Emotions and Activity Recognition. A computer vision approach for augmentation of psychosocial risk evaluation.

Computer vision assistance in psychosocial risk factor evaluation via emotions and activities monitoring.

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Abstract

Psychosocial risk evaluation has played a dominant role in ensuring the wellbeing and health of people. Nevertheless, mechanisms such as interviews and questionaries are susceptible to inaccurate or skewed results due to the lack of data that cannot be acquired during assessments. This work proposes an initial approach to identify activities and emotions that are implicitly queried by current evaluations and have the potential of being detected by cameras. By extracting features from video frames using computer vision, machine learning-oriented classifiers become feasible to conduct continuous and non-intrusive monitoring. Activities and emotions registering could provide additional data to support better-informed psychosocial risk evaluations.

1 Introduction

According to the World Health Organization, a risk factor is defined as any trait or exposure of an individual that could increase the probability of suffering any disease or injury[1]. Among different types of risk factors that can influence health, there are chemical[2]; biological[3]; environmental[4] and psycho-social. This last one, involves physical aspects of the environment, such as noise or temperature[5]; psychological aspects in people such as stress[6] and burnout caused by high workloads or persistent excess in working hours[7][8].

Throughout the last fifty years, several psycho-social assessment methods have been created by medical and psychology professionals, to allow quantitative and qualitative evaluation of psychosocial risk exposure. A psycho-social assessment is an evaluation of mental, physical, and emotional health[]. Usually, it takes the form of a series of questions and screening tools, covering many aspects of a person's life to get a picture of his or her mental state[]. With that information, professionals can draw recommendations about specific environmental issues or treatment plans[].

On the other hand, since the end of the eighties, artificial intelligence has been used for applications in (specify kind of industry) industry, aeronautics, autonomous driving. As it is evolving, it has allowed the manufacturing of many devices for producing and interpreting the text, recognize speech, and even generate entities such as eBay's virtual agents. Artificial intelligence sub-disciplines such as machine Learning provides algorithmic tools to analyze data, as well as to design, train, and deploy models into applications or processes. However, machine learning algorithms and other artificial intelligence approaches are still under research in other areas such as well-being and psycho-social evaluations.

The main goal of the present project is to identify a potential contribution of artificial intelligence to psycho-social risk assessment, by performing a state-of-the-art review of evaluation methods and current technological approaches to support them. This project will present implicit scenarios from questionnaires, where some artificial intelligence disciplines such as computer vision and machine learning, can be applied to obtain additional information for better informed assessments.

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The present work is composed of seven sections, including the previous introduction. In section 2, we present the Psycho-social Risk Assessment (PRIA) advantages and limitations, as well as technological approaches that support some aspects of PRIA. In section 3, we show the problem statement by describing the keywords review about the gap between artificial intelligence and PRIA. Also, it states the motivation of the present work. Section 4 is devoted to the description of questionary items that have the potential of being measured by extracting data captured with surveillance cameras. Section 5 list a set of articles oriented to recognize activities and emotions via single and multi-mode systems. Therefore, it will show techniques and methodologic references for the design and implementation of architectures based on artificial intelligence. Section 6 presents a brief review of motion-capture libraries that can be a potential component for feature extraction. In section 7, experimentation of selected libraries will be shown, using public video databases. Finally, we conclude the presented material in Section 8.

2 Related work

Within the context of psychosocial risk factors, some variants may be inherent individually or together in a work environment. It is essential to clarify that the environments can be external when working outdoors and internal when working indoors. The most common types of risks for both cases are: Physical risks (also known as workplace risk) refer to aspects of the environment where the work takes place. Among the most significant aspects are noise, lighting, or the temperature of the environment[9][10]. Chemical risks are highly related to industrial environments where any worker may have contact with dust, gases, or abrasive products[11][12]. Biological risks involve contact with living things such as fungi, bacteria, or viruses, particularly by the interaction with people who may have a disease, infections, animals, or plants that may be carriers of a harmful organism[13][14]. Mechanical risks may be associated with some aspects of the work environment. It is related to heavy machinery usage or the development of an activity in which any person exposes to the effects of vibration [15][16]. Environmental type risks involve scenes or work, where there is a high probability of floods, storms, or contamination[17][18]. Finally, psychosocial risks occur in the normal execution of daily activities. These are strongly related to the work conditions, people's interaction, and socio-demographic conditions. Among the most studied aspects, it is stress, monotony, and job fatigue due to excess hours worked[19][20]. As this last type of risk is the main focus of the present work, section 2.1 will present the evaluation methods.

2.1 Psychosocial Risk Assesment (PRIA)

Currently, some methods facilitate the evaluation of FRP developed from the integration of models and scales, which seek to qualify risk factors. Some works such as Charria, Sarsosa, and Arenas[21] suggest a taxonomy of mechanisms, taking into account the form in the information extracted and its scope. In this work, there are two large groups of questionnaires oriented to industrial hygiene and psychosocial factors. In the first group, evaluates aspects such as the work environment, the physical effects on workers, and details of hiring and remuneration. The assessments of these aspects use questionnaires that are carried out by an external agent to the organization, who seeks an objective evaluation of the situation. Some examples of this group are the Questionnaire for the Fifth European Survey on Working Conditions[] and the Quality of Life at Work Survey Questionnaire[]. In the second group, there are questionnaires oriented to psychosocial factors acquired through interviews or a self-report procedure. Interview questionnaires collect information related to job satisfaction, burnout, or bullying. On the other hand, self-report questionnaires extract information related to individual aspects of the person, such as the relationship between health and illness, aspects of daily life, and their social interactions. Some examples of this second group are the EAE Stress Assessment questionnaire[], the occupational burnout scale[], the Bocanument and Berján evaluation[], and the Demand-Control model[].

