Emotion Detection from Physiological Markers Using Machine Learning

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Human emotion recognition in computer and robotic systems is crucial because it allows these systems to respond to users in a way that feels natural and supportive. By interpreting emotional cues, these systems can adjust their interactions—offering empathy, encouragement, or even assistance during times of distress—enhancing user satisfaction and making technology more accessible and engaging. Emotion recognition methods include analyzing facial expressions, vocal tone, and physiological signals, with the latter being especially effective because physiological data offers objective, real-time insights that are less susceptible to misinterpretation or masking than visible expressions. In this paper, we conducted an experiment for emotion recognition from physiological markers using machine learning algorithms. Each of the participants involved in the experiment was exposed to video stimuli designed to evoke specific emotions. Using physiological markers such as heart rate (HR) and respiratory rate (RR), seven emotions—anger, sadness, fear, amusement, neutrality, surprise, and happiness/joy—were analyzed. Three classification methods Random-forest, SVM and J48 were used. According to the results from the experimental evaluation, the highest accuracy for classifying emotions, based on both HR and RR across all emotions, was obtained with J48 algorithm. Specifically, the most clearly expressed and distinguishable emotions through RR were fear and sadness, with classification accuracies of 96.43% and 92.86%, respectively. Sadness was also the most accurately classified emotion through HR, with an accuracy of 85.71%. Gender differences were noted, with females reacting more to sadness and males to happiness.

Povzetek: Analizirano je strojno prepoznavanje čustev iz fizioloških markerjev, kot sta srčni utrip in hitrost dihanja. Največjo kvaliteto pri prepoznavanju čustev je dosegel algoritem J48, z največjo ntočnostjo pri strahu in žalosti.

1 Introduction

There has been a long-standing academic debate about the definition of emotion, without any widely agreed and universally accepted definition due to its complexity and diverse perspectives in psychology, neurology, and philosophy. However, contemporary study of emotions is usually based on the James-Lange theory of emotions, which suggests that a perceived stimulus is triggering physiological responses that are consequently felt as an emotion [1]. Emotions could be positive like love, happiness, hope, joy, affection, gratitude or negative such as anxiety, jealousy, frustration etc. Our own emotions can help us make sense of every situation. For example, appraisal theory states that our emotions are accompanied by inferences about the situation or environment in which we find ourselves [2], [3].

For a long period of time, emotions have been attributed to living beings or have been observed as unique human traits because only humans can experience a full range of emotions that are intrinsic to human experience, influencing cognition, behavior, decision-making, and social interactions. Nevertheless, throughout history, there have been various ideas and aspirations to create machines or artificial entities capable of emotions or human-like behaviors. This concept can be traced back to ancient myths, literature, and philosophical works. One of the earliest documented studies of robots with emotions and moral reasoning is Isaac Asimov's work "I, robot", published the mid of the past century. This concept of machines with embedded emotional intelligence has evolved significantly with the development of IT technologies and artificial intelligence and more particular generative AI. Rapid development of Artificial Intelligence (AI) and its widespread has affected various aspects of our daily life, starting from tourism [4], through medicine [5-7], biology [8], education [9-10], robotics [11-15], and in economy [16]. AI is becoming increasingly ubiquitous, and it is considered a transformative force in modern society. One of the tangible goals of the AI based society is creating emotionally intelligent systems. By integrating emotion recognition into AI based systems, they could become more adaptive, responsive, and human-centered.

In many real-world contexts, it is essential to understand an individual's emotional state to tailor interventions or optimize experiences. Understanding customers' emotional responses can permit companies to tailor marketing strategies, making them more effective and targeted. Emotion recognition could be used in safety-critical industries, such as aviation or healthcare, to monitor the emotional states of workers. For example, detecting stress or fatigue in real time could prompt timely interventions, reducing the risk of errors or accidents. In healthcare, emotion recognition can assist in the early diagnosis of mood disorders such as depression or anxiety. In educational settings, monitoring students' emotional responses during learning activities can lead to better personalization and adaptive teaching strategies. Emotional responses are not only fundamental to personal well-being but also play a critical role in learning, decision-making, creativity, and social bonding. Emotional reactions can enhance or impede focus, motivation, and memory retention. For instance, positive emotions are associated with enhanced learning and creativity, while negative emotions such as stress and anxiety can impair cognitive functions and hinder performance.

One of the biggest challenges in human-computer interaction is recognition of emotions. While external cues such as facial expressions, vocal tone, and body language have been widely used to recognize emotions, these methods are not always reliable. People can mask their emotions, consciously or unconsciously, and external indicators may fail to capture the complexity of emotional responses. Some external factors (eg: external lights during facial expression analysis) can also negatively affect and cause errors in emotion recognition process. To address these limitations, emotion recognition through physiological signals has emerged as a more objective and precise approach. Following the James Lange theory, emotions are perception of states of the body and connected to physiological responses of the body [17]. Physiological signals, such as heart rate, respiration rate, skin conductance, and brain activity, are directly linked to the autonomic nervous system and are less prone to manipulation [18-19]. Therefore, using these signals can be the most reliable method for emotion recognition.

Physiological signals, nowadays, can be recorded with various unobtrusive, wearable devices equipped with various sensors, such as the Zephyr BioHarness [20]. This sensor can capture real-time changes in respiratory rate (RR) and heart rate (HR), both of which are closely associated with emotional arousal. Increased heart rate and respiratory rate usually indicate increased emotional stress or arousal, while a calm emotional state is often characterized by lower HR and RR. The non-invasive nature of Zephyr BioHarness sensor makes it well-suited for monitoring emotional responses in different contexts, such as experiments that involve exposure to external stimuli.

