respectively for the physiological, video, and audio baseline. In the following,
 243 we describe the baselines for each modality. The obtained results are reported in Table 2.

244 **Physiological Signals.** In line with the literature on stress recognition from physiological signals [5,
 245 18, 19], we propose a baseline including pre-processing of the signals, feature extraction, and
 246 classification. In a first step, the ECG, EDA, and respiration signals are filtered with Butterworth
 247 filters to reduce high-frequency noise and baseline wander. Then, 35 ECG features, 23 EDA, and
 248 40 respiration features are extracted. These include HRV features in the time domain including the
 249 number of R to R intervals (RR) per minute, the standard deviation of all NN intervals (SDNN), the
 250 percentage of successive RR intervals that differ by more than 20ms and 50ms (pNN20 and pNN50),
 251 or the root mean square of successive RR interval differences (RMSSD), as well as frequency-domain,
 252 and non-linear HRV measures. We have extracted statistical features of the Skin Conductance Level

Table 2: Performances of unimodal baselines for the classification of stress. Each baseline is trained and tested on all available tasks of the corresponding modality.

Baseline	2-class		3-class	
	F1-score	Accuracy	F1-score	Accuracy
Physio. HC features + RF	0.73 ± 0.02	0.72 ± 0.03	0.55 ± 0.04	0.56 ± 0.03
Physio. HC features + SVM	0.71 ± 0.02	0.71 ± 0.02	0.59 ± 0.04	0.59 ± 0.03
Physio. HC features + MLP	0.70 ± 0.03	0.70 ± 0.03	0.54 ± 0.04	0.53 ± 0.04
AUs + kNN	0.70 ± 0.04	0.69 ± 0.04	0.54 ± 0.05	0.53 ± 0.05
AUs + SVM	0.69 ± 0.04	0.69 ± 0.04	0.55 ± 0.05	0.54 ± 0.04
AUs + MLP	0.70 ± 0.03	0.70 ± 0.03	0.55 ± 0.03	0.55 ± 0.03
Audio HC features + kNN	0.67 ± 0.06	0.60 ± 0.05	0.53 ± 0.04	0.52 ± 0.04
Audio HC features + SVM	0.61 ± 0.06	0.54 ± 0.03	0.53 ± 0.08	0.48 ± 0.04
W2V 2.0 classifier	0.70 ± 0.02	0.66 ± 0.03	0.56 ± 0.04	0.52 ± 0.04

253 (SCL) and Skin Conductance Response (SCR) components of the EDA, including the slope and
 254 dynamic range of the SCL, along with time domain features including the number of SCR peaks
 255 per minute, the average amplitude of the peaks, and average duration of SCR responses. In addition,
 256 we have extracted Respiration Rate Variability (RRV) features in the time and frequency domains.
 257 The resulting handcrafted (HC) features are then classified using classical Machine Learning (ML)
 258 algorithms: a Random Forests (RF) classifier, Support Vector Machines (SVM), and a Multi-Layer
 259 Perceptron (MLP) with hyperparameters chosen by Cross-Validation (CV).

260 **Video Data.** We propose a baseline employing Action Units (AU) and eye gaze for the classification
 261 of stress. AUs are commonly used as features in stress recognition applications [20, 25, 2]. They are
 262 fine-grained facial muscle movements [17], each relating to a subset of extracted facial landmarks [38].
 263 Each AU is described in two ways: presence, if the AU is visible in the face, and intensity, indicating
 264 how intense the AU is on a 5-point scale (minimal to maximal). After downsampling the recordings
 265 to 5 frames per second, we use the OpenFace library [8] to extract eye gaze and AUs from each
 266 video frame. We extract the following AUs: 1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26,
 267 28, and 45. As eye gaze features, we use two gaze direction vectors computed individually for each
 268 eye by detected pupil and eye location. The averages and standard deviations of each AU and eye
 269 gaze directions are computed across time frames. The resulting 84-component vector is used as input
 270 to several models: a k-Nearest Neighbors (kNN) algorithm, an SVM, and an MLP with 4 layers of
 271 width 256. In line with [25], the number of layers and layer width of the MLP are chosen by CV in
 272 {2,3,4} and {64, 128, 256} respectively. We use ReLU activation and the MLP is trained for 100
 273 epochs with cross-entropy loss optimized using Adam [29] with an initial learning rate of $1e-3$.

