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Systematic literature review of mental stress recognition using wearable sensor data fusion

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Abstract. Mental stress is a widespread issue in modern society, significantly impacting individuals' well-being and productivity across various demographic groups. Detecting and managing mental stress is crucial to addressing its adverse effects on physical and psychological health. Traditional methods rely on subjective assessments, which may lack accuracy and scalability. This paper presents a systematic review exploring the use of methods that combine information (Fusion Techniques) from various wearable sensors to mental stress recognition by using machine learning algorithms. The focus was on identifying trends in classifiers, data fusion techniques, sensors, and evaluation metrics. The findings highlight Support Vector Machine (SVM) as the most effective classifier, followed by Random Forest (RF) and K-nearest Neighbors (KNN). ECG (Electrocardiogram) and EEG (Electroencephalogram) emerged as the most used sensors due to their ability to monitor cardiovascular and brain activity. Metrics such as accuracy, precision, and F1 score were predominant in evaluating model performance. The review reveals a strong preference for aggregating features extracted from diverse raw data sources which enhances robustness of mental stress detection by using machine learning algorithms. While existing studies demonstrate significant advancements, the findings indicate opportunities for further improvement in hybrid fusion techniques and real-world applications.
Keywords: mental stress, data fusion, artificial intelligence, machine learning, wearable sensors.

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1 Introduction

Mental stress is a constant in modern society, affecting individuals of all ages, genders and socioeconomic levels [1]. The World Health Organization (WHO) defines it as “a state of worry or mental tension generated by a difficult situation” [2]. Stress can arise from external factors such as task overload or health conditions and can be triggered by personal problems or environmental situations such as traffic and noise [3, 11, 12]. Stress is classified into three types according to its duration: chronic stress, acute stress, and acute episodic stress [2]. Chronic stress, resulting from prolonged exposure, can lead to various psychopathologies [2, 4]. Acute stress affects episodic memory, while acute episodic stress is characterized by intense episodes that can resemble life-or-death situations [2, 5, 6]. The COVID-19 pandemic has significantly increased anxiety and depression due to social isolation and fear of contagion, according to the WHO [2]. Detecting and understanding mental stress is crucial for individual and social well-being [11, 12]. Physical symptoms such as fatigue and anxiety are common but often overlooked [7]. Stress can affect academic and work performance [2]. Clinicians use various techniques to detect it, although these may not be completely effective due to individual differences in perception [8, 9, 11].

Machine learning, data fusion [16], and wearable sensors are tools to address this problem. Wearable sensors, such as smart watches and activity bracelets, allow continuous monitoring of physiological variables [32, 33, 35]. Artificial Intelligence (AI) and machine learning in particular, has transformed many fields, offering automation, reduction of human errors, and rapid information processing [13, 14, 15]. Data fusion, a term used to refer to the combination of information from multiple sources [16, 17], using AI techniques can improve the accuracy and generalization of machine learning models [19]. It is important in mental stress recognition because it integrates of multiple physiological signals such as heart rate variability (HRV), electroencephalogram (EEG), and skin conductance. Each signal captures different aspects of the stress response and their combination improves the performance of machine learning models. Previous secondary studies have explored related topics [20, 35]. These contributions underline the potential of machine learning and wearable technology in stress detection, focusing on sensor-based approaches. Sadruddin et al, conducted a secondary study highlighting the use of supervised and unsupervised machine learning algorithms, as well as deep learning techniques, in stress detection in domains such as healthcare, sports, workplace, and education [77]. Their study underscores the importance of data fusion, particularly in scenarios such as driving stress monitoring and workplace stress detection, to improve model accuracy. However, it falls short in addressing the technical implementation and specific methodologies of data fusion, leaving room for further exploration. This paper presents a systematic review focusing on methodologies, classifiers, and data fusion techniques in mental stress recognition. The aim is to synthesize current knowledge, identify gaps, and propose directions for future research.

Section 2 will address the methodology used in the study to identify relevant articles. Section 3 will describe the materials used. Section 4 will detail the planning process, including the research questions, the search string, and the inclusion and exclusion criteria. In section 5 the execution of the search string will be carried out. Section 6 will present the results of the research questions. In section 7 the findings will be discussed and, finally, in section 8 the conclusions will be offered.

2 Methodology

The methodological approach used is the approach of a Systematic Literature Review (SLR) [82], specifically the adaptation proposed by A. Aguileta and O. Gómez, which emphasizes the planning, execution, and reporting to ensure a comprehensive and impartial review of the literature [21]. After analysis, it was concluded that this method is the most suitable for the objectives of the study. The adaptation of the method is divided into three stages:

1. Planning: In this phase, the study protocol is developed through an iterative process. Research questions are formulated, and the objectives are defined. The sources for the searches are also specified, the language of the papers is considered, and inclusion and exclusion criteria are established to select the relevant literature.
2. Execution: Here, the study protocol is implemented, and the search string is executed in the specified sources. The results obtained are evaluated according to the established inclusion and exclusion criteria. The relevant information from the selected articles is synthesized and recorded in an orderly and systematic manner.
3. Report: This phase focuses on communicating the findings of the study. Reports are prepared that highlight the relevant results and conclusions obtained during the literature analysis. This methodological approach enables to the research objectives set out in this mapping study.

3 Planning

This section details the methodological planning for research on stress recognition using wearable mental sensors and data fusion methods. The goal is to understand and address aspects of the state of the art of mental stress detection. To this end, research questions have been formulated and a search chain has been developed to identify relevant studies.

3.1 General objective

3.2

The purpose of this study is to analyze data fusion techniques, classifiers, sensors, and evaluation metrics used for mental stress recognition, highlighting trends, limitations, and opportunities for improvement in this research area.

3.3 Research questions

The seven Research Questions (RQ) that guided the conduct of the study are:

RQ1. How are articles on mental stress recognition distributed over time, and what are the research themes? Objective: Identify trends in the publication timeline and thematic focus of research in mental stress recognition.

RQ2. Which data fusion methods have been most frequently applied in mental stress recognition using wearable sensors? Objective: Provide an overview of the data fusion techniques used and evaluate their characteristics.

RQ3. What classifiers are most frequently used in the recognition of mental stress? Objective: Determine the most used classifiers in the literature on this topic.

RQ4. What are the most used sensors to collect data related to mental stress? Objective: Identify the most common sensors.

RQ5. How is temporal segmentation of data (e.g., overlapping time windows [75]) implemented in mental stress analysis? Objective: To explore the methodologies for dividing data into time windows and assess their impact on detecting stress-related patterns. The term overlapping time windows refers to time segments where successive windows share common portions of data, allowing for more continuous and dynamic signal analysis [75].
RQ6. What evaluation metrics are most frequently used to measure the performance and reliability of mental stress recognition models? Objective: Identify the most relevant metrics to measure the effectiveness of the models.
RQ7. What is the accuracy of the most frequently used classifiers for mental stress recognition? Objective: To evaluate the effectiveness of different mental stress detection approaches in terms of their accuracy.