Concerning the groups of questionnaires mentioned, there are investigations which reveals that some conditions generate effects related to physical health such as musculoskeletal disorders[22] or the behavior of people such as sedentary lifestyle[23]. On the other hand, other studies show effects related to people's mood[24] with mental health such as stress[25] and psychological disorders such as anxiety[26] or depression [27][28]. Although the psychosocial risk is widely related to work, it is not exclusive to these environments. Researches such as that of Abdullah Alotaibi[29], Christian Hederich[30], and Malarvili[31] address the relationship between sleep quality and stress in academic settings. Within the research carried out in the academic context, There are studies of the prevalence and correlation of depression, anxiety, and suicidal tendencies such as Eisenberg's [32]. Other approaches, such as Danuta's[33], seek to identify the relationship of demographic aspects such as the students' place of residence as intervening variables in their state of health. It is also essential to show that in these scenarios, students are not the only actors prone to risk factors. Works such as that of Briones[34] and Pedditzi[8] show a presence of stress and job exhaustion among teachers.

During the last years, many mechanisms have been developed in the form of questionnaires. These mechanisms have favored the improvement of interactions at work, the conditions of their organization, as well as the worker's abilities, needs, culture, and the personal situation outside of work, all of which, through perceptions and experiences, can influence health and performance and job satisfaction. However, the influence not only comes from the work environment[35] but also from the extra-work environment[36]. In this last aspect, psychosocial assessment methods seek to evaluate aspects such as time away from work activities, family relationships, the economy of the family group, commuting to work, among others. Some derivations or generalizations of the exposed evaluation methods have contributed to the improvement of well-being and good practices in the academic context, promoted or the development of a mechanism for the promise of stress management evidenced in Collen's work[37]. Other contributions have allowed approaches to identify the behaviors associated with happiness, well-being, and the stress perceived in university students[6].

The diversity of scenarios where evaluation methods play an essential role, in turn, entails a series of challenges of experimental validation, in which the aim is to establish correlation values of the aspects evaluated with the real scenario[38] or its factor structure[39]. Although there is high statistical support for several of the items raised within the questionnaires, it can be evidenced that the mechanisms and procedures are susceptible to variability and subjectivity in the measures[40][41]. Experimentations have the caveat that samples are related to a particular segment of the population. Also, some items in questionnaires assess relevant aspects of daily activities that are not observed by specialists in occupational safety and health that a. This last issue reduces the amount of evidence drastically to establish reference values[42].

2.2 Technologic approaches supporting PRIA

Some references have addressed some aspects related to the mental health of people in the workplace[43][44]. Some of these works have resulted in technological solutions for monitoring some specific aspects of psychosocial risk, ranging from the implementation of load controls on the extremities and other parts of the body based on sensors[45]. Other approaches focus on reducing accidents by detecting elements or obstacles that can generate an accident. Among these approaches, works that identify liquid spills or tools oriented to the environment can be noted[46]. On the other hand, to identify aspects related to the mental condition in people, approaches have been made through the use of artificial intelligence and computer vision. In some of these approaches, electroencephalogram images analysis is used to assess stress in people[47]. Other works such as those by Zack Zhu[48] or Raffaele Gravina[49], suggest alternative perspectives, based on the recognition of mood, from the capture of signals with portable electronic devices.

Other approaches address the capture and integration with other data sources, resulting in multimodal architectures[50][51], in which the processing of video images, text, signals, among others, is used to support the diagnosis of emotions[52]. Works such as that of Le Yang[53] and Poria Soujana[54] suggest the fusion of paralinguistic analysis, capturing interview responses, features of the face widely addressed[55][56], and eye movement[57]. Some approaches are oriented to detect the effects of psychosocial risk factors, such as stress by performance demands[58] and depression.

As technologies advance, there is plenny of bennefits the research fields could aquire by adopting electronic devices to improve people's health in labor and academic environments. In these approaches, a significant contribution is evident in the analysis of voice patterns, and some aspects that are close related to psichosocial risk are addressed through research and implementation of sensors supported by some machine learning techniques. Nevertheless, even these advances represent significant potential for the manufacturing industry, construction, among others[59], there are studies such as that of Shall Mark's[60], where there is evidence of limitations for its adoption. Amont the most significat implications there is cost affairs, the interruption of work activities, the intrusive nature represented in the discomfort with the devices and the privacy of people.

3 Problem statement

As mentioned in section **2**, there are benefits and limitations in specific psychosocial risk assessment methods, and in the technological approaches using sensors that support some assessments. The limitations related to the interruption of people's daily activities, in turn, entail an interpretation of cost and hindering of work in academic and labor fields. Furthermore, the intrusiveness associated with the use of electronic equipment for testing can provide data bias for testing. The latter corresponds to those cases in which the predisposition of people who are sometimes to electroencephalography, electromyography, or sensors aimed at measuring any skeletal muscle disorder is possible to the predisposition of the people evaluated. In addition to this, qualified personnel who are in charge of promoting the well-being and health of people do not have a detailed record of the risk factors that a particular person could be during the day.

