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# StressID: a Multimodal Dataset for Stress Identification

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## 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.

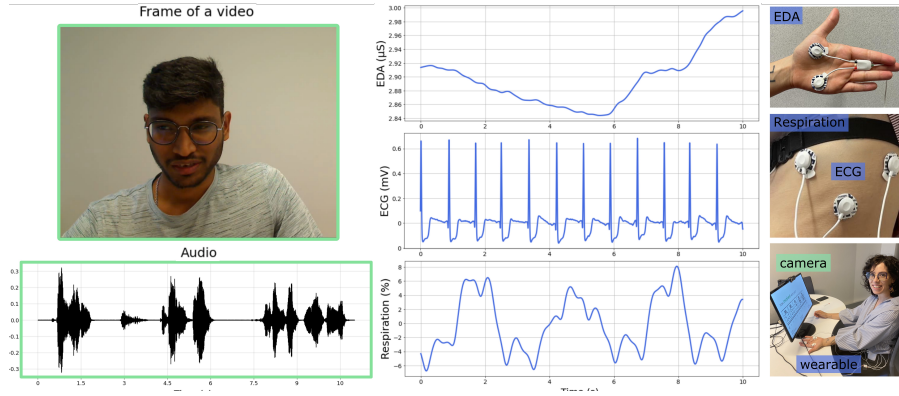


Figure 1: Data collection set-up of StressID.

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>	<b>65</b>	<b>EDA, ECG, Respiration, Face video, Speech</b>	<b>Cognitive load, Public speaking, Audiovisual</b>	<b>SAM, Stress assessment</b>

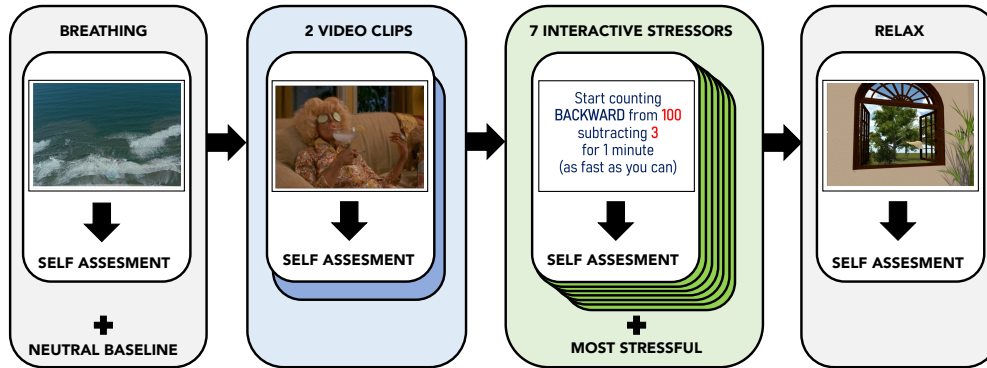


Figure 2: Overview of the experimental protocol. The experiment consists of 11 tasks divided into four blocks: a guided breathing task, 2 emotional video clips, 7 interactive stressors, and a relaxation task.

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 system<sup>1</sup>. 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%

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<sup>1</sup>biosignalsplux, 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

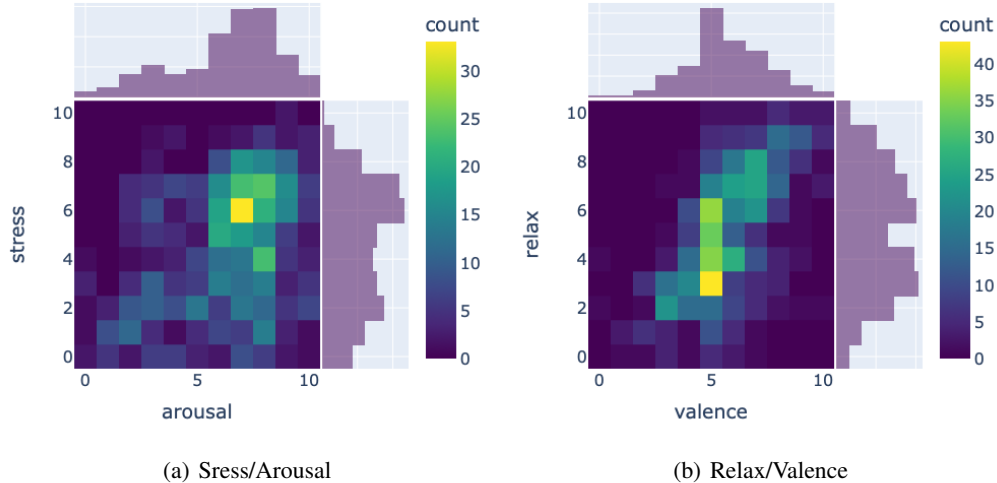


Figure 3: Distribution of the self-assessment answers. (left) Joint and marginal distributions of stress and arousal. (right) Joint and marginal distributions of the relax and valence ratings.

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	<b>0.73 ± 0.02</b>	<b>0.72 ± 0.03</b>	0.55 ± 0.04	0.56 ± 0.03
Physio. HC features + SVM	0.71 ± 0.02	0.71 ± 0.02	<b>0.59 ± 0.04</b>	<b>0.59 ± 0.03</b>
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	<b>0.70 ± 0.03</b>	<b>0.70 ± 0.03</b>	<b>0.55 ± 0.03</b>	<b>0.55 ± 0.03</b>
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	<b>0.70 ± 0.02</b>	<b>0.66 ± 0.03</b>	<b>0.56 ± 0.04</b>	<b>0.52 ± 0.04</b>

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	<b>0.72 ± 0.05</b>	0.64 ± 0.05	0.62 ± 0.05	<b>0.58 ± 0.07</b>
SVM + Product rule fusion	0.71 ± 0.05	0.63 ± 0.05	0.61 ± 0.05	0.56 ± 0.07
<b>SVM + Average rule fusion</b>	<b>0.72 ± 0.05</b>	<b>0.65 ± 0.05</b>	<b>0.63 ± 0.05</b>	<b>0.58 ± 0.07</b>
SVM + Maximum rule fusion	<b>0.72 ± 0.05</b>	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*.

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## 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.