274 **Audio Data.** We propose two baselines for speech signals: the first employs HC features and ML
 275 algorithms, and the second is built on the Wav2Vec 2.0 (W2V) model [46, 6]. Both techniques involve
 276 downsampling from the original 32 kHz audio to 16 kHz, and the application of amplitude-based
 277 voice activity detection (VAD) [30] prior to feature extraction to eliminate non-speech segments.
 278 The first baseline relies on a plethora of specific audio features [43, 4] widely used in the literature
 279 on emotion recognition from speech [1, 5, 33]. These include Mel Frequency Cepstral Coefficients
 280 (MFCCs) and their first and second derivatives, which characterize the short-term power spectrum
 281 and its dynamics. The spectral centroid, bandwidth, contrast, flatness, and roll-off, which together
 282 provide a rich statistical representation of the spectral shape. Harmonic and percussive components
 283 are also extracted, with tonal centroid features being computed for the harmonic component. The zero-
 284 crossing rate is a simple measure of the rate of sign changes; the rate of zero-crossings relates directly
 285 to the fundamental frequency of the speech signal. Last, we include tempogram ratio features [37]
 286 which represent local rhythmic information. We compute the mean and standard deviation over time
 287 for all features, thereby resulting in feature vectors for each, which are then concatenated to form a
 288 comprehensive feature vector of 140 components, and used as input for ML algorithms.

289 The second baseline employs a large, pre-trained W2V model. The W2V model produces features
 290 capturing a wealth of information relevant to diverse tasks including emotion recognition [11, 47, 14].

Table 3: Performances of multimodal baselines for the classification of stress, compared to unimodal models. All baselines are trained and tested only on tasks featuring all modalities, i.e. 370 tasks.

Baseline	2-class		3-class	
	F1-score	Accuracy	F1-score	Accuracy
Physiological only	0.66 ± 0.05	0.58 ± 0.04	0.50 ± 0.05	0.48 ± 0.06
Video only	0.67 ± 0.03	0.62 ± 0.04	0.58 ± 0.05	0.56 ± 0.05
Audio only	0.67 ± 0.04	0.62 ± 0.04	0.56 ± 0.06	0.54 ± 0.06
Feature fusion + SVM	0.64 ± 0.09	0.56 ± 0.05	0.55 ± 0.06	0.51 ± 0.05
Feature fusion + MLP	0.66 ± 0.04	0.61 ± 0.03	0.51 ± 0.07	0.51 ± 0.07
Feature fusion + DBN	0.58 ± 0.06	0.52 ± 0.05	0.30 ± 0.09	0.32 ± 0.04
SVM + Sum rule fusion	0.72 ± 0.05	0.64 ± 0.05	0.62 ± 0.05	0.58 ± 0.07
SVM + Product rule fusion	0.71 ± 0.05	0.63 ± 0.05	0.61 ± 0.05	0.56 ± 0.07
SVM + Average rule fusion	0.72 ± 0.05	0.65 ± 0.05	0.63 ± 0.05	0.58 ± 0.07
SVM + Maximum rule fusion	0.72 ± 0.05	0.64 ± 0.05	0.61 ± 0.06	0.57 ± 0.07

291 Features are extracted every 20 ms and averaged over time to obtain a single 513-component
 292 embedding per utterance, and are then classified using a linear classification layer optimized with
 293 Adam, cross-entropy loss, and an initial learning rate of $1e-3$, until convergence.

294 4.2 Multimodal Baselines

295 Multimodal baselines that combine the features extracted from all 3 sources are evaluated on the
 296 tasks that feature all modalities only, i.e. 370 tasks, to avoid learning with severely missing values.
 297 This subset of `StressID` is composed of talking tasks exclusively, i.e. all tasks without the audio
 298 modality are excluded. In this setting, the dataset presents a strong imbalance in the labels (70%
 299 stress). We use Minority Over-sampling Techniques (SMOTE) [13] to balance the training set in each
 300 of the 10 repetitions, and leave the test sets untouched.