According to these scenarios, a technological challenge can be seen, associated with data extraction, the cost attributed to the use of electronic equipment, and the bias implicit in them, corresponding to a technological challenge. In the works related in the section **2.2** and whose intervention was less intrusive, the focus was on facial recognition requiring close-up shots of the face. Additionally, although the evaluation was supported by measurement scales used in conventional evaluation methods, it can be seen that the extraction of information is strongly linked to the duration of the experimentation. Therefore, they lack continuous monitoring and can be recorded automatically. Another aspect of the problem that should be mentioned is the low number of works in which there is a conjunction between terms related to artificial intelligence and psychosocial risk assessment.

Table 1: Keywords related to psycho-social affairs.

Term.ID	Term	Search.Result	Total.Found
1	stress	302437	370
2	depression	101	186
3	anxiety	54469	38
4	sleep disorder	12516	19
5	eating disorder	11787	9
6	alcohol consumption	8370	4
7	burnout	7909	9
8	environmental risk	2497	12
9	eating habit	999	1
10	boredom	625	3
11	musculoskeletal disorder	463	1
12	tobbacco cunsumption	404	0
13	drowsiness	324	24
14	biological risk	250	3
15	chemical risk	214	4
16	work fatigue	24	0
17	psychosocial	24057	10
18	psychosocial risk	672	2
19	psychosocial assessment	218	0
20	psychosocial evaluation	77	0
21	psychosocial factor	13	3
22	psychosocial risk factor	9	2

In the review carried out in the Web of Science browser, a date filter was applied to get articles published between 2000 and 2019. The quantities of search coincidences were extracted by using terms and keywords that are related to psychosocial risk factors. Additionally, the search for the above terms was executed by adding conjunction operators to terms and keywords related to artificial intelligence and machine learning. With the mentioned procedure, we expected to identify technological approaches where classification or regression tasks were defined to support psychosocial assessment.**Table 1**, shows the summary of amounts of work related to relevant topics in the context of them and their conjunction with terms related to AI. This evidence gives us an initial overview of technological contributions at the research level on issues that surrounds psychosocial risk factors.

During the searching procedure, we add specific terms. A low number of works related to assessment can be seen in conjunction with terms related to artificial intelligence. A keywords selection, coding, and mapping were performed before the executions of queries. The selected terms were *artificial intelligence*, *computer vision*, *machine learning*, *neural network*, *deep learning*, *random forest*, *SVM*, *decision tree*, *linear regression*, *logistic regression*, *naive bayes*, *markov chain*, *fuzzy logic*, and *ensemble models*. Each term was coded in ascending numbering from 1 to 14, using the letter "T" as a prefix (see **Table 2**). Although there was evidences of works that address topics that surround our topic of interest, Their scope was oriented to specific aspects with little or no reference in its use within an interstate psycho-social assessment.

Table 2: Number of articles found with terms conjunction.

Term.ID	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	Total.Found
1	7	4	77	198	12	8	11	4	4	5	0	5	14	21	370
2	5	0	75	63	7	3	7	6	3	10	0	1	2	4	186
3	5	1	17	6	0	0	3	1	0	5	0	0	0	0	38
4	0	1	9	8	1	0	0	0	0	0	0	0	0	0	19
5	0	0	2	2	0	0	1	2	0	2	0	0	0	0	9
6	0	0	1	0	1	0	0	1	0	1	0	0	0	0	4
7	1	0	0	5	0	0	0	0	1	1	1	0	0	0	9
8	0	0	2	3	2	1	1	0	0	1	0	0	2	0	12
9	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
10	0	0	2	1	0	0	0	0	0	0	0	0	0	0	3
11	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	2	13	3	1	3	0	0	1	0	0	1	0	24
14	0	0	1	1	0	0	0	1	0	0	0	0	0	0	3
15	0	0	1	1	1	0	0	1	0	0	0	0	0	0	4
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	1	0	2	2	0	2	0	1	0	2	0	0	0	0	10
18	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	1	0	0	2	0	0	0	0	0	0	0	0	0	0	3
22	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2

Given the prior statement, it is taking into account the lack of direct observation and the lack of automatic and intelligent follow-up and the intrusive limitations. The following question was issued as a motivation for this project ***¿How to calculate indicators based on the detection of emotions and activities for monitoring and supporting the evaluation of psycho-social risk factors through automatic non-intrusive monitoring, using artificial intelligence techniques and computer vision?***.

Based on the research question, the present work will focus on the extraction of activities and emotions that are related to quantifiable aspects within the psycho-social assessment. There are activities and emotions, implicit in the validation questionnaires. Data corresponding to daily activities in work and academic contexts could be a valuable source of information that can complement evaluations by providing metrics and indicators, or complementing the information that is currently acquired through the support systems previously seen. In the next section, the activities and emotions will be addressed and how the information inherent in them could constitute a contribution to the gap of artificial intelligence and its implication in the psycho-social assessment.

4 Implicit Activities and emotions in PRIF-EM

From the review of the works related to the measurement of physical and psychological aspects in work and academic settings, a potential opportunity is found, for the use of artificial intelligence as a support component in the psycho-social assessment. The questionnaires currently used for quantitative and qualitative assessment implicitly contain activities, emotions, moods, and situations that the person providing the test answers may experience. In this project, we will limit ourselves to extracting the functional activities that are to support the physical, social, and psychological well-being of a person and allows that person to function in society []. Additionally, they will extract the Instrumental Activity of Daily Living (IADL), which is defined as those activities that allow an individual to live independently in a community. according[]. On the other hand, the emotions within the items of the questionnaires will be extracted, taking as reference the study of emotions by Paul Ekman [].