Emotional elicitation is an essential and often challenging task in the emotional recognition process. Previous studies utilized various stimuli to elicit emotions, such as: video/film clips [21-28], pictures [29-32], or music [33-36]. These stimuli are often pre-assigned to different categories based on a single model. Among these stimuli, video/film clips are the most naturalistic in intensity, that can be standardised and have a relatively high degree of ecological validity. Their cost-effectiveness, and the ability to evoke strong emotions while recreating some situations from the reality, makes them the most powerful method for emotions elicitation within a laboratory setting. The impact of videos clips on user emotions and psychology is especially important nowadays, with the rapid spread of social network and short-form videos. These videos, with a duration of less than 3min., are a new form of internet entertaining especially for the young population. The key psychological principle behind their popularity is attention span. Studies have shown that the average human attention span is decreasing, making it harder for people to stay focused on lengthy content. The videos also use visual and auditory cues to create strong and immediate emotional impact. This ability to evoke strong emotions in a short period encourages further user engagement, and cause addiction. Because of this, the emotions evoked by short-form videos should be well researched and recognized.

This paper proposes an approach for human emotion recognition based on physiological signals. Seven emotions: anger, sadness, fear, amusement, neutrality, surprise and happy/joy are analyzed using physiological signals such as HR (heart rate) and RR (respiratory rate). Emotions were elicited by visual stimuli such as different types of videos[1], each selected to induce specific emotional states (e.g., joy, fear, sadness, surprise). The proposed methodology was experimentally evaluated and the data from physiological signals obtained with Zephyr sensor were processed and analyzed. The results were cross-checked with the emotions felt and reported by the users. Statistical analysis, using ANOVA and t-test as two fundamental and powerful statistical techniques, were conducted on different groups to detect the possible existence of significant differences. Three classification methods for emotion recognition Random-forest, SVM and J48 were compared. Results of the experimental evaluation are elaborated and discussed in the following.

2 Related research

Emotions in people can be seen as a body response to external or internal stimuli. They are expressed in different ways that could be broadly classified as behavioral expressions - often manifest through observable behaviors, such as facial expressions, gestures, and vocal

[1] Neutral - https://www.youtube.com/watch?v=RpjwxyYefYc
Anger – https://www.youtube.com/watch?v=gG22XNhtnoY
Surprise – https://www.youtube.com/watch?v=-eREiQhBDIk
Fear - https://www.youtube.com/watch?v=WDpipB4yehk
Amusement - https://www.youtube.com/watch?v=R6rfCUDTbVE&list=RD_KOhxBGm5qA&index=3
Sadness - https://www.youtube.com/watch?v=cl-HNdzYh7Y
Happy/joy - https://www.youtube.com/watch?v=8tJoIaXZ0rw

changes and physiological responses - automatic bodily reactions controlled by the autonomic nervous system. These include changes in heart rate, respiration rate, sweating, and hormone release. Physiological signals are spontaneous reactions of the human body and consequently they are less prone to human alteration. They contain important information about the current emotional status of the person, and they are continuously following the changes of emotions. Consequently, two main approaches for emotion recognition could be identified in the literature. The first approach is based on classification of the emotional behavior of the user, such as his/her facial expressions and micro-actions, voice, body motion, body gestures, etc. While the second one is based on analysis of physiological signals of the human body, such as electrocardiogram (ECG), photoplethysmography (PPG), electroencephalogram (EEG), electrodermal activity (EDA) etc.

Facial expressions are the predominant mechanism utilized for emotion recognition. Saadon et al. [37] have proposed real-time emotion detection by quantitative facial motion analysis, while the authors in [38] proposed enhanced feature extraction technique through spatial deep learning model for facial emotion detection. Convolutional neural networks have also been tested for facial emotion recognition from regular video streams [39] while in [40] multiple machine learning techniques have been evaluated on emotion recognition from thermal and digital images. The conclusions derived in previous studies have also been reported in other scientific studies [41] where it is explained that facial emotions can easily be biased, therefore they should be used as an additional method or in combination with other behavioral methods to obtain valid results. Considering these conclusions Duan [42] combined facial expression data with physiological signals (skin conductance and heart rate variability) to enable improved emotion recognition in the context of mental health education. Emotion recognition in the context of mental health, was also conducted in [43], where SVM, traditional CNN, and improved CNN models were used on a self-built face database.

Recently published comprehensive review studies for emotion recognition from gait analyses [44] as well as a study reviewing the current state of the art related to approaches that combine facial expression and body gesture emotion recognition [45] suggest that the fusion of physical information and physiological signals can provide useful features of emotional states and lead to higher accuracy.

Physiological methods use various sensors to measure physiological responses, like change in skin conductance, changes in heart rate, breathing rate, pupil size, or even brain activity. Several studies published in the 1990s introduced the concept of emotion detection based on physiological signals obtained using wearable devices. The concept of “affective wearable” device capable of recognizing the human’s affective state using multiple integrated sensors for measurement of blood volume pressure, galvanic skin response (GSR), hearth rate (HR) and electromyogram (EMG) was introduced by Picard and Healey [46]. Saganowski et al. [47] conducted systematic literature review of the research conducted in the past three decades related to emotion recognition using physiological signals from wearables. Multiple physiological measures and methods of emotion elicitation (used stimuli for inducting emotions) have been identified. Petrantonakis et al. [29] and Valenza et al. [30] have used the International Affective Picture System (IAPS) to measure various emotions using an electroencephalogram (EEG) signal. The same picture database was also used by Basu et al. [31], but they measure GSR, HR, RR and Skin Temperature (ST) for emotion recognition. Images of natural scenes, labelled positive and negative, were used by Lan et al. [32] to evoke emotions that were then recognized by analyzing EEG data. Music stimuli has also been used in a few studies. Various emotions, like joy, anger, sadness and pleasure, were measured using various physiological signals: EMG, RR, ECG, skin conductance (SC) [33-34] and EEG [35-36]. Methods requiring subjects’ active participation, like playing computer games, were also used. Drachen et al. [48] measured HR and EDA during participants’ play of three different commercial first-person shooter games. A similar approach, using computer games, was used in other studies, but the focus was on measuring electrical signals in the heart (ECG) [50], as well as HR and skin perfusion [49]. More recently immersive VR-games were used for emotion induction, and a software platform for collecting player's physiological data [51]. Video clips, as effective stimuli, are widely applied in research studies that use physiological data for emotion recognition (Leila et al. [24] used ECG and respiration (RSP) data; Shin D. et al. [25] analyzed complex EEG/ECG bio-signals; Ayata et al. [72] proposes a model for emotion recognition using PPG and GSR). In [23] Valenza et al. have proved that synchronization exists between breathing patterns and heart rate during emotional visual elicitation. Emotion inducting film clips are also widely used in research studies. They are used in [26] where emotion recognition is performed using signal fusion: ECG, RSP, temperature (T), Electrodermal activity, EMG, Capnography and facial muscle activity; in [23] where EEG signal is used; in [27] where RR data were measured; in [28] where Skin conductance level (SCL) and HR were used.