301 We propose fusion models combining all features using the most prominent fusion methods in the
 302 literature: feature-level and decision-level fusion [1, 36]. For **feature-level fusion**, unimodal HC
 303 features are combined into a single high-dimensional feature vector, used as input for learning
 304 algorithms. Similarly to [26, 12], we evaluate feature-level fusion combined with SVM, MLP
 305 classifiers, and Deep Belief Networks (DBN). For **decision-level fusion**, following [54, 42], we train
 306 independent SVMs for each modality using the HC features as input, and integrate the results of the
 307 individual classifiers at the decision level, i.e. the results are combined into a single decision using
 308 ensemble rules. The results for all multimodal baselines for the 2-class and 3-class classification are
 309 reported in Table 3. To ensure fairness in the comparison, the multimodal baselines are evaluated
 310 against best-performing HC and ML-based unimodal baselines (Section 4.1), trained on the subset
 311 of the 370 tasks featuring all modalities. Additional results for all other modality combinations are
 312 reported in the supplementary material.

313 5 Limitations

314 First, this dataset is recorded in a controlled environment specifically designed to elicit responses.
 315 Experiments conducted in laboratory settings do not take into consideration the external factors that
 316 contribute to the psychological mental state of participants and typically assume a stress reaction is
 317 an isolated occurrence. In reality, human emotions are complex and are influenced by combinations
 318 of factors. In addition, the process of attaching electrodes to the participants may be stressful in
 319 itself. Therefore, the signals recorded in this setting are not necessarily representative of real-life
 320 situations. In consequence, although models built on the `StressID` dataset can learn to reliably
 321 recognize a response to stress-inducing stimuli, the discrimination between positive and negative,
 322 or short-term and long-term stress is a more sensitive task. Second, relying on self-assessed scales
 323 for data annotation is a participant-subjective process, and can lead to bias in subsequent analyses.
 324 Perception of stress and relaxation can vary a lot from one participant to another. Nevertheless,

325 analyses described in 3.3 highlight a coherent distribution of the self-reported annotations across
326 participants and the whole experiment. Third, although all participants recruited for the study are
327 proficient in English, the act of speaking English itself can be stress-inducing for non-native speakers.
328 Fourth, the audio component of the dataset suffers from an uneven distribution of labels, as the verbal
329 tasks are associated with higher levels of stress. Finally, *StressID* suffers from missing modalities
330 for some participants.

331 **6 Ethical Considerations and Dataset Accessibility**

332 The recording and usage of human activity data are associated with ethical considerations. The
333 *StressID* project is approved by the ethical committee of the Université Cote d'Azur (CER). The
334 experiments have been conducted under agreement n° 2021-033 for data collection, and n° 2023-016
335 for the publication of the dataset. The participants explicitly consent to the recording of their session,
336 the dataset creation, and its release for research purposes following General Data Protection Rules
337 (GDPR). The personal information (sex, age, education), and the acquired physiological and audio
338 signals are pseudonymized, and an alphanumeric code is given for each participant. Video data can
339 not be anonymized and is treated as sensitive data.

340 Given the identifying nature of the facial videos, the dataset is made accessible through open
341 credentialized access only, for research purposes. Users are required to sign an end-user license
342 agreement to request the data. Once validated a secured link grants access to the dataset. The dataset
343 uses a proprietary license for research purposes and is hosted on Inria servers using storage intended
344 for long-term availability. The code uses an open-source license. We are aware that despite all
345 precautions, the dataset can be misused by bad-intentioned users. The data and the code for the
346 baselines are available at <https://project.inria.fr/stressid/>.

347 Lastly, systems that use the dataset for modeling and understanding the mechanisms of human stress
348 conditions need to be aware of the potential imbalance in representation in the dataset. Participants for
349 the data collection were included in our dataset without restrictions on gender, race, age, or education
350 level – instead favoring sample size.