4.1 Methodology of extraction

analysis of the mechanisms used in the publications. There are different motivations for the use of the mechanisms. It was found validation in specific population segments [], methodological quantification support for experimental validation [], and adaptation of some of its items in a defined context[]. The motivation, in this case, will be to identify the questionnaires mentioned in articles that establish their focus on aspects related to psychosocial risks in the work and academic contexts. After this, there was an extraction of application domains that group different items or questions made to the evaluated people. Each item was decomposed in order to identify implicit the activities, emotions. Also, activities frequencies considerations were extracted as a complement in activity characterization. This whole process was conducted by taking Melzer's work [61] as references, which deals with the recognition of emotions from body movements. This approach not only represents a methodological reference but also fits with the scope of the work for the identification and characterization of scenarios in which actions carried out by people are involved and can be captured by video cameras.

Within the selected references, we could establish a separation between our two contexts of interest. Although the workplace context contains a wide variety of contributions evidenced in new assessment mechanisms development and possible improvements could be identified over other publications[], there is a considerable number of situations that have brought the attention of experts in medicine and psychology in the academic environment[]. The aspects evaluated in the academic field do not differ entirely from those studied in the workplace. There are few variations in the place where they take place and the role that people perform in these contexts. For instance, during the execution of the role of the teaching, psychosocial risk factors related to work could be present. Table 3 shows the mechanisms extracted from the selected articles.

Table 3: Articles oriented to academic environments

Author	**Assesement mechanism or scale**
Alotaibi-2020[62]	Pittsburgh Sleep Quality Index (PSQI) Kessler Psychological Distress Scale (K10)
Calderon-2019[63]	Ryff Scales of Psychological Well-being
Thomas-2019[64]	Perceived Scale Test (PSS) The Three-Factor Eating Questionnaire
Ben Ami-2018[65]	Survey of personal and social development
Moy-2014[66]	Smoking-alcohol consumption and physical activities (IPAQ) The job content questionnaire (JCQ) Depression-anxiety and stress scale (DASS)
Conley-2013[67]	Psychometric analysis and refinement of the Connor Davidson Resilience Scale (CD-RISC) The Dysfunctional Attitude Scale

Moreover, the selection of articles related to the work environment is made (see table 4). An analysis is performed to each related evaluation mechanism in order to extract the components of the questionnaires. Also, the analysis will permit to identify scales that support qualification.

Table 4: Articles oriented to Work environments

Author	**Environment**
Golonka-2019[68]	Maslach Burnout Inventory General Survey (MBI-GS)-NEO Five-Factor Inventory-Beck's Depression Inventory

Author	Environment
Maeda-2016[69]	International Neuropsychiatric Interview
Najder-2016[70]	The Psychosocial Risk Scale (PRS)
Luca-2014[71]	Beck Depression Inventory (BDI)
Charria-2012[72]	Cuestionario Encuesta de Calidad de Vida en el trabajo Cuestionario para la Evaluación del Estrés-Batería para la evaluación de factores de riesgo psicosocial Utrecht Work Engagement Scale Cuestionario Psicosocial de Copenhague (CoPsoQ)
Blanch-2010[73]	El cuestionario FPSICO El Cuestionario de Bienestar Laboral General
Rodríguez-2009[74]	Hipótesis de la tensión del trabajo Karasek
Boyes-2002[75]	Hospital Anxiety and Depression Scale-Short-form Supportive Care Needs Survey
Mausner-2000[76]	Quality of Employment Surveys

The analysis process includes the understanding of the scope covered by the mechanism. One of the primary references in this work is the battery of psychosocial risk factor evaluation [] which takes up elements from the Karasek, Theorell (1990) and Jonhson models of demand-control-social support, from the imbalance model effort-reward of Siegrist (1996 and 2008) and of the dynamic model of the psychosocial risk factors of Villalobos (2005). The disposition of this evaluation mechanism suggests a construct of intra-labor conditions, which is made up of domains and dimensions. The domain of work demands includes the dimensions of quantitative demands, mental load, emotional, workday, environmental and physical effort. The control domain quantifies the dimensions related to autonomy overwork, clarity of the role, opportunities for development, the use of skills and abilities. The domain of leadership and control includes dimensions of characteristics of social relations at work, performance feedback, and the relationship with subordinates. Finally, the reward domain that includes the dimensions of recognition, compensation, and rewards derived from belonging to the organization, and the work is done.

On the other hand, the battery evaluates extra-labor conditions, which include aspects of the worker's family, social, and economic environment. In turn, they cover the conditions of the place of residence, which can influence the health and well-being of the individual. Time away from work, family relationships, communication, and interpersonal relationships, the financial situation of the family group, among others. The individual's conditions refer to a series of characteristics characteristic of each worker or socio-demographic characteristics such as sex, age, marital status, educational level, occupation (profession or trade), city or place of residence, scale socio-economic (socio-economic stratum), the type of dwelling and the number of dependents. These socio-demographic characteristics can modulate the perception and effect of intra-occupational and extra-occupational risk factors. They could be used as a complement to the characteristics used in classification or regression models to contribute to the support metrics for psychosocial assessment. Although the interest of this work focuses on the features related to activities and emotions, the mentioned scenarios will be extracted in the ongoing review of the different questionnaires.