Table 1 shows the details of the work of previous similar studies that address emotion recognition by measuring physiological data. All of them used visual stimuli (image, videos or film clips), and some used audio stimuli in addition to visuals. Most of them used data from various bio signals obtained using complex systems. However, authors in [24] shows that it is not necessary to make a data fusion to achieve better accuracy, a single well-chosen and measured signal can sometimes perform better. This of course depends also on classification algorithm as well as experimental procedures.

Several emotion recognition scenarios can be identified in the controlled lab environment. Most of them assume that there is a correlation between the subjective and conscious recognition of experienced emotions. However, studies that show variations between self-reported and measured data also exist [28].

Considering the inconsistencies in output results, we have decided to conduct an experiment for emotion recognition using only HR and RR as physiological markers.

Table 1: State of the art (SOTA)

Ref.	Physiological markers	Elicitation stimuli	Emotions	Classification algorithms	Dataset/ No of participants	Results
24	ECG, Respiration	music video clips	Low/high arousal, Positive/negative valence	SVM	Database for Emotion Analysis using Physiological Signals (DEAP) / 32 DEAP subjects	Resp. signal alone: liking = 73% arousal =72% valence =70% Both ECG and Resp.: liking = 76% arousal =74% valence =74%
25	ECG, EEG	video image data	amusement, fear, sadness, joy, anger, and disgust	Multi-layer perceptron (MLP), (SVM), Bayesian network (BN)	Self measurement /15 male and 15 female	EEG signal alone: MLP=44.86% SVM=24.99% BN=62.28% Complex bio-signal: MLP=83.97% SVM=63.97% BN=98.06%
26	ECG, RSP, temperature, EDA, EMG, capnography, facial muscle activity	Film clips	Fear, sadness, neutral	Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Multilayer Perceptron (MLP), Radial Basis Function Network (RBFN), K-Nearest Neighbours (KNN).	Self measurement / 34 participants	Subject-independent classification: RBFN Stimulus-independent classification: LDA
23	EEG	Film clips	Amused, disgusted, sad and neutral	SVM	Self measurement / 9 participants	SVM=97.2%
27	Respiration	Film clips/ narrative slide films with back. music	Love, sadness, joy, fear, and anger	k-Nearest Neighbour (k-NN), Probabilistic Neural Network (PNN).	Self measurement 33 participants	Average classification rate: 88%
28	SCL, HR	Film clips	Anger, fear, sadness, disgust, amusement, tenderness and neutral	//	Self measurement / 123 participants	A set of emotion-eliciting films was able to induce physiological changes in SCL and HR.
71	Respiratory, PPG, temperature	Music video	Arousal and valence levels	RF, SVM and logistic regression (LR)	DEAP / 32 participants	Best results with RF (arousal/valence): Respiratory=71.32% /70.62% PPG=68.59% /70.23% Temperature=69.68% /67.73% Fused=73.08% /72.18%
72	PPG, GSR	Video clips	Amusement, sadness, neutral	Linear SVM, LDA, multinomial regression (MN), decision trees (DT), and naive Bayes (NB).	Self measurement / 37 participants	Best result using Linear SVM: amusement=96% sadness=91% neutral=86%

3 Methodology

Our study for emotion recognition assumes that experienced emotions produce physiological changes in the human body and consequently they can be recognized using physiological markers and compared with subjective self-perception. The study is conducted according to the experimental scenario presented in Fig. 1. Our methodology was designed to recognize seven emotional states: anger, sadness, fear, amusement, surprise, happy /joy and neutral. Five of them (anger, sadness, fear, surprise, happy/joy) are widely accepted as basic emotions that we all feel, transcending language, regional, cultural, and ethnic differences [52]. Anger is a strong emotional response characterized by feelings of displeasure, frustration, or hostility, often triggered by perceived wrongs, injustice, or threats. It is typically associated with physiological arousal, such as increased heart rate and tension. Sadness is a negative emotional state marked by feelings of loss, disappointment, or helplessness. It is often accompanied by reduced energy, withdrawal from others, and a sense of melancholy. Fear is an intense emotional response to a perceived threat or danger, either real or imagined. It involves heightened physiological arousal, such as increased heart rate and adrenaline, and prepares the body for a fight-or-flight response. Surprise is an emotional reaction to an unexpected event or situation, characterized by a sudden feeling of astonishment or shock. It can be positive, negative, or neutral, depending on the context of the surprising event. Happy/joy is a positive emotional state associated with feelings of pleasure, contentment, or satisfaction. It is often marked by a sense of well-being, optimism, and energy. Amusement is an emotion with positive valence and high physiological arousal (causing a rapid heartbeat). It is one of the most important positive emotions that encourages people to engage in social interactions and promotes social bonding [53]. Neutral, on the other hand, is an emotional state where there is no strong positive or negative feeling. It is characterized by a balanced, calm demeanor, with little or no noticeable emotional arousal. However, they are still important because they can be experienced as a state of emotional balance, allowing a person to remain calm and objective in challenging or stressful circumstances.

The seven emotional states influence our thoughts, behaviors, and overall well-being. Therefore, by acknowledging and recognizing them, we can develop emotional intelligence and cultivate healthier relationships with ourselves and others.

Our methodological approach is described in the following.

Participants: A total of 78 healthy subjects participated in this study; all students at Faculty of Computer Science at Goce Delcev University in Stip. Fifty of them participated in the selection of emotional film clips, used in this research. The answers of these 50 participants were used to confirm the reliability of the selected film clips in eliciting the target emotions before the experiment commenced.