3.4 Search string

To build the search string, key keywords were identified: “mental stress,” “data fusion,” “artificial intelligence,” and “wearable sensors.” Logical operators such as AND and OR were used to combine these keywords, ensuring coverage of the literature:
"Mental stress" AND ("data fusion" OR "artificial intelligence" OR "machine learning" OR "multiview learning" OR "multi view learning" OR "multiview" OR "multi view") AND ("wearable sensors" OR "sensors " OR "wearable" OR "time series" OR "Non-Invasive Sensors")

3.5 Inclusion and exclusion criteria

These criteria guarantee the selection of publications:

Table 1. Inclusion and Exclusion Criteria

Criterion	Description
IC1	Articles published in English.
IC2	Articles completed and published.
IC3	Articles describing the procedure for providing an analysis.
IC4	Articles no more than eleven years old.
EC1	Articles that do not present any of the previously mentioned characteristics.
EC2	All articles that are surveys, proposals, research studies or any derivative thereof.
EC3	Retracted articles.
EC4	Articles that deal with stress, but not mental stress
EC5	Articles that do not offer explicit information about the data fusion method used or that do not allow a clear inference about said method.

4 Execution

This section describes the research execution process, from the selection of the database to the application of the inclusion and exclusion criteria, as well as the results obtained with the previously defined search string.
For information retrieval, Scopus was chosen, a bibliographic reference database from the company Elsevier with recognition in the scientific context. These databases were chosen as a source for retrieving articles due to their coverage of scientific literature reviewed by experts in multiple disciplines, including engineering, computer science, and health. This ensures access to publications of recognized quality for the scope of this review [22].

4.1 Selection of primary results

After defining the inclusion and exclusion criteria, the search string was run in Scopus in November 2024. Information is obtained through a systematic review process that includes keyword-based searches in Scopus, reading of the found article, then filtering by inclusion/exclusion criteria and synthesizing data into predefined categories such as methodologies, classifiers and sensors. Each article is evaluated based on its contribution to answering the research questions. Articles are considered detailed

if they explicitly describe the methodologies used, data fusion techniques, and provide quantitative evaluations of classifiers and sensors and critically analyze their findings in specific contexts with clear references to previous work.
Results:

Source: Scopus
No. of results: 163
No. of publications included: 49
No. of publications excluded: 114

As a result, forty-nine articles were identified and integrated into the research.

5 Report

This section presents the results of the research, structured and analyzed based on the questions posed during the planning phase. Each question guides the exploration and discussion of the findings.

RQ1. How are articles on mental stress recognition distributed over time, and what are the research themes?
In recent years, mental stress detection through wearable sensors and data fusion methods has become a research area. This research can be classified into three areas:
Category 1: Detection of mental stress using physiological signals and wearable technology:
1.1 Development of systems and devices
1.2 Accuracy and effectiveness evaluation
1.3 Validation of machine learning algorithms
Category 2: Mental stress detection applications:
2.1 Work environments
2.2 Situations (e.g., chess games)
2.3 Groups (e.g., firefighters, drivers)
2.4 Medical and public health contexts
2.5 Populations (e.g., students, people on the autism spectrum)
Category 3: Development and evaluation of specific systems and technologies:
3.1 Development of portable systems and devices for the detection of mental stress
3.2 Evaluation and improvement of classification and machine learning algorithms for the detection of mental stress
3.3 Development of intelligent and cyber-physical models for the detection and prediction of mental stress.
Figure 1 shows the frequency of articles in each category. Category 1 is the most frequent with fifty-four articles, followed by Category 2 with nineteen and Category 3 with twenty-five. An item can belong to multiple categories and subcategories.

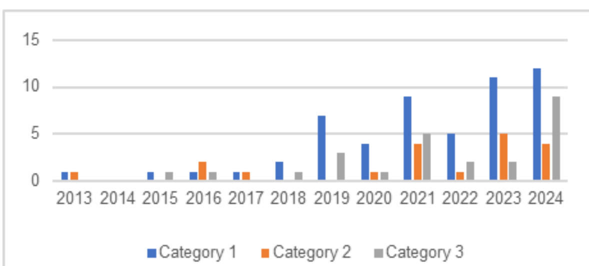

Fig. 1. Frequency of Articles in Each Category

An analysis of the temporal distribution and research objectives is shown in Table 1 and provides an understanding of the field of mental stress recognition, highlighting trends and areas of focus in literature.

Table 1 presents the distribution of research articles across the three categories. Each category reflects a focus, such as the development of stress detection systems or the application of wearable technology in specific contexts. Overlaps were observed as some studies contribute to multiple categories. The discrepancy in the number of articles arises because certain studies address multiple research topics, leading to their inclusion in more than one category.

Table 1. Temporal Distribution and Research Objectives in Mental Stress Recognition

Year	Category 1: Detection of mental stress using physiological signals and wearable technology				Category 2: Mental stress detection applications					Category 3: Development and evaluation of specific systems and technologies		
Sub.	1	2	3	4	5	6	7	8	9	10	11	12
2013	[23]					[23]						
2014												
2015			[24]								[24]	
2016	[26]				[26]		[25]			[25]		
2017	[27]				[27]							
2018	[28] [29]									[28]		
2019	[30] [40] [41] [42] [43] [5]	[5]								[42] [43]	[41]	
2020	[44] [45]		[4]	[3]	[45]						[4]	
2021	[48] [6]	[47] [49] [50] [7]	[46] [51]	[48]		[6]	[7]	[46] [48]		[47]	[49] [50]	[46] [50]
2022	[52] [53] [56]	[54]	[55]					[52]		[56]	[54]	
2023	[58] [60] [61] [62] [63] [64] [66]	[59]	[67]	[65] [67]			[58] [57]		[60] [61] [57]	[58]	[67]	
2024	[68] [78] [80]	[68] [77]	[69][70] [77] [79] [81]	[69] [70]				[70]	[68] [70] [77]	[68] [78] [80]	[69] [77] [79]	[70] [78] [81]

RQ2. Which data fusion methods have been most frequently applied in mental stress recognition using wearable sensors?
The results of research question RQ2 illustrate the classification of abstraction-level data fusion methods employed by the articles. Figure 2 presents a pie chart showing the frequency of use of these methods.

For this question, the classification proposed by Hassan and Abid [10] will be used, which divides the fusion methods into three levels: Feature-Level Data Fusion, Data-Level Data Fusion, and Decision-Level Data Fusion.

The discrepancy in article count arises because not all studies used a single data fusion method. Therefore, the results are presented in two types, first the studies that performed a single data fusion method are presented and then the studies that used more than one data fusion method are presented.

Figure 2 presents the distribution of data fusion methods used in the analyzed articles. The methods are classified into data fusion at feature level, data fusion at data level, and data fusion at decision level. This figure allows us to observe which methods predominate in the studies.

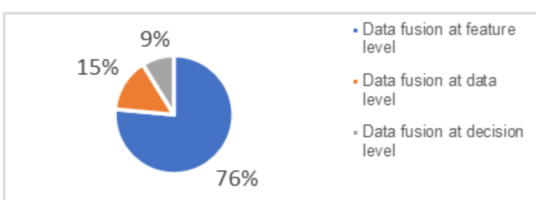

Fig. 2. Frequency of use of data fusion method

As seen in Figure 2, the most used method is data fusion at the feature level, with a total of 26 articles [3, 4, 6, 7, 24, 25, 28, 29, 30, 41, 42, 43, 45 , 47, 48, 49, 50, 51, 53, 54, 56, 57, 63, 70, 79, 81]. Second, data fusion at the data level has been used by 5 papers [5, 23, 44, 55, 58]. Finally, 3 articles have employed decision-level data fusion [46, 52, 78].