4.2 Activities and emotions inventory

In addition to identifying the scope, we proceed to identify the items or questions that may implicitly contain any activity or emotion experienced by the person evaluated. Table **??** describes the evaluation mechanisms and a total of seventy-nine potential items. For each item, we identify what type of emotion or activity it could belong to as well as the related context. As can be seen, the Perceived Scale Test (PSS) questionnaire contains questions related to emotions as well as the frequency in which the evaluated person experiences these situations. These types of questions suggest a type of periodic control that could be used for the generation of a monthly indicator.

Meanwhile, the Depression, anxiety, and stress scale (DASS21) manifest some activities that are noticeable such as body tremors or breathing difficulties. This representation of physical symptoms may be related to moods or medical conditions that are of interest for monitoring. Other activities that can be captured

Table 5: Items from questioneirs

ID	ITEM	TYPE	AFFAIR
Perceived Scale Test (PSS)			
1	In the last month, how often have you been upset because of something that happened unexpectedly?	Emotion	Anger
2	In the last month, how often have you felt nervous and "stressed"?	Emotion	Fear
3	In the last month, how often have you been able to control irritations in your life?	Emotion	Anger
4	In the last month, how often have you been angered because of things that were outside of your control?	Emotion	Anger
Depression, anxiety and stress scale (DASS21)			
5	I experienced breathing difficulty (e.g. excessively rapid breathing, breathlessness in the absence of physical exertion).	Activity	Physical symptoms
6	I experienced trembling (e.g. in the hands)	Activity	Physical symptoms
7	I found myself getting agitated.	Activity	Physical symptoms
8	I found it difficult to relax.	Activity	Physical symptoms
9	I felt down-hearted and blue.	Emotion	Sadness
10	I was unable to become enthusiastic about anything.	Emotion	Sadness, disgust
11	I felt scared without any good reason	Emotion	Fear
The Three-Factor Eating Questionnaire			
12	When I feel anxious, I find myself eating.	Activity	Eat - anxiety
13	Sometimes when I start eating, I just can't seem to stop	Activity	Eat
14	When I feel blue, I often overeat.	Activity	Eat - sadness
15	How often do you feel hungry?	Activity	Physical symptoms
The Kessler Psychological Distress Scale (K10)			
16	During the last 30 days, about how often did you feel tired out for no good reason?	Activity	Physical symptoms - drowsiness
17	During the last 30 days, about how often did you feel nervous?	Emotion	Fear - anxiety
18	During the last 30 days, about how often did you feel so nervous that nothing could calm you Down?	Emotion	Fear - anxiety or stress
19	During the last 30 days, about how often did you feel so restless you could not sit still?	Activity	Restless - drowsiness
20	During the last 30 days, about how often did you feel depressed?	Emotion	Sadness - depression
21	During the last 30 days, about how often did you feel so sad that nothing could cheer you up?	Emotion	Sadness, disgust
The Pittsburgh Sleep Quality Index (PSQI)			
22	During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?	Activity	Drowsiness
Survey of personal a social development			
23	In the past month, how often did you engage in aerobic exercise?	Activity	Aerobic Excercise
24	In the past month, what is the average number of days per week that you engaged in aerobic exercise?	Activity	Aerobic Excercise
25	In the past week, how many days did you engage in aerobic exercise?	Activity	Aerobic Excercise
26	How would you describe your smoking during your last year in high school?	Activity	Smoking habits
27	During the past month, how many cigarettes have you smoked on an average day?	Activity	Smoking habits
28	In the past month, were there times when you tried to cut back or quit smoking?	Activity	Smoking habits
29	In the past month, have you felt sad almost all the time?	Emotion	Sadness
30	In the past month, about how many times did you actually get drunk?	Activity	Alcoholism
31	Do you usually snack instead of eating regular meals?	Activity	Eating habits
Maslach Burnout Inventory			
32	Working directly with students causes me stress.	Emotion	Disgust, Anger - stress
33	I feel motivated after working in contact with students.	Emotion	Happiness
Occupational burnout scale			
34	I have a hard time being courteous to the users of my work.	Emotion	Disgust, Anger - stress
35	A long time ago I stopped doing my job with passion.	Emotion	Disgust, Anger - stress
36	The situations that I face in my work do not cause any tension.	Emotion	Neutral
37	In my work they all seem strange to me, so I am not interested in interacting with them.	Activity	Social interaction
38	Although a user of my work is rude to me, I treat him well.	Activity	Social interaction
39	You feel depressed (very sad).	Emotion	Sadness
40	You have headaches.	Activity	Physical symptoms
41	Your arm and leg joints hurt.	Activity	Physical symptoms
42	You have pain in the abdomen.	Activity	Physical symptoms
43	Your back and neck hurts	Activity	Physical symptoms
44	Your chest hurts.	Activity	Physical symptoms
Stress Assessment Questionnaire			
45	Neck and back pain or muscle tension.	Activity	Physical symptoms
46	Respiratory problems.	Activity	Physical symptoms
47	Headache.	Activity	Physical symptoms
48	Sleep disorders such as drowsiness during the day or sleeplessness at night.	Activity	Drowsiness
49	Difficulty staying still or difficulty starting activities.	Activity	Drowsiness
50	Difficulty in relationships with other people.	Activity	Social interaction
51	Feeling of isolation and disinterest.	Emotion	Disgust, fear
52	Tiredness, tedium or reluctance.	Activity	Drowsiness, burnout
53	Feeling of anguish, worry, or sadness.	Emotion	Sadness, fear
54	Consumption of alcoholic beverages or coffee or cigarette.	Activity	Alcohol, coffee, tobacco consumption
Cuestionario psicosocial de Copenhague			
55	Do you have to work very fast?	Activity	Quantitative psychological demands
56	Do you have to stay after the established departure time?	Activity	Quantitative psychological demands
57	Does your job require you to hide your emotions?	Emotion	Requirements to hide emotions
58	Is your job isolated from that of your colleagues?	Activity	Possibilities of social relationship
59	Can you talk to your colleagues while you are working?	Activity	Possibilities of social relationship
Inventario de depresión de Beck			
60	I feel sad much of the time.	Emotion	Sadness
61	I am sad all the time.	Emotion	Sadness
62	I am so sad or unhappy that I can't stand it.	Emotion	Sadness
63	I don't cry anymore than I used to.	Activity	Crying
64	I cry more than I used to.	Activity	Crying
65	I cry over every little thing.	Activity	Crying
66	I feel more restless or wound up than usual	Activity	Agitation
67	I am so restless or agitated, it's hard to stay still	Activity	Agitation
68	I am so restless or agitated that I have to keep moving or doing something	Activity	Agitation
69	I am not more irritable than usual	Emotion	Anger/Irritability
70	I am more irritable than usual	Emotion	Anger/Irritability
71	I am much more irritable than usual	Emotion	Anger/Irritability
72	I am irritable all the time	Emotion	Anger/Irritability
73	I have not experienced any change in my appetite	Activity	Changes in Appetite
74	My appetite is somewhat less than usual	Activity	Changes in Appetite
75	My appetite is somewhat greater than usual	Activity	Changes in Appetite
76	My appetite is much less than before	Activity	Changes in Appetite
77	My appetite is much greater than usual	Activity	Changes in Appetite
78	I have no appetite at all	Activity	Changes in Appetite
79	I crave food all the time	Activity	Changes in Appetite