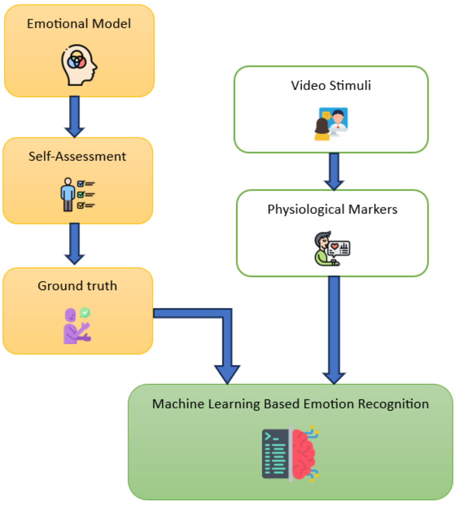

Figure 1: Emotion recognition scenario applied

The remaining 28 participants (20 male and 8 females) were involved in the experimental research. The average age of the participants was 22, with a minimum age of 21 and a maximum age 24. All participants use computers often and often watch videos with different content.

All measurements were performed in laboratory conditions. Informed consent was obtained from all participants, before the start of the experiment, confirming their willingness to participate in the study. Additionally, they signed a document ensuring their anonymity and consent to be part of the examination group. The procedure was explained to each participant and then each watched the videos alone, in the laboratory, and independently responded to the questionnaire without any external influences and suggestions.

Video stimuli selection: As the initial step, we selected 35 emotional film clips (5 for each selected emotion) from databases with prior evidence of reliability and validity in eliciting targeted emotions [54-58]. Fifty subjects participated in the selection phase to further refine and validate the selection of film clips. After watching the film clips, they completed a simple discrete emotion questionnaire, based on Emotion-Rating Form [59]. Of these 35 film clips only 7 were chosen (one for each emotion) for further use in this research study.

Experimental procedure: The study took place at the Laboratory of Robotics and Intelligent Systems at the Faculty of Computer Science (Goce Delcev University in Stip). Upon participant’s arrival and environmental accommodation, a research assistant explained the experimental procedure (Fig. 2). Then the written consent was signed by the participant, and demographic data were collected. After placing the sensor on the participant, it was tested to ensure its proper functioning. The second phase of the experiment consists of three repeated stages: relax, stimuli and self-report. Participants first watched a 2 min. relaxing video, in order to rest and to calm emotions before next stimuli. This is important for establishing the baseline as a reference level. Then an emotion-eliciting video was played, after which participants filled out a self-assessment questionnaire. Each video lasted from 1:30-3 minutes. The order of the film clips was the same for all participants. Participants reported their momentary feelings of anger, sadness, fear, amusement, surprise, happy/joy and neutral using a 5-point rating scale: “I did not feel it at all” (1), “I felt very little” (2), “I felt it a little” (3), “I felt it” (4) and “I felt it very strongly” (5). The entire experiment lasted about 50 minutes, depending on the time spent on the questionnaires.

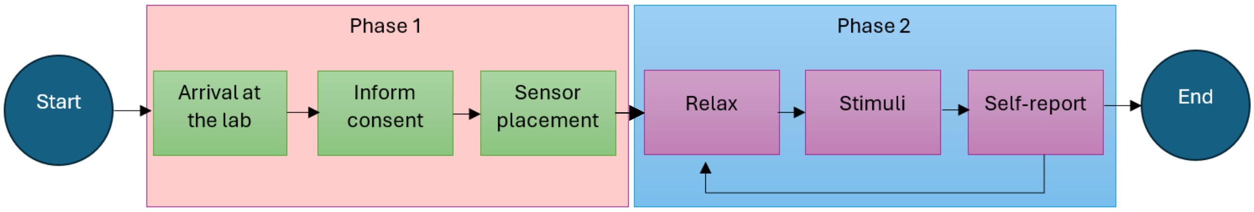

Figure 2: Experimental procedure

Physiological markers: Heart rate and respiration rate were used as physiological markers in this study. They were extracted from the signals captured using Zephyr BioHarness device. It is a physiological monitoring telemetry device intended for real-time monitoring. It consists of a chest strap and an electronics module that attaches to the strap. The module has a microprocessor and can directly compute HR and RR, but it can also stream the captured signals to a personal computer via integrated Bluetooth Low Energy (BLE) module.

Heart rate (HR) – is the frequency of the heartbeat measured by the number of contractions of the heart per minute. A normal resting heart rate, for adults, is between 60 to 100 beats per minute, but it can vary from minute to minute. The rate can be affected by numerous factors, including body's physical needs, physical fitness, genetics, hormonal status, environment, stress or psychological status… Heart rate increased when we are exposed to situations that evoke certain emotions, positive or negative (it increased to a greater degree in negative than in positive emotions). Therefore, it can be used as a valid physiological marker of emotional processes such as valence and arousal [60-62].

Respiratory rate (RR) - Respiration can be measured as the rate or volume at which an individual exchanges air in their lungs. Rate of respiration and depth of breath are the most common measures of respiration [63]. The respiratory rate is the rate at which breathing occurs; it is set and controlled by the respiratory center of the brain. A person's respiratory rate is usually measured in breaths per minute.

The normal resting respiratory rate of adults falls within the range of 16 to 20 breaths per minute. However, RR can be impacted by changes in emotions such as happiness, fear, sadness, surprise etc. Calm and positive emotions cause a lower breathing rate, a more regular breathing pattern, and a longer exhalation time than inhalation time, otherwise stress and fight situations cause a higher breathing rate, a more irregular breathing pattern, and a longer inhalation time than exhalation time. The connection between emotional states and respiration is investigated in several studies [64-67]

The breathing rate is the second “clock” of the body, in addition to the heart rate.

4 Analysis of results

A. *Descriptive statistic*

Seven types of videos (film clips) were used in the study: anger, fear, sadness, neutral, amusement, surprise and happiness. According to results, no one had seen the neutral and the surprise video before, just a few participants had seen the anger, fear and the happy video before. Most of participants had seen amusement video, while sadness video had almost the same number of participants who had watched the video before the measuring and those who had not (Table 2).

The anger and fear videos did not evoke positive feelings in most participants. Sad and surprise videos simultaneously cause positive and negative feelings. In addition, the rest 3 videos: happy, amusement and neutral are the most pleasant to watch according to the participants (Table 3).