The articles show a diversity in the use of data fusion methods, each offering advantages depending on the type of data available and the objectives of the study. Combining multiple fusion methods often provides greater accuracy and robustness by taking advantage of the strengths of each method. Some studies have implemented more than one data fusion method, as presented in Figure 3.

Figure 3 illustrates the combinations, such as feature-level and decision-level fusion and feature-level and data-level fusion.

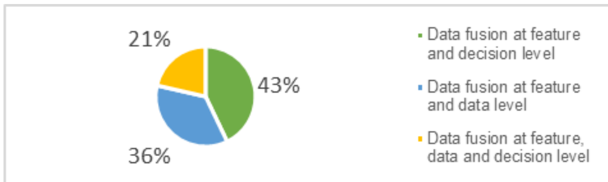

Fig. 3. Frequency of combining data fusion methods

Data fusion at the feature and decision level is the most used, with 6 articles [27, 40, 60, 61, 69, 80]. Second is data fusion at the feature and data level, with 5 articles [26, 59, 65, 66, 77]. Finally, the data fusion method at the features, data and decision level has been used in 4 articles [62, 64, 67, 68].

RQ3. What classifiers are most frequently used in the recognition of mental stress?

The results of question RQ3 show the frequency of classifiers used in mental stress recognition. Although more classifiers have been used in the articles, only those with the highest usage will be presented, as illustrated in Figure 4. Figure 4 details the classifiers used in the reviewed articles, with a focus on methods such as Support Vector Machine (SVM), Random Forest (RF), and K-nearest Neighbors (KNN).

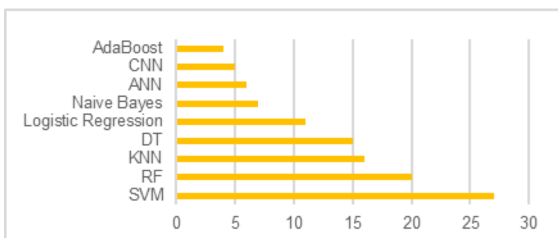

Fig. 4. Frequency of Classifiers Used in Mental Stress Recognition

In the articles, 36 classifiers were identified for the detection of mental stress, although not all were widely used. The Support Vector Machine (SVM) [31] is the most used classifier, appearing in 27 articles [4, 6, 7, 23-28, 30, 40, 44, 45, 46, 48, 49, 52, 54, 58, 59, 60, 61, 64, 66, 67, 69, 77]. It is followed by Random Forest (RF) [33], present in 20 articles [3, 4, 5, 7, 29, 40, 42, 43, 49, 53, 54, 57, 59, 60, 61, 63, 66, 68, 69, 77], and then the K-nearest neighbors (KNN) [35], with 16 references [4-7, 30, 42, 45, 54, 58, 59, 60, 61, 63, 66, 67, 69]. Other classifiers include the Decision Tree (DT) [37] , which appears in 15 articles [4, 6, 7, 30, 42, 44, 53, 54, 58, 59, 60, 61, 63, 66, 77], and Logistic Regression [38], used in 11 articles [3, 5, 7, 30, 44, 49, 53, 58, 60, 61, 64, 67, 68, 77]. Naive Bayes (NB) [70], Multilayer Perceptron (MLP) [71] and Artificial Neural Network (ANN) [72] classifiers appearing in 7 [6, 45, 53, 54, 60, 61, 69], 5 [5, 23, 26, 58, 61] and 6 [4, 24, 41, 46, 66, 78] articles respectively. Classifiers such as AdaBoost [73], Convolutional Neural Networks (CNN) [74] have a lower frequency of use, each appearing in 5 articles [3, 4, 27, 78] and 4 articles [3, 41, 52, 78] respectively.

RQ4. What are the most used sensors to collect data related to mental stress?

The results of question RQ4 show the frequency of sensors used in mental stress recognition. Although more sensors have been used in the articles, only those with the highest usage will be presented. Figure 5 details the frequency of use of these sensors.

Figure 5 shows the sensors for collecting physiological data related to mental stress, such as ECG (Electrocardiogram) and EEG (Electroencephalogram). These sensors capture physiological signals that reflect the stress response, and their use varies depending on the application context.

Among the articles, 34 sensors used for mental stress detection are identified. The most common sensor is the ECG (Electrocardiogram) sensor, present in 24 articles [26, 29, 40, 43, 45, 46, 47, 49, 53, 54, 55, 56, 57, 58, 60, 61, 63, 66, 67, 69, 77, 78, 79, 81]. It is followed by the EEG (Electroencephalogram) sensor, used in 15 articles [29, 35, 40, 43, 49, 50, 53, 56, 57, 60, 64, 67, 77, 80, 81]. The temperature sensor appears in 12 articles [5, 25, 26, 40, 46, 51, 55, 57, 62, 65, 68, 77], followed by the respiration sensor and the accelerometer, present in 11 [3, 11, 14, 15, 20, 29, 57, 58, 61, 62, 81] and 9 [5, 25, 26, 30, 41, 46, 51, 57, 68] articles, respectively.

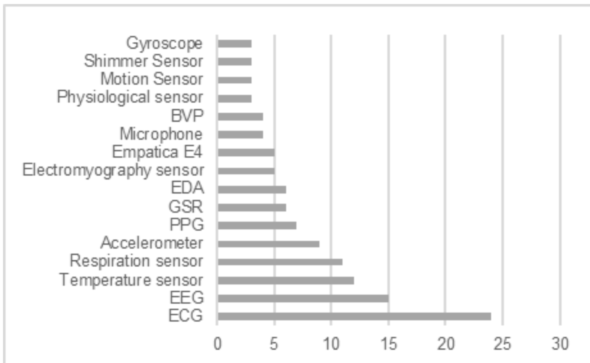

Fig. 5. Frequency of Sensors Used in Mental Stress Recognition

The PPG sensor and the electromyography sensor are found in 7 [5, 30, 48, 60, 65, 67, 77] and 5 [43, 53, 60, 62, 66] articles, respectively. Furthermore, GSR Sensor and EDA Sensor are each present in 6 articles [26, 27, 40, 43, 77, 80], [5, 27, 43, 77, 80], respectively. Additionally, the Empatica E4, Microphone, and BVP Sensor are each present in 4 articles [42, 44, 45, 59], [6, 25, 30, 41], [29, 44, 49, 60] respectively. Lastly, the Physiological Sensor, Motion Sensor, Shimmer, and Gyroscope are each present in 3 items.

RQ5. How is temporal segmentation of data (e.g., overlapping time windows) implemented in mental stress analysis?
Not all relevant articles provide information about the time windows used in their research. Data to address research question RQ5 were extracted from articles that provided details about the time windows used. In Figure 6, approaches to segmenting temporal data are discussed, highlighting overlapping time windows and uniform length windows. This analysis helps understand how data are structured in experimental studies and their impact on detecting stress-related patterns.

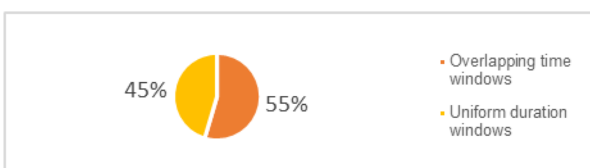

Fig. 6. Frequency of Different Types of Time Windows Used in Mental Stress Recognition Studies

It can be observed that overlapping time windows, which refer to time segments where successive windows share common portions of data, allow for more continuous and dynamic signal analysis [75] are the most frequent, used in 6 articles [23, 28, 42, 44, 49, 64]. Uniform-length time windows were used in 5 papers [24, 30, 40, 57, 69]. These uniform-length time windows refer to divisions of time into equal intervals, used to segment temporal signals or data into consistent blocks for analysis [76].