are those mentioned in The Three-Factor Eating Questionnaire. In this mechanism, activities are not only related to eating habits but also suggests a condition of anxiety in cases of a high frequency of food intake.

Like the PSS test, the Kessler Psychological Distress Scale (K10) includes items that inquire about emotional states over a while, being this a little more diverse in situations that suggest emotions and including drowsiness, which is addressed by The Pittsburgh Sleep Quality Index (PSQI). The Survey of personal and social development is an assessment-oriented questionnaire in academic settings. It mainly concerns the relevant aspects of the daily life of students and their habits. Also, this mechanism relates activities such as aerobic exercise or cigarette or alcohol consumption. For this academic context, an adaptation of the Maslach Burnout Inventory was reviewed as well, as it focuses on the emotions of the teaching staff during their working day as their motivation.

Other types of physical or somatic representations are dealt with on the Occupational burnout scale. In this mechanism, activities are around the actions that a person can have when experiencing physical pain or discomfort. In addition to these activities, actions related to stress can be identified. The Stress Assessment Questionnaire lists sleep disorders, difficulty staying still, and consumption of alcoholic beverages or smoking. As we can see, the Copenhagen psycho-social questionnaire contains a set of activities that include interaction and social isolation. Finally, other mechanisms relate situations and activities to anxiety and depression, such as the Beck Anxiety Inventory [77] and the Beck Depression Inventory.

5 Artificial intelligence in activites and emotion recognition

As could be evidenced in the previous section, some activities and emotions can be captured by cameras and whose analysis can constitute a significant source of data in the form of metrics and indicators to facilitate psychosocial evaluation. However, data extraction and its interpretation constitute a technological challenge that has been widely addressed by disciplines such as computer vision [78], wich main tasks focus on the Acquisition, processing, analysis, and understanding real-world images. This discipline has brought new opportunities to take advantage of image data using machine learning algorithms and, in some cases, supporting itself in high-performance computing systems[].

Unlike object recognition using static images, activity recognition involves analyzing and processing frames at a specific time interval. When trying to identify an action such as lifting a leg to take a step, it constitutes a series of images that allow identifying this action. By repeating this action for a prolonged period, the development of the activity "walking" would be obtained. Within the literature, we can found various definitions of the term activity. Some of them correspond to the physical point of view, and others correspond to the psychological point of view. For this work, an activity will be defined as a repeated and recurring composition of actions in a given period.

5.1 Actions and Activities Recognition

Among the recent approaches, we can find methods that guide the classification of actions once they have been carried out. According to this, there are works were key poses are distinguished for the identification of an action. In this case, deep neural networks are used to extract the features of the images, and then they are interpreted using an Adaboost classifier, to finally classify the actions using their proposed weighted local naive Bayes nearest neighbor classifier. Works such as Sahoo's [79] employ methods of detecting points of interest by proposing a local maximum of difference. In the article published by Somandundaram [80], it is proposed a new global Spatio-temporal self-similarity measure to score saliency using the ideas of dictionary learning and sparse coding. On the other hand, there are works whose objective is to carry out the early detection of activities or recognizing the category of an ongoing human action from a video stream. From this perspective, we can find works such as Wang's [81], whose method works on a recurrent neural network that computes the probability of a frame to be the starting point by comparing the dynamics of the actions before and after the frame stand out.