Table 2: Frequency of participants' previous viewing experience by video type

Film clip	Yes	No
Anger	5	23
Fear	2	26
Sadness	14	14
Neutral	0	28
Surprise	0	28
Happiness	5	23
Amusement	21	7

Table 3: Feelings on the scale from 1 to 10

Film clip	1-5	6-10
Anger	24	4
Fear	19	9
Sadness	14	14
Neutral	9	19
Surprise	14	14
Happiness	4	24
Amusement	4	24

B. Emotion classification

Several classification algorithms such as: Random Forrest, Support Vector Machine (SVM) and J48, have been used to build the classification models. Random Forest (RF), SVM, and J48 offer a strong combination of flexibility, robustness, and generalization capability, making them suitable for a wide range of classification tasks, particularly those involving non-linear decision boundaries, high-dimensional data, and noisy environments. These characteristics make them more versatile and powerful options compared to other algorithms in many real-world scenarios.

Random Forest is an extension of decision trees that uses multiple decision trees, each trained on a sample of individuals [68]. For each split, a subset of random attributes is selected, and the best attribute is chosen for splitting. In the classification process, everyone is classified based on the majority vote from the group of trees. RF creates many trees, and each tree is built in the same way. Trees that split on the x variable will be built as far as possible with the y variable. The more data provided; the more trees can be grown. The placement of trees far from each other means that if one tree grows around the x variable, it is the development of the x tree. RF uses an ensemble method called "bagging" to reduce the risk of overfitting, especially when dealing with small datasets.

SVM method is a binary classification method by supervised learning [69]. The aim is to learn the $h(x)$ function through a training set given below:

$$\{(x_1, l_1), (x_2, l_2), \ldots\ldots (x_p, l_p)\} \epsilon\ RN\ x\ \{-1, 1\} \quad (1)$$

where l_k are the labels, x_k are input vectors, being in a space R^N and p is the size of the training set.

The technique seeks a separating hyperplane $h(x) = wx + w_0$ which minimizes the number of errors through the introduction of variable spring ξ_k, which can relax the constraints on the training vectors.

$$l_k(wx_k + w_0) \geq 1 - \xi_k, \xi_k > 0, 1 \leq k \leq p \quad (2)$$

With the previous constraints, the optimization problem is modified by a penalty term which penalizes high variables, spring ξ_k:

$$Minimise\ \frac{1}{2}\|w\|^2 + C\sum_{k=1}^{p} \xi_k, C > 0 \quad (3)$$

where C is a constant that controls the compromise between the number of classification errors and the margin width (the margin width being the smallest distance between training set and separating hyperplane).

J48 is a version of an earlier ID3 algorithm. It generates non-binary tree, uses measure called gain ratio to construct decision tree, the attribute with highest normalized gain ratio is taken as the root node, and the dataset is split based on the root element values. Again, the information gain is calculated for all the sub-nodes individually and the process is repeated until the prediction is completed. C4.5 is an evolution and refinement of ID3 that accounts for missing data values, continuous attribute value ranges, and pruning of decision trees and so on. Error–based pruning is performed after the growing phase. J48 can handle both continuous and discrete attributes, training data with missing attribute values and attributes with differing costs and provide an option to prune trees after creation. There are several parameters related to tree pruning in the J48 algorithm and should be used with care as they can make a noteworthy difference in the quality of results. J48 employs two post-pruning methods, namely sub tree replacement and sub tree raising [70].

C. Experimental results

We employed three classification algorithms-Support Vector Machine (SVM), Random Forest (RF), and J48 - to analyze the physiological data collected from 28 student participants in our experiment. The results for heart rate (HR) and respiratory rate (RR), categorized across seven distinct emotions, are presented in Tables 3 and 4, respectively.

For RR classification, six categories were defined. Given that the normal RR range for healthy individuals falls between 16 and 20 breaths per minute, we assigned class labels as follows: 0 for values below 16 (a low RR, often observed in relaxed states, especially during deep breathing or rest), 1 for values between 16 and 17 (slightly above normal, can indicate a mild increase in stress or alertness), 2 for values between 17 and 18 (moderate RR, potentially showing moderate anxiety or mild exertion), 3 for values between 18 and 19 (higher RR, typical of more stressed or anxious states), 4 for values between 19 and 20 (elevated, often associated with heightened anxiety, nervousness, or physical exertion), and 5 for values exceeding 20 (high RR, usually associated with intense emotional states like panic, fear, or excitement) (Table 4). Each emotion was analyzed individually, and a 10-fold cross-validation approach was employed, where 90% of the dataset was used for training, while the remaining 10% served as the test set. In 10-fold cross-validation, the dataset is divided into 10 equal parts. Each fold is used as a test set once, while the remaining 9 are used for training. This process repeats 10 times, and the results are average for reliable performance evaluation.

Similarly, we defined six categories for the heart rate (HR) classification. Since the normal HR range for healthy individuals spans from 60 to 100 beats per minute, we classified the data as follows: 0 for values below 60, (relaxed states, deep sleep, or well-trained athletes), 1 for values between 60 and 70 (moderate, which is within the normal resting range for most individuals), 2 for values between 70 and 80 (still within a normal resting range but could indicate slight arousal or anticipation), 3 for values between 80 and 90 (slightly elevated, often associated with moderate stress, anxiety, or physical exertion), 4 for values between 90 and 100 (elevated HR, which could correspond to emotional arousal, stress, or excitement), and 5 for values exceeding 100 (high HR, often linked to intense emotional states such as fear, anger, or high excitement). These HR thresholds reflect the natural response of the body to different emotional stimuli. Each emotion was analyzed individually, following the same classification approach (Table 5).

According to the results, the J48 algorithm produced the most accurate overall results for both heart rate (HR) and respiratory rate (RR) across all emotions. When comparing the other algorithms, Support Vector Machine (SVM) demonstrated superior performance for HR

classification, while Random Forest performed better for RR classification.
These results were also confirmed by the recall, precision, and F-measure values given in Table 6.