RQ6. What evaluation metrics are most frequently used to measure the performance and reliability of mental stress recognition models?
The results of question RQ6 show the frequency of metrics used in mental stress recognition. Although more sensors have been used in the relevant articles, only those with the highest usage will be presented. Figure 7 illustrates the frequency of use of these metrics.

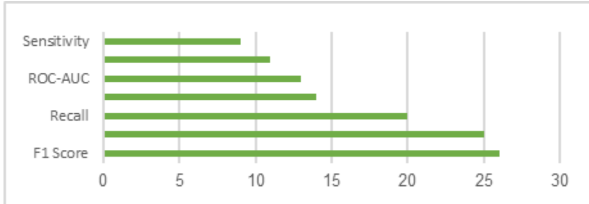

Fig. 7. Frequency of Metrics Used in Mental Stress Recognition

The most used metric is Precision, present in 29 relevant articles [5, 23, 24, 25, 28, 30, 41, 42, 44, 45, 46, 48, 49, 51, 52, 53, 54, 56, 58, 59, 61, 62, 63, 67, 77, 78, 80, 81]. Subsequently, the most frequent metrics are Accuracy and Precision, each used in 25 articles[4, 6, 23, 26, 27, 29, 30, 40, 41, 42, 45, 48, 49, 51, 52, 53, 54, 55, 57, 58, 61, 62, 63, 65, 67, 81], and 25 articles[5, 23, 25, 26, 27, 29, 30, 40, 41, 43, 44, 46, 49, 50, 51, 54, 56, 58, 59, 60, 61, 62, 65, 69, 77], respectively. Recall appears in 20 articles [5, 6, 23, 25, 27, 28, 29, 30, 40, 41, 42, 45, 48, 51, 53, 59, 62, 63, 68, 69], the confusion matrix in 14 articles [5, 23, 25, 27, 29, 30, 40, 42, 49, 57, 59, 61, 68, 69], and the area under the ROC curve (ROC-AUC) in 13 articles [5, 7, 23, 24, 29, 30, 40, 41, 44, 59, 65, 67, 69]. Specificity is mentioned in 11 articles [3, 24, 28, 29, 37, 44, 51, 53, 59, 69. 81], and finally, Sensitivity in 10 articles [24, 25, 28, 29, 37, 44, 47, 58, 69, 81].

RQ7. What is the accuracy of the most frequently used classifiers for mental stress recognition?
Figure 8 presents a bar chart showing the average accuracy of the most frequently used classifiers in mental stress detection, according to the relevant articles.

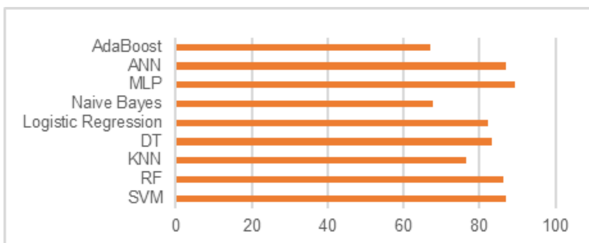

Fig. 8. Average Accuracy of the Most Frequently Used Classifiers in Mental Stress Detection

The model with the highest accuracy is MLP, with an average accuracy of 89.50%. SVM, ANN, and RF also show similar levels of accuracy, with averages of 86.89%, 86.83%, and 86.20% respectively. K-nearest Neighbors (KNN) has an accuracy of 76.41%, Decision Tree (DT) of 83.41%, and Logistic Regression of 82.21%. In contrast, Naive Bayes and AdaBoost show the lowest levels of accuracy, with accuracies of 67.77% and 67.00% respectively. These results indicate that AdaBoost and Naive Bayes are the least accurate classifiers for mental stress detection.

6 Discussions

When examining the research objectives of the articles, a variety of approaches and topics addressed is observed, as detailed in the three main categories and their subcategories. The most frequent category is “Mental stress detection using physiological signals and wearable technology”, which suggests a focus on the development of systems and devices for mental stress detection, as well as the evaluation of their accuracy and effectiveness. On the other hand, “Applications of mental stress detection” and “Development and evaluation of systems and technologies” also receive attention in the research, although to a lesser extent compared to the first category. These categories cover application contexts, from mental stress detection in work environments to the development of models for mental stress prediction. Table 1 complements the visualization of these findings, showing the distribution of articles in each of the categories over time. The frequency of the category of mental stress detection through physiological signals and wearable technology stands out, followed by the category of applications for the detection of mental stress and development and evaluation of systems and technologies, although with a difference in the number of articles.

In summary, the results of research question 1 (RQ1) suggest an interest and research activity in the field of mental stress recognition, with a focus on the development of technologies and systems for its detection. However, applications and technological approaches are also explored, reflecting the breadth of research in this area.

The results of research question RQ2 show that feature-level data fusion is the prevalent method in mental stress recognition. This approach was employed by 24 articles [3, 4, 6, 7, 24, 25, 28, 29, 30, 41, 42, 43, 45 , 47, 48, 49, 50, 51, 53, 54, 56, 57, 63, 70, 79, 81], indicating a clear preference for integrating features derived from different data sources to improve model accuracy and robustness. Feature-level data fusion is frequently utilized for combining diverse signals into a single feature vector, which can facilitate the application of advanced machine learning techniques and improve model performance in certain contexts. This method is especially useful when handling heterogeneous data, as it allows capturing the variability and complementarity of different data types. Secondly, data-level data fusion has been used in 5 articles [5, 23, 44, 55, 58]. This approach involves the combination of raw data from multiple sources before any feature extraction process, which can be advantageous when the integrity of the original signals and their temporality are intended to be maintained. However, this technique can be complex to implement due to the need for data synchronization and alignment. Decision-level data fusion, used in only 3 papers [46, 52, 78], involves combining results from multiple models or algorithms to make a final decision.

Although this method can improve accuracy by averaging the results of classifiers, its lower frequency of use may be due to the complexity of designing appropriate voting or weighting systems. The combination of multiple fusion methods, as shown in Figure 2, highlights the tendency of some studies to leverage the strengths of each approach to improve the accuracy and robustness of the models. Data fusion at the feature and decision level is the most common, used in 6 articles [27, 40, 60, 61, 69, 80], followed by feature and data fusion in 5 articles [26, 59, 65, 66, 77], and the combination of features, data, and decision in another 4 papers [62, 64, 67, 68]. These results suggest that although feature-level data fusion is predominant, the implementation of hybrid approaches can provide additional benefits by incorporating multiple levels of data integration, thus improving the effectiveness of mental stress recognition systems.

In Research Question 3 (RQ3) the results reveal a variety of classifiers used in mental stress recognition, with Support Vector Machine (SVM) standing out as the most used among the articles. This preference for SVM can be attributed to its ability to handle complex and high-dimensional datasets, making it a choice for classification in this context. Random Forest (RF) and K-nearest neighbors (KNN) are the other most frequent classifiers, suggesting that these classifiers are also considered effective for mental stress recognition. The popularity of RF may be due to its ability to handle noisy and high-dimensional datasets, while KNN is known for its simplicity and ability to adapt to different types of data.