Within this project, the use of activity detection with techniques and algorithms similar to those used in the mentioned articles becomes relevant. However, the use of abnormality detection techniques is highly engaging as we can detect significant deviation from an individual's usual behavioral routine. Works such as [82], highlights the identification of abnormality in activities of daily living using ensemble models. The detection of anomalies employing video images have been widely addressed during the last 20 years, and they address tasks such as the detection of risk situations such as outbreaks, detection of abandoned objects or objects located in particular areas, detection of falls of people, among others [83] [84]. Several of these detection objectives are relevant to the detection of activities related to psychosocial risk factors, to the extent that the identification of routines can be recorded and identified, in order to determine a change in these routines later. We can evidence an example of its application in works such as that of Kim [85], in which fuzzy clustering is used to identify patterns in smoking cessation. This particular example could be used to provide information to questionnaires, such as the survey of personal and social development mentioned in the previous section.

Another relevant topic is gait analysis. Among the authors who have contributed significantly is Dr. Jacquelin Perry [86]. Gait analysis consists of detecting and recording human movements taking into account characteristics such as step length, cadence, speed, dynamic base, line of progression, foot angle, among others. This area of research has contributed to the construction of models for the analysis of brain problems from displacement [87]. Other works such as Kitade's [88] use gait analysis to study the expressive, appellative, or communicative meaning of body movements in the diagnosis of musculoskeletal disorders and which are highly relevant in the evaluation of psychosocial risk.

In addition to the exposed approaches, we can find jobs with application results used mostly in the automotive industry. This scenario corresponds to the detection of drowsiness in drivers for accident prevention. Some approximations of this type are the usage of an enhanced image processing technique inspired by the human visual system mentioned in Hedyeh's work [89], or the usage mixed-effect ordered logit model considering a time- cumulative effect proposed by Zhang [90].

5.2 Emotion Recognition

In the same way, we have mentioned some techniques to detect activities; we intend to identify emotions evaluated with psycho-social questionnaires and which can be experienced at work or a university as an academic environment. The emotions recognition, have become a widely explored research area with contributions such as the Hourglass of Emotions[91] as this work proposes a biologically-inspired and psychologically-motivated categorization for emotions. Also, some approaches have shown challenges alternatives to infer specific medical conditions by detecting emotional state changes from facial cues [92][93]. Nevertheless, most of these approaches as its seen in works such as Bevilacqua's [94] or Jain's [95] requires a face close up to capture those images that will be processed later. As emotions can take place in several situations, to gather emotional content expressed by the body becomes an alternative that we intend to explore.

There is some research aimed at automating emotion recognition. However, this type of approach entails a challenge that constitutes the representation of body gestures. Works such as that of Piana [96], define a series of characteristics called gesture primitives. The association of movements is made by relating the emotions Anger, fear, happiness, disgust, sadness, and surprise that will be interpreted by in an architecture that extracts characteristics from low to a high level using mechanisms based on sparse dictionary learning, which can finally be classified by an SVM. Another similar work is that of Ferdous Ahmed [97], who uses previously conceived concepts such as Gait Analysis. In this case, the association of body movements with basic emotions is also performed by identifying emotions in poses and actions such as sitting or walking. Another notable difference is the conformation of a group of characteristics appropriate for the classification that is carried out employing assembly techniques and model stacking.

A technique frequently used in the identification of emotions is the extraction of characteristics through Deep Learning, using variation in the convolutions that develop in its topology. We previously mentioned emotion recognition using facial cues and several papers and reviews related to it[98][99]. Nevertheless, works such as Santhoshkumar's [100] not only address concepts of kinesics but also employ the extraction of saliency information at multiple scales and the Block Average Intensity Value that reflects changes in the image after a systematic segmentation of the photograms.

Within the review of the mentioned articles, it was possible to identify techniques for the extraction of characteristics and their selection using genetic algorithms. Likewise, classification mechanisms and public databases used for experimental validation were identified. One of the most significant contributions is the use of hardware components such as Microsoft Kinect and libraries for the extraction of characteristics of body gestures from the identification of limbs and joint points. In the next section, some libraries will be explored, and experimentation will be carried out in order to identify their features and use potential.

6 Feature extraction via computer vision

One of the critical aspects for the detection of emotions and activities, it is the extraction of the most to determine patterns that allow for the distinction between the labels arranged for a classification task. The extraction of characteristics starts from an initial set of measured data. It creates derived values (known as features) intended to be informative and not redundant, facilitating the steps of later learning and generalization. One of the alternatives that have been most frequently addressed not only at the research level but also established as a commercial product is the use of sensors attached to the body. Within this type of alternative, there are brands such as xsense[], Nansese[], or Optitrack[] that offer specialized suits for capturing movement, providing information on the spatial location of the extremities. However, for the terms of the present work in which the use of said elements is not feasible, another alternative becomes relevant by capturing and processing images.

Under the mentioned scenario, there are alternatives such as cameras that include motion detection that suits mainly for surveillance purposes. Other hardware artifacts such as Microsoft Kinect allows the extraction of the articulation points and their positioning. However, the inconvenience of its implementation at a practical level persists, since, in the described context of the psycho-social evaluation, there would be available camera systems such as CCTV or, if applicable, the use of cameras included in mobile devices or desktops. This kind of restriction leads us to the use of software tools that can use the captured images and extract the necessary data to carry out analytical tasks on data, and consequently to identify potentials in the classification of emotions and activities. Then, we will list a set of software libraries capable of the extraction motion features.