351 **7 Conclusion**

352 We present *StressID*, a dataset for stress identification with three data modalities and three different
353 types of stimuli. The experimental protocol designed to collect the *StressID* dataset is easy
354 to replicate and can be adapted to additional sensors or stressors. The equipment used for the
355 data collection is affordable, and the selected devices guarantee low noise in the recordings. The
356 multimodal nature of *StressID* offers a large set of possibilities for the analysis of stress. On one
357 hand, diverse modalities carry complementary information that can be jointly exploited: video and
358 audio capture the behavioral component of emotions, the reactions that are visible from outside, while
359 the physiological signals capture valuable internal states not visible on camera such as cardiac activity,
360 or skin sweating. By providing access to multiple synchronized modalities, *StressID* enables cross-
361 modal analyses and has the potential of improving the understanding of the relationships between
362 video, audio, and physiological responses to stress. On the other hand, the dataset design also offers
363 the possibility to develop models of different natures, by focusing on a single modality. Moreover,
364 it allows a wide range of applications, including subject-specific, or task-specific studies. As an
365 example, the video component could be used to investigate the difference between stress responses in
366 verbal and non-verbal tasks.

367 To foster reproducibility, *StressID* also offers a set of baseline experiments. Although the proposed
368 baselines focus on predicting two discrete labels designed to illustrate the predictive potential of our
369 dataset, they represent a good starting point for future work, to which researchers and developers can
370 benchmark their work. In this context, a natural extension of this work would be the implementation
371 of a web service that tracks and centralizes the performances of models developed using *StressID*.

372 Acknowledgments and Disclosure of Funding

373 HC, VS, FB and MAZ are supported by the French government, through the 3IA Côte d’Azur
374 Investments in the Future project managed by the National Research Agency (ANR) (ANR-19-P3IA-
375 0002). MP, NE and MT are supported by the ANR RESPECT Project (ANR-18-CE92-0024). LMF
376 has been partially supported by the Ville de Nice and the French government, through the UCAJEDI
377 Investments in the Future project managed by the ANR (ANR-15-IDEX-01).

378 References

- 379 [1] Naveed Ahmed, Zaher Al Aghbari, and Shini Girija. A systematic survey on multimodal emotion
380 recognition using learning algorithms. *Intelligent Systems with Applications*, 17:200171, 2023.
- 381 [2] Jonathan Aigrain, Michel Spodenkiewicz, Severine Dubuisson, Marcin Detyniecki, David
382 Cohen, and Mohamed Chetouani. Multimodal stress detection from multiple assessments. *IEEE*
383 *Transactions on Affective Computing*, 9(4):491–506, 2016.
- 384 [3] Andrew P Allen, Paul J Kennedy, Samantha Dockray, John F Cryan, Timothy G Dinan, and
385 Gerard Clarke. The trier social stress test: principles and practice. *Neurobiology of stress*,
386 6:113–126, 2017.
- 387 [4] Alo Allik, György Fazekas, and Mark B. Sandler. An ontology for audio features. In *Internation-*
388 *ational Society for Music Information Retrieval Conference*, 2016.
- 389 [5] Aamir Arsalan, Syed Muhammad Anwar, and Muhammad Majid. Mental stress detection using
390 data from wearable and non-wearable sensors: a review. *arXiv preprint arXiv:2202.03033*,
391 2022.
- 392 [6] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0:
393 A framework for self-supervised learning of speech representations. *Advances in neural*
394 *information processing systems*, 33:12449–12460, 2020.
- 395 [7] Anjana Bali and Amteshwar Singh Jaggi. Clinical experimental stress studies: methods and
396 assessment. *Reviews in the Neurosciences*, 26(5):555–579, 2015.
- 397 [8] Tadas Baltrušaitis, Amir Zadeh, Yao Chong Lim, and Louis-Philippe Morency. Openface 2.0:
398 Facial behavior analysis toolkit. In *2018 13th IEEE international conference on automatic face*
399 *& gesture recognition (FG 2018)*, pages 59–66. IEEE, 2018.
- 400 [9] Margaret M Bradley and Peter J Lang. Measuring emotion: the self-assessment manikin and the
401 semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25(1):49–59,
402 1994.
- 403 [10] J Douglas Bremner. Traumatic stress: effects on the brain. *Dialogues in clinical neuroscience*,
404 2022.
- 405 [11] Fabio Catania. Speech emotion recognition in italian using wav2vec 2.0 and the novel crowd-
406 sourced emotional speech corpus emozionalmente. 2023.
- 407 [12] Valentina Chaparro, Alejandro Gomez, Alejandro Salgado, O Lucia Quintero, Natalia Lopez,
408 and Luisa F Villa. Emotion recognition from eeg and facial expressions: a multimodal approach.
409 In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology*
410 *Society (EMBC)*, pages 530–533. IEEE, 2018.
- 411 [13] Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote:
412 synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–
413 357, 2002.