It is interesting to note that although Decision Tree (DT) and Logistic Regression are also common classifiers in this field, their frequency of use is relatively lower compared to SVM, RF, and KNN. This could be due to the limitations of these classifiers in terms of their ability to model complex relationships between variables and handle data sets with high dimensionality. In addition, the presence of other classifiers such as the Fully Connected Single Layer Neural Network with a Rectified Linear Activity Unit (ReLU) and the Self-Organizing Map (SOM) reflects the diversity of approaches and techniques employed in research on mental stress recognition. These classifiers may offer unique insights or specific solutions for certain types of data or application contexts.

The diversity in the use of classifiers in mental stress recognition reflects the complexity of the problem and the need to explore a range of approaches to obtain results. The selection of the most suitable classifier will depend on several factors such as the nature of the data, the objectives of the study, and the limitations of the application context.

In Research Question 4 (RQ4) we can notice the diversity of sensors used in mental stress recognition, this diversity reflects the complexity of capturing and understanding the physiological signals associated with this emotional state. The fact that the ECG Sensor is the most used one could be attributed to its ability to measure the electrical activity of the heart in a precise and non-invasive manner, making it a tool to assess the cardiovascular response to stressful situations. On the other hand, the presence of the EEG Sensor in several studies suggests a interest in understanding the characteristics of brain activity related to mental stress. The EEG provides information about the electrical activity of the brain, allowing to detect specific patterns associated with stress and other emotions. The Temperature Sensor, the Breathing Sensor and the Accelerometer are also widely used sensors in mental stress detection. Body temperature, respiratory rate and physical movements can be important indicators of a person's physiological and emotional state, making them valuable options for monitoring stress.

In addition to these common sensors, others such as the PPG Sensor, Electromyography Sensor, and Microphone are also used in multiple studies. The PPG Sensor, for example, can provide information on heart rate and pulse variability, while Electromyography can detect electrical activity of muscles, both of which are relevant to understanding stress response. Some sensors, such as the Video Sensor, GPS, and Light Sensor, have also been used in mental stress detection, suggesting a broad approach incorporating visual, location, and environmental cues in stress assessment. The variety of sensors used in mental stress detection underscores the importance of considering multiple physiological and environmental aspects to gain a full understanding of this phenomenon. The selection of appropriate sensors will depend on the specific objectives of each study and the information to be collected about the experience of stress in different contexts and populations.

In Research Question 5 (RQ5), we can see that overlapping time windows are more prevalent, suggesting a preference for a more dynamic and flexible approach to capturing physiological and behavioral data. These windows allow for a continuous analysis of signals over time, which can be crucial for identifying patterns of stress response across different times and situations. On the other hand, the use of time windows of uniform length may indicate an interest in segmenting data into predefined intervals. This may facilitate direct comparison between different time periods and simplify data analysis by standardizing the time units used. The choice between overlapping and uniform length time windows may depend on several factors, including the research objectives, the nature of the physiological or behavioral signals being analyzed, and the methodological preferences of the researcher.

Furthermore, other, less common types of time windows may also offer advantages in certain contexts, such as detecting specific events or capturing abrupt changes in stress response. In other words, choosing the right time window is a crucial aspect in the design of studies on mental stress, as it can influence researchers' ability to capture and understand the complex temporal dynamics associated with this condition. The diversity in the use of time windows across the relevant articles underlines the importance of carefully considering this methodological aspect in future stress research.

The results of question RQ6 reveal a clear preference for certain metrics in the assessment of mental stress recognition. This preference may be influenced by several factors, such as the nature of the data, the purpose of the study, and the particularities of the model used. Figure 7 effectively illustrates the frequency of use of these metrics, providing a comprehensive overview of current trends in research. The F1 score, with a presence in 25 relevant articles, emerges as the most used metric. This is not surprising, given that the F1 score is a measure that combines precision and recall into a single metric, offering a balance between the two. In the context of mental stress recognition, where both false positives and false negatives can have significant implications, the F1 score becomes a logical choice. Its frequent use indicates that researchers value a balanced assessment of model performance, avoiding bias towards one metric over the other.

The diversity in the metrics used reflects the complexity and multidimensionality of mental stress recognition. The choice of metrics depends largely on the specific objective of each study and the characteristics of the data and models used. The trend towards the use of the F1 score and other balanced metrics underlines the importance of a comprehensive and balanced evaluation of the performance of models in this field.

The results of question RQ7 provide a clear insight into the relative effectiveness of various classifiers in the task of mental stress recognition. Figure 8 visually presents this data, highlighting the differences in performance of the most used models. The most relevant findings are discussed below. The Multilayer Perceptron (MLP) model stands out with an average accuracy of 89.50%, suggesting that this classifier is particularly effective in detecting mental stress. MLP's ability to capture complex non-linear relationships in data may be a key factor contributing to its high performance. This makes it an attractive option for researchers and practitioners looking to maximize accuracy in their mental stress classification models.

Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Random Forests (RF) models also show levels of accuracy, with averages of 86.89%, 86.83%, and 86.20% respectively. These results indicate the robustness of these classifiers in the task of mental stress recognition. SVM is known for its ability to handle high-dimensional spaces, while ANN can model relationships. RF, on the other hand, handles noisy data and prevents overfitting, which explains its accuracy. The K-nearest Neighbors (KNN) classifier exhibits an accuracy of 76.41%, which, although lower than the previously mentioned models, is still reasonably high. Decision Tree (DT) and Logistic Regression show accuracies of 83.41% and 82.21% respectively. The lower accuracy of KNN can be attributed to its sensitivity to noise and data distribution, while DT and Logistic Regression are generally simpler and less flexible than models such as MLP and SVM, which may explain their slightly lower performance. Naive Bayes and AdaBoost show the lowest levels of accuracy, with accuracies of 67.77% and 67.00% respectively.

These results indicate that these classifiers are less effective for mental stress detection compared to the other models evaluated. The simplicity of Naive Bayes and its assumption of feature independence may limit its ability to capture the complexity of mental stress-related data. AdaBoost, although a powerful ensemble method, may not be suitable for this specific domain due to its sensitivity to noisy and imbalanced data.

7 Conclusions

When examining research objectives in mental stress recognition, a prevalence of studies focused on detection using physiological signals and wearable technology stands out. This trend suggests a predominant focus on the development of systems and devices to monitor stress, with a notable attention to their accuracy and effectiveness. Although other areas such as specific applications and technological developments also receive attention, they do so to a lesser extent.

Regarding data fusion methodologies, feature-level fusion is the most prevalent, employed by most articles. This approach allows for effective integration of data from various sources, improving the accuracy and robustness of models. Other methods, such as data fusion at the data and decision levels, are less common but offer specific benefits in certain contexts. The combination of multiple fusion methods, as observed in 30.61% of the reviewed studies, suggests an effort to leverage the complementary strengths of each approach for improved model robustness and accuracy. Research on classifiers for mental stress recognition shows a preference for Support Vector Machine (SVM), followed by Random Forest (RF) and K-nearest neighbors (KNN). These classifiers stand out for their ability to handle complex and high-dimensional data. Although other classifiers such as Decision Tree and Logistic Regression are used, they are less frequently used, suggesting limitations in their ability to model complex relationships between variables. Finally, the most used sensors include ECG and EEG, due to their ability to accurately measure cardiovascular and brain activity, respectively. Sensor selection is crucial to capture multiple physiological and environmental aspects of mental stress. Regarding evaluation metrics, accuracy, precision, and F1 Score are the most frequent, reflecting the importance of correctly classifying mental stress. LDA and MLP models stand out for their high precision, although their use is less frequent, indicating a potential yet to be fully explored. This systematic review highlights significant progress in mental stress recognition through wearable sensors and Fusion Methods AI. Feature-level data fusion and classifiers like SVM and RF stand out for their effectiveness, while ECG and EEG remain the most utilized sensors. Future research should focus on hybrid data fusion techniques and evaluating systems in diverse populations to enhance their practical applicability.