Table 4: Results for RR for different emotions examined by SVM, RF and J48

Emotion / RR	Neutral	Anger	Surprise	Fear	Amusement	Sadness	Happiness
RR (SVM)	57.1429%	50 %	64.2857%	67.8571%	71.4286%	71.4286%	71.4286%
RR (RF)	64.2857%	64.2857%	67.8571%	85.7143%	78.5714%	82.1429%	78.5714%
RR (J48)	78.5714%	75 %	85.7143%	96.4286%	78.5714%	92.8571%	82.1429%

Table 5: Results for HR for different emotions examined by SVM, RF and J48

Emotion / HR	Neutral	Anger	Surprise	Fear	Amusement	Sadness	Happiness
HR (SVM)	64.2857%	67.8571%	64.2857%	57.1429%	67.8571%	53.5714%	82.1429%
HR (RF)	53.5714%	67.8571%	57.1429%	46.4286%	67.8571%	64.2857%	60.7143%
HR (J48)	75 %	78.5714%	82.1429%	78.5714%	82.1429%	85.7143%	75%

Table 6: Precision, recall and F1- score values

	Emotions	**precision**			**recall**			**F1-score**		
		J48	RF	SVM	J48	RF	SVM	J48	RF	SVM
HR	Happiness	0.759	0.703	0.803	0.75	0.714	0.821	0.753	0.708	0.812
	Amusement	0.881	0.646	0.646	0.821	0.679	0.679	0.850	0.662	0.662
	Surprise	0.839	0.543	0.518	0.821	0.571	0.643	0.828	0.553	0.574
	Fear	0.796	0.496	0.603	0.786	0.536	0.571	0.791	0.502	0.568
	Sadness	0.871	0.717	0.577	0.857	0.679	0.536	0.862	0.697	0.538
	Neutral	0.786	0.601	0.699	0.75	0.571	0.643	0.761	0.578	0.659
	Anger	0.806	0.743	0.714	0.786	0.714	0.679	0.796	0.728	0.696
RR	Happiness	0.717	0.762	0.589	0.821	0.786	0.714	0.765	0.774	0.646
	Amusement	0.683	0.79	0.674	0.786	0.786	0.714	0.731	0.788	0.693
	Surprise	0.917	0.621	0.517	0.857	0.714	0.643	0.886	0.664	0.573
	Fear	0.976	0.889	0.66	0.964	0.893	0.679	0.965	0.891	0.667
	Sadness	0.967	0.869	0.521	0.929	0.893	0.714	0.948	0.881	0.602
	Neutral	0.774	0.637	0.452	0.786	0.679	0.571	0.777	0.657	0.505
	Anger	0.741	0.565	0.406	0.75	0.607	0.5	0.745	0.579	0.443

In our study, the SVM model tends to have lower accuracy compared to RF and J48, especially for some emotions such as fear (57.14% for HR, 67.86% for RR). This is consistent with findings from previous studies where SVM sometimes struggles with non-linear patterns in physiological data. The RF model performs better than SVM in most cases and shows comparable results with J48 for several emotions. RF is generally known for its robustness in handling high-dimensional, noisy data, which may be why it performs well in this context. The J48 decision tree classifier shows the highest accuracy across most emotions, particularly in fear (96.43% for RR and 78.57% for HR). Decision trees are often preferred in many studies for emotion classification due to their interpretability and ability to capture decision boundaries effectively, especially when combined with boosting or pruning methods.

When comparing our results to those of SOTA (Table 1), it is important to note that our study utilizes Heart Rate (HR) and Respiratory Rate (RR) as the primary physiological signals, which distinguishes it from other studies in this area. This makes the results not directly comparable to other studies which have used data from several physiological signals, as well as different elicitation techniques. However, if we compare the results of [24] or [27] or [71] - where respiration data are used -

we can see that in all three studies the obtained accuracy is lower than in our case when using J48 decision tree classifier. This fact indicates that using HR and RR for emotion recognition remains a valuable approach, especially in contexts where simplicity and non-invasiveness are a priority.

D. Correlation

Of the 28 participants, 8 were female, and all frequently use computers to watch videos, though -they do not often view content with varied genres. Regarding the four offered genres—comedy, horror, action, and films with a sad ending—it was found that males generally preferred action, while females favored both comedy and action. When asked about their prior exposure to the same videos, all female participants reported that they had not previously seen the videos that evoke fear, neutrality, or surprise, while some of the participants had seen the videos evoking sadness, happiness and amusement. The male participants also had not prior experience with the neutral and surprise-inducing videos, while most of them had watched the amusing video.

In order to find out whether previous viewing experience influences the level of target emotions produced, we conducted some statistical tests. An independent samples t-test was chosen, since we only have two groups to compare (participants who have and participants who have not previously watched the videos). According to the results, given in Table 7, for females, there is no statistically significant difference in emotional responses of sadness, happiness and amusement, based on the p-values (> 0.05) and t-stat (< t-critical) between first-time watchers and watched before groups. These three emotions were chosen, because there was a group of female students who has previously watched these videos.

Table 7: Analysis of female participants (have seen/have not seen the video before)

Female participants	**t-stat**	**t-critical**	**p-value**
sadness	0.0751	2.4469	0.9426
happiness	0.9020	2.4469	0.4018
amusement	2.0702	2.4469	0.0839

The same three emotions (sadness, happiness, and amusement) were also chosen for the male student group. According to the results obtained by t-test given in Table 8, for males, there is statistically significant difference in emotional responses of sadness and amusement, based on the p-values (> 0.05) and t-stat (< t-critical) between first-time watchers and watched before groups. This means that these videos had a different emotional impact on first-time watchers in male group. In fact, subjects who hadn't seen film clips before reported greater levels of target emotions than subjects who had previously seen these film clips. However, watching happy film clip before, does not significantly affect emotional response in happiness video, where t-stat (1.048) is less than the t-critical (2.101), and the p-value (0.309) is greater than 0.05. This means that there is no statistically significant difference between the two groups, indicating that there is no substantial difference in the emotional response to happiness among male participants who have already seen the happy video and those who are watching it for the first time.

Table 8: Analysis of male participants (have seen/have not seen the video before)

Male participants	**t-stat**	**t-critical**	**p-value**
sadness	2.672	2.101	0.016
happiness	1.048	2.101	0.309
amusement	3.029	2.101	0.007

Table 9 presents the self-assessed emotional responses from all participants, as well as separate data for male and female participants. Responses were rated on a scale from 1 to 5 for all emotions experienced while watching the different videos. The most prominent emotions identified were sadness, neutrality, happiness, and amusement, corresponding to the specific video content. According to the self-assessment, female participants experienced the strongest emotions while watching the sad video, while male participants expressed more emotion during the amusing and happy videos. Overall, it can be observed, that female participants reported more intense emotional experience then male, for all emotional states, which is consistent with the other findings [73], [74].