- 414 [14] Li-Wei Chen and Alexander Rudnicky. Exploring wav2vec 2.0 fine tuning for improved speech
415 emotion recognition. In *ICASSP 2023-2023 IEEE International Conference on Acoustics,
416 Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023.
- 417 [15] Sven-Åke Christianson. Emotional stress and eyewitness memory: a critical review. *Psycholog-
418 ical bulletin*, 112(2):284, 1992.
- 419 [16] Joel E Dimsdale. Psychological stress and cardiovascular disease. *Journal of the American
420 College of Cardiology*, 51(13):1237–1246, 2008.
- 421 [17] Paul Ekman and Wallace V Friesen. Facial action coding system. *Environmental Psychology &
422 Nonverbal Behavior*, 1978.
- 423 [18] Shruti Gedam and Sanchita Paul. A review on mental stress detection using wearable sensors
424 and machine learning techniques. *IEEE Access*, 9:84045–84066, 2021.
- 425 [19] Giorgos Giannakakis, Dimitris Grigoriadis, Katerina Giannakaki, Olympia Simantiraki, Alexan-
426 dros Roniotis, and Manolis Tsiknakis. Review on psychological stress detection using biosignals.
427 *IEEE Transactions on Affective Computing*, 13(1):440–460, 2019.
- 428 [20] Giorgos Giannakakis, Mohammad Rami Koujan, Anastasios Roussos, and Kostas Marias. Auto-
429 matic stress detection evaluating models of facial action units. In *2020 15th IEEE international
430 conference on automatic face and gesture recognition (FG 2020)*, pages 728–733. IEEE, 2020.
- 431 [21] Auriane Gros, Emmanuelle Chapoulie, Remy Ramadour, Vincent Robert, Julie de Stoutz,
432 Stephane Guetin, Damoun Chaïma, Emeline Wyckaert, Valeria Manera, Philippe Robert, et al.
433 Rel@ x: Sensory and virtual immersion to reduce the anxiety of patients consulting for the first
434 time in nice memory center. *Alzheimer’s and Dementia*, 13(7):P609–P610, 2017.
- 435 [22] Sandra G Hart. Nasa task load index (tlx). 1986.
- 436 [23] Jennifer Anne Healey. *Wearable and automotive systems for affect recognition from physiology*.
437 PhD thesis, Massachusetts Institute of Technology, 2000.
- 438 [24] Yu Huang, Chenzhuang Du, Zihui Xue, Xuanyao Chen, Hang Zhao, and Longbo Huang. What
439 makes multi-modal learning better than single (provably). *Advances in Neural Information
440 Processing Systems*, 34:10944–10956, 2021.
- 441 [25] Mimansa Jaiswal, Cristian-Paul Bara, Yuanhang Luo, Mihai Burzo, Rada Mihalcea, and
442 Emily Mower Provost. Muse: a multimodal dataset of stressed emotion. In *Proceedings
443 of the Twelfth Language Resources and Evaluation Conference*, pages 1499–1510, 2020.
- 444 [26] Apichart Jaratrotkamjorn and Anant Choksuriwong. Bimodal emotion recognition using deep
445 belief network. In *2019 23rd International Computer Science and Engineering Conference
446 (ICSEC)*, pages 103–109. IEEE, 2019.
- 447 [27] Tzyy-Ping Jung, Terrence J Sejnowski, et al. Utilizing deep learning towards multi-modal
448 bio-sensing and vision-based affective computing. *IEEE Transactions on Affective Computing*,
449 13(1):96–107, 2019.
- 450 [28] Hye-Geum Kim, Eun-Jin Cheon, Dai-Seg Bai, Young Hwan Lee, and Bon-Hoon Koo. Stress
451 and heart rate variability: a meta-analysis and review of the literature. *Psychiatry investigation*,
452 15(3):235, 2018.
- 453 [29] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua
454 Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations,
455 ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015.
- 456 [30] Tomi Kinnunen and Haizhou Li. An overview of text-independent speaker recognition: From
457 features to supervectors. *Speech communication*, 52(1):12–40, 2010.