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References

1. Lin, Q., Li, T., Shakeel, P. M., & Samuel, R. D. J. (2021). Advanced artificial intelligence in heart rate and blood pressure monitoring for stress management. Journal of Ambient Intelligence and Humanized Computing, 12(3), 3329-3340. https://doi.org/10.1007/s12652-020-02650-3
2. World Health Organization: WHO (World Health Organization). (2022). COVID-19 pandemic triggers 25% increase in prevalence of anxiety and depression worldwide. World Health Organization. https://www.who.int/news/item/02-03-2022-covid-19-pandemic-triggers-25-increase-in-prevalence-of-anxiety-and-depression-worldwide
3. Mozafari, M., Firouzi, F., & Farahani, B. (2020). Towards IoT-enabled Multimodal Mental Stress Monitoring. En 2020 International Conference on Omni-layer Intelligent Systems (COINS). https://doi.org/10.1109/coins49042.2020.9191392
4. Bobade, P., & Vani, M. (2020). Stress Detection with Machine Learning and Deep Learning using Multimodal Physiological Data. En 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA). https://doi.org/10.1109/icirca48905.2020.9183244
5. Can, Y. S., Chalabianloo, N., Ekiz, D., & Ersoy, C. (2019). Continuous Stress Detection Using Wearable Sensors in Real Life: Algorithmic Programming Contest Case Study. Sensors, 19(8), 1849. https://doi.org/10.3390/s19081849
6. Sevil, M., Rashid, M., Hajizadeh, I., Askari, M. B., Hobbs, N., Brandt, R., Park, M., Quinn, L., & Cinar, A. (2021b). Discrimination of simultaneous psychological and physical stressors using wristband biosignals. Computer Methods and Programs in Biomedicine, 199, 105898. https://doi.org/10.1016/j.cmpb.2020.105898
7. Kim, N., Seo, W., Kim, S., & Park, S. S. (2021). Electrogastrogram: Demonstrating Feasibility in Mental Stress Assessment Using Sensor Fusion. IEEE Sensors Journal, 21(13), 14503-14514. https://doi.org/10.1109/jsen.2020.3026717
8. Crosswell, A. D., & Lockwood, K. G. (2020). Best practices for stress measurement: How to measure psychological stress in health research. Health psychology open, 7(2), 205510292093307. https://doi.org/10.1177/2055102920933072
9. Diccionario de cáncer del NCI. (s. f.). Instituto Nacional del Cáncer. https://www.cancer.gov/espanol/publicaciones/diccionarios/diccionario-cancer/def/conductividad-de-la-piel
10. Hassan, M. M., Abid, M. M. A., & Alotaibi, M. A. H. (2018). Data fusion for human activity recognition: A survey. Sensors, 18(1), 133. https://doi.org/10.3390/s18010133

11. Ferguson, S. (2022). How Can You Measure Stress? Healthline. https://www.healthline.com/health/stress/stress-measurement#expected-stress-levels

12. Copeland, B. (2023). Artificial intelligence (AI) | Definition, Examples, Types, Applications, Companies, & Facts. Encyclopedia Britannica. https://www.britannica.com/technology/artificial-intelligence

13. West, D. M., & Allen, J. R. (2023). How artificial intelligence is transforming the world. Brookings. https://www.brookings.edu/research/how-artificial-intelligence-is-transforming-the-world/

14. SITNFlash. (2020). The History of Artificial Intelligence - Science in the News. Science in the News. https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/

15. Movement, Q.-. P. A. P. W. (2023). Applications of Artificial Intelligence Across Various Industries. Forbes. https://www.forbes.com/sites/qai/2023/01/06/applications-of-artificial-intelligence/?sh=71e4ee1b3be4

16. Meng, T., Jing, X., Yan, Z., & Pedrycz, W. (2020). A survey on machine learning for data fusion. Information Fusion, 57, 115-129. https://doi.org/10.1016/j.inffus.2019.12.001

17. Hassan, M. M., Abid, M. M. A., & Alotaibi, M. A. H. (2018). Data fusion for human activity recognition: A survey. Sensors, 18(1), 133. https://doi.org/10.3390/s18010133

18. Alahmadi, A. A., Alotaibi, M. A., & Alghamdi, A. A. (2020). Data fusion for intelligent transportation systems: A survey. Sensors, 20(18), 5438. https://doi.org/10.3390/s20185438

19. Mandreoli, F., & Montangero, M. (2019). Dealing With Data Heterogeneity in a Data Fusion Perspective. En Data handling in science and technology (pp. 235-270). https://doi.org/10.1016/b978-0-444-63984-4.00009-0

20. Elzeiny, S., & Qaraqe, M. (2018). Machine Learning Approaches to Automatic Stress Detection: A Review. https://doi.org/10.1109/aiccsa.2018.8612825

21. Aguileta, A. A., & Gómez, O. S. (2016). Software Engineering Research in Mexico: A Systematic Mapping study. International Journal of Software Engineering and its Applications, 10(12), 75-92. https://doi.org/10.14257/ijseia.2016.10.12.07

22. Scopus database | Scientific Resources. (n. d.). https://www.recursoscientificos.fecyt.es/licencias/productos-contratados/scopus

23. Eggert, C., Lara, O., & Labrador, M. A. (2013). Recognizing mental stress in chess players using vital sign data. https://doi.org/10.1109/secon.2013.6567512

24. Barua, S., Begum, S., & Ahmed, M. U. (2015). Supervised machine learning algorithms to diagnose stress for vehicle drivers based on physiological sensor signals. Studies in health technology and informatics, 211, 241–248.

25. Sandulescu, V., & Dobrescu, R. (2015). Wearable system for stress monitoring of firefighters in special missions. En E-Health and Bioengineering Conference. https://doi.org/10.1109/ehb.2015.7391578

26. Hagad, J. L., Moriyama, K., Fukui, K., & Numao, M. (2016). Modeling Work Stress Using Heart Rate and Stress Coping Profiles. En Lecture Notes in Computer Science. Springer Science+Business Media. https://doi.org/10.1007/978-3-319-46218-9_9

27. Mozos, O. M., Sandulescu, V., Andrews, S., Ellis, D., Bellotto, N., Dobrescu, R., & Ferrández, J. M. (2017). Stress Detection Using Wearable Physiological and Sociometric Sensors. International Journal of Neural Systems, 27(02), 1650041. https://doi.org/10.1142/s0129065716500416

28. S. Betti et al. (2018), "Evaluation of an Integrated System of Wearable Physiological Sensors for Stress Monitoring in Working Environments by Using Biological Markers," in IEEE Transactions on Biomedical Engineering, vol. 65, no. 8, pp. 1748-1758, Doi: 10.1109/TBME.2017.2764507