Table 9: Results from self-assessment

		All Participants							Males							Females						
		An	F	S	N	Su	H	A	An	F	S	N	Su	H	A	An	F	S	N	Su	H	A
Anger (An)	**1**	7	22	17	23	15	28	26	7	16	11	15	12	20	19		6	6	8	3	8	7
	2	9	4	6	4	8		2	7	3	4	4	6		1	2	1	2		2		1
	3	5	1	2	1	2			2	1	2	1	1			3				1		
	4	7	1	3		3			4		3		1			3	1			2		
	5																					
Fear (F)	**1**	13	3	25	27	14	28	27	10	3	18	19	11	20	19	3		7	8	3	8	8
	2	8	10	2	1	9		1	6	7	1	1	6		1	2	3	1		3		
	3	2	7	1		4			1	6	1		3			1	1			1		
	4	5	5			1			3	3						2	2			1		
	5		3							1							2					
Sadness (S)	**1**	2	21		11	22	28	28	1	15		9	17	20	20	1	6		2	5	8	8
	2	7	5	1	11	5			6	4	1	6	3			1	1		5	2		
	3	6	2	4	6	1			5	1	4	5				1	1		1	1		
	4	10		12					7		10					3		2				
	5	3		11					1		5					2		6				
Neutral (N)	**1**	18	18	13	1	14	1	7	11	13	7	1	7		1	7	5	6		7	1	6
	2	7	7	8	1	6	2	5	6	5	8	1	6	1	5	1	2				1	
	3	2		4	6	4	10	10	2		3	4	4	9	9			1	2		1	1
	4	1	3	3	17	4	11	6	1	2	2	14	3	8	5		1	1	3	1	3	1
	5				3		4							2					3		2	
Surprise (Su)	**1**	17	5	12	19	1	19	14	12	3	9	13	1	12	8	5	2	3	6		7	6
	2	10	7	8	6	4	3	6	7	4	7	4	3	3	6	3	3	1	2	1		
	3	1	8	4	2	11	4	6	1	8	2	2	8	4	5			2		3		1
	4		6	4	1	10	2	2		5	2	1	8	1	1		1	2		2	1	1
	5		2			2											2			2		
Happiness (H)	**1**	27	22	14	5	14		5	19	16	10	3	9		2	8	6	4	2	5		3
	2	1	3	4	5	5	1	9	1	3	3	3	4	1	5			1	2	1		4
	3		2	2	11	6	5	6		1	2	9	5	4	6		1		2	1	1	
	4		1	4	6	2	15	6			2	4	2	12	6		1	2	2		3	
	5			4	1	1	7	2			3	1		3	1			1		1	4	1
Amusement (A)	**1**	21	8	14	3	6			15	6	9	2	3			6	2	5	1	3		
	2	5	6	7	11	4	3	3	4	3	6	9	2	3	2	1	3	1	2	2		1
	3	2	11	5	5	4	6	5	1	9	4	4	3	3	4	1	2	1	1	1	3	1
	4		1	1	8	12	11	10		1		5	11	9	7			1	3	1	2	3
	5		2	1	1	2	8	10		1	1		1	5	7		1		1	1	3	3

According to the female participants, the video intended to evoke anger does not generate positive feelings for any of them. Additionally, videos eliciting fear, sadness, and surprise tend to evoke negative emotions. In contrast, videos associated with happiness, as well as those intended to induce amusement and neutrality, generally elicit positive emotions. For the male participants, videos featuring anger and fear were similarly deemed unpleasant, while amusing and happy videos were perceived positively.

Further statistical tests, including ANOVA and t-tests, were conducted to assess the intensity of sadness among female participants when watching the sad video. The ANOVA yielded a p-value of 0.33, which exceeds the significance threshold ($\alpha = 0.05$), suggesting no statistically significant difference in this case. The t-value obtained was 1.53, which is smaller than the critical t-value of 2.36 for 7 degrees of freedom. Both tests indicate that sadness is indeed a prominent emotion among female participants when watching the sad video.

For male participants, we conducted the same ANOVA and t-tests to examine the emotion of happiness during the happy video. The ANOVA returned to a p-value of 0.15, which is also greater than the significance level ($\alpha = 0.05$), suggesting no significant difference. The t-value obtained was 2.05, which is smaller than the critical t-value of 2.09 for 19 degrees of freedom. Both the ANOVA and t-test results confirm that male participants indeed experience strong feelings of happiness when watching the happy video.

From these statistical analyses, we can conclude that the most effective videos in terms of eliciting emotional responses were the sad and happy videos. Males predominantly reacted to happy scenes, while females were more emotionally affected by the sad video. Based on the participants' self-assessment ratings (scores of 4 or 5 indicating strong emotional responses), a correlation table was created to identify relationships between different emotions. This allowed us to further explore how emotions are interconnected during the viewing experience.

According to the results from Table 10, participants experienced strong emotions while watching the corresponding videos. Notably, there is a strong correlation between the emotions of sadness and anger, happiness and neutrality, and amusement and happiness. Given that the correlation value between amusement and happiness is the closest to 1, we selected the videos eliciting happiness and amusement for further analysis. We conducted ANOVA tests to compare amusement and happiness with all other emotions, as presented in Table 11.

The results presented in Table 11 confirm the correlation identified in Table 10 between amusement and happiness. Specifically, the findings indicate that watching happy videos elicits feelings of amusement; however, viewing amusing videos does not necessarily provoke feelings of happiness.