- 458 [31] Saskia Koldijk, Maya Sappelli, Suzan Verberne, Mark A Neerincx, and Wessel Kraaij. The
459 swell knowledge work dataset for stress and user modeling research. In *Proceedings of the 16th*
460 *international conference on multimodal interaction*, pages 291–298, 2014.
- 461 [32] Eun-Hyun Lee. Review of the psychometric evidence of the perceived stress scale. *Asian*
462 *nursing research*, 6(4):121–127, 2012.
- 463 [33] Surendra Malla, Abeer Alsadoon, and Simi Kamini Bajaj. A dfc taxonomy of speech emotion
464 recognition based on convolutional neural network from speech signal. In *2020 5th International*
465 *Conference on Innovative Technologies in Intelligent Systems and Industrial Applications*
466 *(CITISIA)*, pages 1–10, 2020.
- 467 [34] Valentina Markova, Todor Ganchev, and Kalin Kalinkov. Clas: A database for cognitive load,
468 affect and stress recognition. In *2019 International Conference on Biomedical Innovations and*
469 *Applications (BIA)*, pages 1–4. IEEE, 2019.
- 470 [35] Maria D McManus, Jason T Siegel, and Jeanne Nakamura. The predictive power of low-arousal
471 positive affect. *Motivation and Emotion*, 43:130–144, 2019.
- 472 [36] Asif Iqbal Middy, Baibhav Nag, and Sarbani Roy. Deep learning based multimodal emotion
473 recognition using model-level fusion of audio–visual modalities. *Knowledge-Based Systems*,
474 244:108580, 2022.
- 475 [37] Geoffroy Peeters. Rhythm Classification using spectral rhythm patterns. In *ISMIR*, pages –,
476 London, United Kingdom, September 2005. cote interne IRCAM: Peeters05b.
- 477 [38] Nazil Perveen and Chalavadi Krishna Mohan. Configural representation of facial action units
478 for spontaneous facial expression recognition in the wild. In *VISIGRAPP (4: VISAPP)*, pages
479 93–102, 2020.
- 480 [39] PLUX wireless biosignals S.A. *Electrocardiography (ECG) Sensor User Manual*, 2020.
- 481 [40] PLUX wireless biosignals S.A. *Electrodermal Activity (EDA) Sensor Datasheet*, 2021.
- 482 [41] PLUX wireless biosignals S.A. *Respiration (PZT) Sensor User Manual*, 2021.
- 483 [42] K Prasada Rao, MVP Chandra Sekhara Rao, and N Hemanth Chowdary. An integrated approach
484 to emotion recognition and gender classification. *Journal of Visual Communication and Image*
485 *Representation*, 60:339–345, 2019.
- 486 [43] Md. Sahidullah, Tomi Kinnunen, and Cemal Haniłçi. A comparison of features for synthetic
487 speech detection. In *INTERSPEECH 2015, 16th Annual Conference of the International Speech*
488 *Communication Association, Dresden, Germany, September 6-10, 2015*, pages 2087–2091.
489 ISCA, 2015.
- 490 [44] Alexandre Schaefer, Frédéric Nils, Xavier Sanchez, and Pierre Philippot. Assessing the effec-
491 tiveness of a large database of emotion-eliciting films: A new tool for emotion researchers.
492 *Cognition and emotion*, 24(7):1153–1172, 2010.
- 493 [45] Philip Schmidt, Attila Reiss, Robert Duerichen, Claus Marberger, and Kristof Van Laerhoven.
494 Introducing wesad, a multimodal dataset for wearable stress and affect detection. In *Proceedings*
495 *of the 20th ACM international conference on multimodal interaction*, pages 400–408, 2018.
- 496 [46] Steffen Schneider, Alexei Baevski, Ronan Collobert, and Michael Auli. wav2vec: Unsupervised
497 pre-training for speech recognition, 2019.
- 498 [47] Mayank Sharma. Multi-lingual multi-task speech emotion recognition using wav2vec 2.0. In
499 *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing*
500 *(ICASSP)*, pages 6907–6911. IEEE, 2022.