6.1 Motion capture libraries

Existen soluciones de software y librerias (tanto libres como comerciales) que comprenden el uso de técnicas de machine learning como deep learning, para la extracción de caracteristicas del cuerpo y tiene como objetivo mapear todos los píxeles humanos de una imagen RGB a la superficie 3D del cuerpo humano. Un ejemplo de esta aproximación es el proyecto DensePose-RCNN[101] el cual se implementa en el marco de Detectron[102] y funciona con Caffe2 que ahora es parte del framework de machine learning, PyTorch[103].Otras aproximaciones se centran en el la triangulación de las articulaciones y con ello reconstruir una representación de la distrubición de las extremidades partiendo del procesamiento de imágenes en 2dimensiones. Bajo este tipo se

openpose

wrnch

DensePOse Dense human pose estimation

Figure ??.

sensores empleados para la validación

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6.2 Expermentation and benchmarking

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Activities * Eating and smoking habits * Aggresive conduct * Recurrent extensions of work shift or activities

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7 Results

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7.1 Activities results analysis

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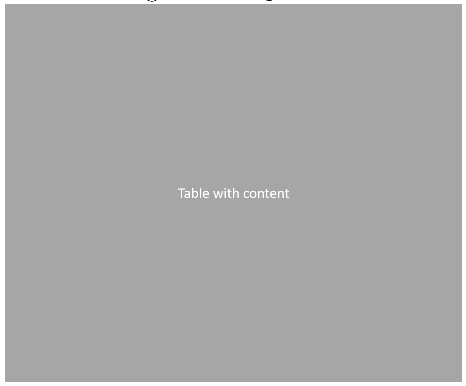
Figure 1: A picture



7.2 Emotions results analysis

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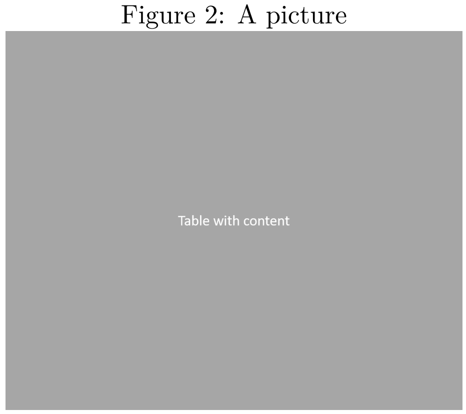

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8 Conclusions

Paragraph of the contribution summary of this article. Durante el desarrollo del presente trabajo, se han presentado diferentes aspectos relevantes y mecanismos para la evaluación de factores de riesgo psico-social. Estos mecanismos han sido abordados desde la perspecteciva de desarrollo convencional y bajo la visión de los aportes de la inteligencia artificial. Se han relacionado ventajas, desventajas y algunos de los retos presentes para la implementación tecnológica. Adicionalmente, se presenta una relacion de las actividades y emociones presentes en los cuestionarios de evaluación que pueden ser potenciales para su detección medianta cámaras de vido. Frente a esto, se manifiestan algunas alternativas disponibles para la detección de la cinésica en personas y cómo puede ser empleado como insumo para la identificación de actividades y emociones para evaluación psicosocial. Esta exploración y análisis permitirán la concepción de una propuesta de arquitectura de software para la asistencia en la evaluación de factores de riesgo psicosocial.

El aporte de inteligencia artificial, especificamente desde las technical de machine learning empleadas en la detección de patrones en imágenes. La detección de emociones y actividades tienen un gran pontencial para cooperar en la inferencia y detección de aspectos psicologícos que pueden no ser perceptibles al momento de evaluar factores de riesgo psicosocial. Sin embargo, existen retos asociados a la preparación y concepción de una herramienta de automatización temprana que permita la prevención de situaciones o estados de ánimo que puedan perjudicar a largo plazo a trabajadores o estudiandos. Por el momento, se puede notar la relevancia del trabajo multidisciplinar, contanto con el trabajo de profesionales correspondientes y que estos cuenten con una herramienta que les permita ampliar el conocimiento a partir del uso de la observación continua, asistida por la inteligencia artificial.

This paragrapsh will mention Implementation challenges. Entre los aspectos técnicos considerados como retos para la implementación de un sistema oclusion computo por cntidad de personas large variety of appearances images comming for several viewpoint Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed eiusmod tempor incidunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodi consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

this paragraph will mention Ethical Implications Un aspecto relevante para el desarrollo del presente trabjo son los de indole ético. A pesar de que la observación continua en ambientes experimentales es controlada mediante el concentimiento informado, en la practica, puede tener implicaciones que sobrepasen la privacidad de las personas. Este trabajo no incluye dentro de su alcance la exploración de los aspectos éticos y morales de la intervención de sistemas inteligentes y en su lugar se enfoca en los aspectos técnicos de la implementación y asistencia en la medición. Sin embargo, en trabajos futuros se debe contemplar la revisión de los trabajos recientes con el fin direccionar de forma apropiada los componentes de seguridad de la información relevantes para una propuesta de uso práctico.

trabajo actual + trabajo futuro. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed eiusmod tempor incidunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodi consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

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