Table 10: Correlation table for filing strong emotion while watching videos

Emotions	**Anger**	**Fear**	**Sadness**	**Neutral**	**Surprise**	**Happiness**	**Amusement**
Anger	1						
Fear	-0,39768	1					
Sadness	0,702116	-0,57597	1				
Neutral	-0,52806	-0,16743	-0,25453	1			
Surprise	-0,66052	0,342058	-0,41427	0,177023	1		
Happiness	-0,67762	-0,29805	-0,19136	0,718203	0,335352	1	
Amusement	-0,58905	-0,14804	-0,26649	0,512828	0,67609	0,808552	1

Table 11: Comparison of amusement and happiness with other emotions (ANOVA p-values)

Video/emotion	**Anger**	**Fear**	**Sadness**	**Neutral**	**Surprise**	**Happiness**	**Amusement**
Happy/happiness	2.87E-27	2.87E-27	2.87E-27	0.051	5.32E-14	1	0.3
Amusing/amusement	1.14E-20	3.34E-21	8.98E-22	4.93E-06	1.69E-10	6.808E-05	1

Additionally, we analyzed the correlation between the self-assessment results and the experimental data for heart rate (HR) and respiratory rate (RR). We focused on the emotions of anger, fear, surprise, and neutrality. For instance, we compared the self-assessment of anger given after viewing the angry video with the corresponding experimental RR data obtained while watching the same video. The results from the ANOVA test ($p = 0.53$) and the t-test ($0.56 < 2.05$) indicate that there is no significant difference between the self-assessment and experimental results for respiratory rate (RR). This suggests that participants accurately expressed the emotions they experienced.

We conducted a similar correlation analysis between the self-assessment results and the experimental data for both RR and HR while watching a neutral video. We focused on this analysis, as the emotion of neutrality is associated with a decrease in both the breathing rate and heart rate.

The results from the ANOVA ($p = 0.75$ for RR and $p = 0.59$ for HR) and the t-tests ($0.30 < 2.05$ for RR and $0.58 < 2.05$ for HR) further demonstrate that there is no significant difference between the self-assessment and experimental results for both RR and HR. This indicates that participants accurately conveyed their emotional responses while watching the neutral video.

Additionally, we examined the emotions of fear and surprise, as both are associated with an increase in heart rate. We compared the self-assessment ratings for fear during the viewing of a scary video with the corresponding HR experimental results for the same video, utilizing

ANOVA and t-tests. This process was similarly applied to the video inducing surprise.
The results presented in Table 12 further confirm that the experimental data for heart rate (HR) during the viewing of scary and surprising videos aligns with the self-assessment responses provided by participants regarding their emotions of fear and surprise while watching these videos. This consistency reinforces the validity of the emotional responses reported by participants in relation to their physiological measurements.

Table 12: ANOVA and t-test (self- assessment and experimental RR/HR)

	Angry	Neutral		Fear	Surprise
	RR	HR	RR	HR	HR
ANOVA (p-value)	0.5346	0.5902	0.758	0.60364	0.701368
t-test (t-stat)	0.56266	0.582772	0.309365	0.5587	0.82735

5 Conclusion and summary

Human emotion recognition is essential for computer and robotic systems because it enables these systems to interact with people in a more empathetic, responsive, and adaptive manner. By understanding emotional cues, such as facial expressions, tone of voice, or physiological signals, robots and AI-driven interfaces can tailor their responses to meet the emotional needs of users, creating a more engaging and satisfying experience. This is particularly valuable in fields like healthcare, where emotionally aware systems can offer comfort and companionship to patients, and in customer service, where adaptive responses improve user satisfaction. Emotionally intelligent systems can also assist in education by gauging student engagement and adjusting lessons, ultimately making technology more intuitive and human centered.
The use of various physiological signals such as heart rate, skin conductance, EEG, EMG, brain activity, etc. allows for more precise and nuanced recognition of emotions. Emotion recognition through physiological signals is particularly effective because it provides objective, real-time insights into emotional states that may not be visible through external behaviors.
In this paper, we conducted an experiment for emotion recognition from physiological markers (HR and RR) using machine learning. We have selected HR and RR as these physiological signals are easy to collect with relatively compact and ergonomic wearable devices, which allows recording not only in a laboratory environment, but also in home conditions or outdoors. Seven distinct film clips, each selected to evoke a specific emotional response (anger, sadness, fear, amusement, surprise, happy/joy and neutral), were presented to the participants. The data from HR and RR were analyzed using three machine learning algorithms: SVM, Random Forest, and J48. The results showed that J48 consistently yielded the highest accuracy for classifying emotions based on both HR and RR across all emotions. SVM demonstrated greater effectiveness in classifying emotions based on HR, while RF performed better with RR. These algorithms have also been used in previous studies, but they have not always shown good results. For example, the accuracy of the SVM algorithm ranges from 24.99% in [49] to 97.2% in [47]. However, the small participant size (only 9 subjects) in the last study can be considered as a limitation. Also, the studies used different psychological markers (not HR and RR), as well as diverse datasets. This limits the direct comparison with our study. In many of the previous studies, classifications have been made on a two-dimensional scale (valence and arousal). Random forest, for example, has been chosen as the best classification algorithm in [69], with accuracy of 71.32% for arousal, and 70.62% for valence, when using respiration, as a physiological marker. On the other hand, in our study, we have used the categorical emotional model, measuring seven discrete emotions. The emotions most clearly expressed and distinguishable through RR were fear and sadness, with classification accuracies of 96.43% and 92.86%, respectively. Sadness was also the most accurately classified emotion through HR, with an accuracy of 85.71%. Additionally, gender differences were observed, with female participants displaying stronger emotional responses to the sad video, while male participants showed more pronounced reactions to the happy video. This is partially in line with the previous study [52] which shows that women react more intensively to sadness than man. However, the gender differences should be investigated in more detail considering socio-cultural differences as well as preferences and personality traits (since emotions are highly subjective).
The correlation analyses that were conducted showed that the strongest correlation was between happiness and amusement, while other notable correlations were observed between happiness and neutral, as well as sadness and anger. Furthermore, when comparing the experimental results for HR and RR with participants' self-reported emotions, we found that participants were generally truthful in their emotional self-assessments. Taking into consideration that people often mask their feelings and don’t want to show and admit them (especially male), this is a positive fact.
However, the number of subjects used in the experiment, and facts that they have same cultural background and similar ages, is a limitation of this study. Our future research should include more diverse participants, as well as conducting experiments in real-world settings rather than in the laboratory.

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