29. Zanetti, M., Faes, L., De Cecco, M., Fornaser, A., Valente, M., Guandalini, G. M. A., & Nollo, G. (2018). Assessment of Mental Stress Through the Analysis of Physiological Signals Acquired from Wearable Devices. En Lecture notes in electrical engineering (pp. 243-256). Springer Science+Business Media. https://doi.org/10.1007/978-3-030-05921-7_20

30. Wang, F., Wang, Y., Wang, J., Xiong, H., Zhao, J., & Zhang, D. (2019). Assessing Mental stress Based on smartphone sensing data: An Empirical study. https://doi.org/10.1109/smartworld-uic-atc-scalcom-iop-sci.2019.00200

31. Support Vector Machine (SVM). (s. f.). MATLAB & Simulink. https://es.mathworks.com/discovery/support-vector-machine.htmlSensores. (s. f.). National Institute of Biomedical Imaging and Bioengineering. https://www.nibib.nih.gov/espanol/temas-cientificos/sensores

32. Senra, I. (2022). Qué es wearable - definición, significado y ejemplos. Arimetrics. https://www.arimetrics.com/glosario-digital/wearable

33. Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324

34. Gedam, S. R., & Paul, S. (2021). A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques. IEEE Access, 9, 84045-84066. https://doi.org/10.1109/access.2021.3085502

35. Cunningham, P., & Delany, S. J. (2021). K-Nearest Neighbour Classifiers - a tutorial. ACM Computing Surveys, 54(6), 1-25. https://doi.org/10.1145/3459665

36. Iovino, M., Javorka, M., Faes, L., Pernice, R. (2023). Comparison of Machine Learning Approaches for Physiological States Classification Using Heart Rate and Pulse Rate Variability Indices. In Proceedings of the Eighth National Congress of Bioengineering (pp. 679-682). Pàtron editore.

37. Kotsiantis, S.B. Decision trees: a recent overview. Artif Intell Rev 39, 261–283 (2013). https://doi.org/10.1007/s10462-011-9272-4

38. Kleinbaum, D. G., & Klein, M. (2010). Logistic regression. En Statistics in the health sciences. https://doi.org/10.1007/978-1-4419-1742-3

39. Lima, R., Osório, D.N., & Gamboa, H. (2019). Heart Rate Variability and Electrodermal Activity in Mental Stress Aloud: Predicting the Outcome. International Conference on Bio-inspired Systems and Signal Processing.

40. Acikmese, Y., & Alptekin, S. E. (2019). Prediction of stress levels with LSTM and passive mobile sensors. Procedia Computer Science. https://doi.org/10.1016/j.procs.2019.09.221

41. Montesinos, V., Dell'Agnola, F., Arza, A., Aminifar, A., & Atienza, D. (2019). Multi-Modal acute stress recognition using Off-the-Shelf wearable devices. https://doi.org/10.1109/embc.2019.8857130

42. Gurel, N. Z., Jung, H., Hersek, S., & Inan, O. T. (2019b). Fusing Near-Infrared spectroscopy with wearable hemodynamic measurements improves classification of mental stress. IEEE Sensors Journal, 19(19), 8522–8531. https://doi.org/10.1109/jsen.2018.2872651

43. Carreiro, S., Chintha, K. K., Shrestha, S., Chapman, B. P., Smelson, D. A., & Indic, P. (2020). Wearable sensor-based detection of stress and craving in patients during treatment for substance use disorder: A mixed methods pilot study. Drug and Alcohol Dependence, 209, 107929. https://doi.org/10.1016/j.drugalcdep.2020.107929

44. Han, H. J., Labbaf, S., Borelli, J. L., Dutt, N., & Rahmani, A. M. (2020). Objective stress monitoring based on wearable sensors in everyday settings. Journal of Medical Engineering & Technology, 44(4), 177–189. https://doi.org/10.1080/03091902.2020.1759707

45. Dham, V., Rai, K., & Soni, U. (2021). Mental stress detection using artificial intelligence models. Journal of Physics: Conference Series, 1950(1), 012047. https://doi.org/10.1088/1742-6596/1950/1/012047

46. Faro, A., Giordano, D., & Venticinque, M. (2021). Finding the Proper Mental Stress Model Depending on Context using Edge Devices and Machine Learning. https://doi.org/10.1109/iotais50849.2021.9359701

47. Asha, N. E. J., Ehtesum-Ul-Islam, & Khan, R. (2021). Low-Cost heart rate sensor and mental stress detection using machine learning. In 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI). https://doi.org/10.1109/icoei51242.2021.9452873

48. Zanetti, M., Mizumoto, T., Faes, L., Fornaser, A., De Cecco, M., Maule, L., Valente, M., & Nollo, G. (2019). Multilevel assessment of mental stress via network physiology paradigm using consumer wearable devices. Journal of Ambient Intelligence and Humanized Computing, 12(4), 4409–4418. https://doi.org/10.1007/s12652-019-01571-0

49. Liu, Y., Habibnezhad, M., Jebelli, H., & Monga, V. (2021). Worker-in-the-Loop Cyber-Physical system for safe Human-Robot collaboration in construction. In Computing in Civil Engineering 2021. https://doi.org/10.1061/9780784483893.132

50. Faro, A., & Giordano, D. (2021). Prognostics and Management of Mental Stress by AIoT monitoring and Schlegel Diagrams. https://doi.org/10.1109/isc253183.2021.9562844

51. Roy, A., Acharya, A., Biswas, S., Ray, S., & Ganguly, B. (2022). Identification and Classification of Human Mental Stress using Physiological Data: A Low-Power Hybrid Approach. https://doi.org/10.1109/catcon56237.2022.10077709

52. Heyat, M. B. B., Akhtar, F., Abbas, S. J., Al-Sarem, M., Alqarafi, A., Stalin, A., Abbasi, R., Muaad, A. Y., Lai, D., & Wu, K. (2022). Wearable flexible electronics based cardiac electrode for researcher mental stress detection system using machine learning models on single lead electrocardiogram signal. Biosensors, 12(6), 427. https://doi.org/10.3390/bios12060427Evaluation of Feature Selection and Multi-Class Prediction Methods for Metal Stress.

53. Chatterjee, D., Dutta, S., Shaikh, R., & Saha, S. (2022). A lightweight deep neural network for detection of mental states from physiological signals. Innovations in Systems and Software Engineering. https://doi.org/10.1007/s11334-022-00470-6

54. Sheeraz, M., Aslam, A. R., & Altaf, M. a. B. (2022). Multiphysiological shallow neural Network-Based mental stress detection system for wearable environment. In 2022 IEEE International Symposium on Circuits and Systems (ISCAS). https://doi.org/10.1109/iscas48785.2022.9937517

55. Shermadurai, P., & Thiyagarajan, K. (2023). Deep Learning Framework for Classification of Mental Stress from Multimodal Datasets. Revue D'intelligence Artificielle, 37(1), 155–163. https://doi.org/10.18280/ria.370119

56. Siam, A. I., Gamel, S. A., & Talaat, F. M. (2023). Automatic stress detection in car drivers based on non-invasive physiological signals using machine learning techniques. Neural Computing and Applications, 35(17), 12891–12904. https://doi.org/10.1007/s00521-023-08428-w

57. Banerjee, J. S., Mahmud, M., & Brown, D. J. (2023). Heart Rate Variability-Based Mental Stress Detection: An Explainable Machine Learning approach. SN Computer Science, 4(2). https://doi.org/10.1007/s42979-022-01605-z

58. S. Mandal, B. Ghosh and R. Naskar, "A Photoplethysmography (PPG) Sensor based Stress Level Monitoring System for Undergraduate Students of Technical Education," 2023 IEEE 20th India Council International Conference (INDICON), Hyderabad, India, 2023, pp. 197-202, doi: 10.1109/INDICON59947.2023.10440913.