- 501 [48] Charles D Spielberger, Fernando Gonzalez-Reigosa, Angel Martinez-Urrutia, Luiz FS Nata-
502 licio, and Diana S Natalicio. The state-trait anxiety inventory. *Revista Interamericana de*
503 *Psicologia/Interamerican journal of psychology*, 5(3 & 4), 1971.
- 504 [49] Herman JM Steeneken and John HL Hansen. Speech under stress conditions: overview of the
505 effect on speech production and on system performance. In *1999 IEEE International Conference*
506 *on Acoustics, Speech, and Signal Processing. Proceedings. ICASSP99 (Cat. No. 99CH36258)*,
507 volume 4, pages 2079–2082. IEEE, 1999.
- 508 [50] J Ridley Stroop. Studies of interference in serial verbal reactions. *Journal of experimental*
509 *psychology*, 18(6):643, 1935.
- 510 [51] Salah Taamneh, Panagiotis Tsiamyrtzis, Malcolm Dcosta, Pradeep Buddharaju, Ashik Khatri,
511 Michael Manser, Thomas Ferris, Robert Wunderlich, and Ioannis Pavlidis. A multimodal dataset
512 for various forms of distracted driving. *Scientific data*, 4(1):1–21, 2017.
- 513 [52] Thi-Dung Tran, Junghee Kim, Ngoc-Huynh Ho, Hyung-Jeong Yang, Sudarshan Pant, Soo-
514 Hyung Kim, and Guee-Sang Lee. Stress analysis with dimensions of valence and arousal in the
515 wild. *Applied Sciences*, 11(11):5194, 2021.
- 516 [53] David Watson, Lee Anna Clark, and Auke Tellegen. Development and validation of brief
517 measures of positive and negative affect: the panas scales. *Journal of personality and social*
518 *psychology*, 54(6):1063, 1988.
- 519 [54] Fen Xu and Zhe Wang. Emotion recognition research based on integration of facial expression
520 and voice. In *2018 11th International Congress on Image and Signal Processing, BioMedical*
521 *Engineering and Informatics (CISP-BMEI)*, pages 1–6. IEEE, 2018.

522 Checklist

- 523 1. For all authors...
- 524 (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s
525 contributions and scope? [Yes]
- 526 (b) Did you describe the limitations of your work? [Yes] See Section 5.
- 527 (c) Did you discuss any potential negative societal impacts of your work? [Yes] See
528 Section 6 and Appendix B.2 of the supplementary material.
- 529 (d) Have you read the ethics review guidelines and ensured that your paper conforms to
530 them? [Yes]
- 531 2. If you are including theoretical results...
- 532 (a) Did you state the full set of assumptions of all theoretical results? [N/A]
- 533 (b) Did you include complete proofs of all theoretical results? [N/A]
- 534 3. If you ran experiments (e.g. for benchmarks)...
- 535 (a) Did you include the code, data, and instructions needed to reproduce the main ex-
536 perimental results (either in the supplemental material or as a URL)? [Yes] See
537 <https://github.com/robustml-eurecom/stressID>
- 538 (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they
539 were chosen)? [Yes] See Section 4 and Appendix F.1.
- 540 (c) Did you report error bars (e.g., with respect to the random seed after running experi-
541 ments multiple times)? [Yes] See Section 4.1 and Section 4.2.
- 542 (d) Did you include the total amount of compute and the type of resources used (e.g., type
543 of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix F.1.
- 544 4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

- 545 (a) If your work uses existing assets, did you cite the creators? [Yes] .
546 (b) Did you mention the license of the assets? [N/A] .
547 (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]
548 See <https://project.inria.fr/stressid/>
549 (d) Did you discuss whether and how consent was obtained from people whose data you're
550 using/curating? [Yes] See Section 3.2.1.
551 (e) Did you discuss whether the data you are using/curating contains personally identifiable
552 information or offensive content? [Yes] See Sections 3.2.1 and 6.
553 5. If you used crowdsourcing or conducted research with human subjects...
554 (a) Did you include the full text of instructions given to participants and screenshots, if
555 applicable? [Yes] See Appendix D.2.
556 (b) Did you describe any potential participant risks, with links to Institutional Review
557 Board (IRB) approvals, if applicable? [Yes] See Section 6 and Appendix C.
558 (c) Did you include the estimated hourly wage paid to participants and the total amount
559 spent on participant compensation? [N/A] Participants are volunteers. See Sec-
560 tion 3.2.1.