59. P. Verma and R. Singh, "Mental Stress Prediction Using Wrist Wearable Through Machine Learning Approaches," 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET), Ghaziabad, India, 2023, pp. 475-481, doi: 10.1109/ICSEIET58677.2023.10303348.

60. M. Benouis, Y. S. Can and E. André, "A Privacy-Preserving Multi-Task Learning Framework For Emotion and Identity Recognition from Multimodal Physiological Signals," 2023 11th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW), Cambridge, MA, USA, 2023, pp. 1-8, doi: 10.1109/ACIIW59127.2023.10388160.

61. S. Das, N. N. Goswami, A. P. Kalaskar, S. Mondal, P. Kumar Samanta and S. Kumar Gannamaneni, "IoT Based Framework Design for Automated Human Emotion Recognition," 2023 2nd International Conference on Ambient Intelligence in Health Care (ICAIHC), Bhubaneswar, India, 2023, pp. 01-06, doi: 10.1109/ICAIHC59020.2023.10431467.

62. Shermadurai, P., & Thiyagarajan, K. (2023). Deep Learning Framework for Classification of Mental Stress from Multimodal Datasets. Revue D Intelligence Artificielle, 37(1), 155-163. https://doi.org/10.18280/ria.370119

63. Sharifi-Heris, Z., Yang, Z., Rahmani, A. M., Fortier, M. A., Sharifiheris, H., & Bender, M. (2023). Phenotyping the autonomic nervous system in pregnancy using remote sensors: potential for complication prediction. Frontiers In Physiology, 14. https://doi.org/10.3389/fphys.2023.1293946

64. Shermadurai, P., & Thiyagarajan, K. (2023b). Deep Learning Framework for Classification of Mental Stress from Multimodal Datasets. Revue D Intelligence Artificielle, 37(1), 155-163. https://doi.org/10.18280/ria.370119

65. P. S. Ramteke and S. Khandelwal, "Comparing Conventional Machine Learning and Large-Language Models for Human Stress Detection Using Social Media Posts," 2023 2nd International Conference on Futuristic Technologies (INCOFT), Belagavi, Karnataka, India, 2023, pp. 1-8, doi: 10.1109/INCOFT60753.2023.10425133.

66. Benchekroun, M., Istrate, D., Zalc, V., Lenne, D. (2023). A Multi-Modal Dataset (MMSD) for Acute Stress Bio-Markers. In: Roque, A.C.A., et al. Biomedical Engineering Systems and Technologies. BIOSTEC 2022. Communications in Computer and Information Science, vol 1814. Springer, Cham. https://doi.org/10.1007/978-3-031-38854-5_19

67. Jayanthi, S., Priyadharshini, V., Kirithiga, V., & Premalatha, S. (2023). Mental health status monitoring for people with autism spectrum disorder using machine learning. International Journal Of Information Technology. https://doi.org/10.1007/s41870-023-01524-z

68. Iovino, M., Lazic, I., Loncar-Turukalo, T., Javorka, M., Pernice, R., & Faes, L. (2024). Classification of Physiological States Through Machine Learning Algorithms Applied to Ultra-Short-Term Heart Rate and Pulse Rate Variability Indices on a Single-Feature Basis. En IFMBE proceedings (pp. 114-124). https://doi.org/10.1007/978-3-031-49062-0_13

69. Chandra, V., & Sethia, D. (2024). Machine learning-based stress classification system using wearable sensor devices. IAES International Journal Of Artificial Intelligence, 13(1), 337. https://doi.org/10.11591/ijai.v13.i1.pp337-347

70. Wickramasinghe, I., Kalutarage, H. Naive Bayes: applications, variations and vulnerabilities: a review of literature with code snippets for implementation. Soft Comput 25, 2277–2293 (2021). https://doi.org/10.1007/s00500-020-05297-6

71. Kruse, R., Mostaghim, S., Borgelt, C., Braune, C., Steinbrecher, M. (2022). Multi-layer Perceptrons. In: Computational Intelligence. Texts in Computer Science. Springer, Cham. https://doi.org/10.1007/978-3-030-42227-1_5

72. Katal, A., Singh, N. (2022). Artificial Neural Network: Models, Applications, and Challenges. In: Tomar, R., Hina, M.D., Zitouni, R., Ramdane-Cherif, A. (eds) Innovative Trends in Computational Intelligence. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-78284-9_11

73. Zhang, Q., & Wang, T. (2024). Deep Learning for Exploring Landslides with Remote Sensing and Geo-Environmental Data: Frameworks, Progress, Challenges, and Opportunities. Remote Sensing, 16(8), 1344. https://doi.org/10.3390/rs16081344

74. Montesinos López, O.A., Montesinos López, A., Crossa, J. (2022). Convolutional Neural Networks. In: Multivariate Statistical Machine Learning Methods for Genomic Prediction. Springer, Cham. https://doi.org/10.1007/978-3-030-89010-0_13

75. Xu, X., Lin, Z., Zhang, W. et al. Multi-tank joint replenishment problem with overlapping time windows in refined oil distribution. Ann Oper Res (2023). https://doi.org/10.1007/s10479-023-05512-1

76. Dorndorf, U. (2002). Project Scheduling with Time Windows. En Contributions to management science. https://doi.org/10.1007/978-3-642-57506-8

77. Sadruddin, S., Khairnar, V. D., & Vora, D. R. (2024). Issues and Challenges in Detecting Mental Stress from Multimodal Data Using Machine Intelligence. SN Computer Science, 5(4). https://doi.org/10.1007/s42979-024-02730-7

78. Alahmadi, A., Khan, H. A., Shafiq, G., Ahmed, J., Ali, B., Javed, M. A., Khan, M. Z., Alsisi, R. H., & Alahmadi, A. H. (2023). A privacy-preserved IoMT-based mental stress detection framework with federated learning. The Journal Of Supercomputing, 80(8), 10255-10274. https://doi.org/10.1007/s11227-023-05847-3

79. Saini, S. K., & Gupta, R. (2024). A Novel Method for Mental Stress Assessment Based on Heart Rate Variability Analysis of Electrocardiogram Signals. Wireless Personal Communications. https://doi.org/10.1007/s11277-024-11317-7

80. Kader, L. A., Al-Shargie, F., Tariq, U., & Al-Nashash, H. (2024). One-Channel Wearable Mental Stress State Monitoring System. Sensors, 24(16), 5373. https://doi.org/10.3390/s24165373

81. Kim, N., Lee, S., Kim, J., Choi, S. Y., & Park, S. (2024). Shuffled ECA-Net for stress detection from multimodal wearable sensor data. Computers In Biology And Medicine, 183, 109217. https://doi.org/10.1016/j.compbiomed.2024.109217

82. Keele, Staffs.Guidelines for performing systematic literature reviews in software engineering. Vol. 5. Technical report, ver. 2.3 ENSE Technical Report, (2007).