Real-Time Emotion Assessment System in Smart Classrooms Using Wearable Bracelets

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***Abstract*—Smart classrooms are the next frontier in education to accelerate and improve both teaching and learning processes. These environments integrate sensors, ubiquitous computing systems, Artificial Intelligence (AI) techniques, and high-speed data networks to create more cognitive, effective, interactive, and adaptive learning settings. Among other applications, students' emotions are key to maintain a positive learning atmosphere. Unlike traditional video analysis approaches, emotions can be detected through physiological data, such as electrodermal activity, heart rate, and skin temperature, which can be collected using non-invasive and user-friendly wearable devices. To this end, this paper presents a real-time emotion assessment system intended for both students and teachers within smart classrooms. A prototype has been developed using EmotiBit bracelets and a Raspberry Pi. Initial testing in laboratory settings has shown the system could smoothly run in off-the-shelf technology. However, the deployment of this system in real-world classrooms reveals several challenges that must be addressed, namely data volume, battery duration, data security concerns, and the lack of training datasets for the AI model.**

Keywords-smart classroom; emotions; bracelets; wearables; EmotiBit; artificial intelligence; education.

I. INTRODUCTION

The adoption of the Information and Communication Technologies (ICT) paves the way for the creation of smart environments capable of collecting and analysing data from users and their context, facilitating the adjustment of processes in real-time and providing stakeholders with valuable insights. In the field of education, this technology can lead to significant advancements, as the concept of smart classrooms. Such environments prioritise students-centred learning, enhance teaching effectiveness, and relieve teachers from routine tasks, thereby reducing their stress and preventing burnout. To this end, smart classrooms leverage technology to enhance the quality of teaching and learning processes by collecting and processing information from students, teachers, and the environment, thus enabling adequate decision-making [1]. Smart classrooms can be implemented using several distributed, interconnected systems that autonomously gather data from embedded sensors, which are seamlessly integrated within the physical learning environment [2][3]. Among such systems, the *Classroom Agent* is responsible for collecting and analysing information from the individuals and their context using Artificial Intelligence (AI) while providing stakeholders with visualisation and interaction tools.

Among the numerous opportunities within smart classrooms, understanding students' emotions can foster a positive emotional climate in the classroom that results in improved academic performance [4]. Affective states, encompassing a broad range of feelings, moods, and emotions, can be detected and monitored by the smart classroom to track the overall mood of students during specific activities or analyse which activities perform better at different times of the day. Various theoretical models have been proposed to define and categorise emotions. The most popular models are the Ekman's model of the six basic emotions, which identifies universal emotions, such as joy, sadness, fear, surprise, disgust, and anger [5], and the Russell's circumplex model, which organises emotions in a two-dimensional space based on valence (pleasant-unpleasant) and arousal (low-high) [6].

Most proposals for detecting emotions, moods, and feelings in smart classrooms rely on video analysis, conducted either in real-time or post-lecture. For instance, the studies in [7][8][9] proposed real-time emotion recognition systems, where the latter assigns numerical scores to students based on their concentration levels. However, video-based solutions might be limited by lighting conditions, occlusions, or even individual differences in expressing emotions. Moreover, implementing these solutions in real classrooms would require robust privacy-preserving methods to safeguard the privacy and confidentiality of underage students in accordance to ethical and legal standards. These constraints could be relaxed by detecting emotions using alternative data sources, such as wearables combined with air quality sensors and acoustic sensors. Specifically, recent technological advancements in physiological sensing have enabled novel methods for detecting and monitoring emotions through wearable technology. For instance, sensor-equipped wearables capable of measuring Electrodermal Activity (EDA), Heart Rate (HR), Heart Rate Variability (HRV), skin temperature (SKT), and electroencephalography (EEG) can help track students' emotional states in real-time [10][11][12]. With usability in mind, bracelets are generally accepted by users for detecting biological markers. However, the majority operate within a closed model paradigm, such as the research-oriented Empatica, Shimmer, and BIOPAC bracelets, requiring

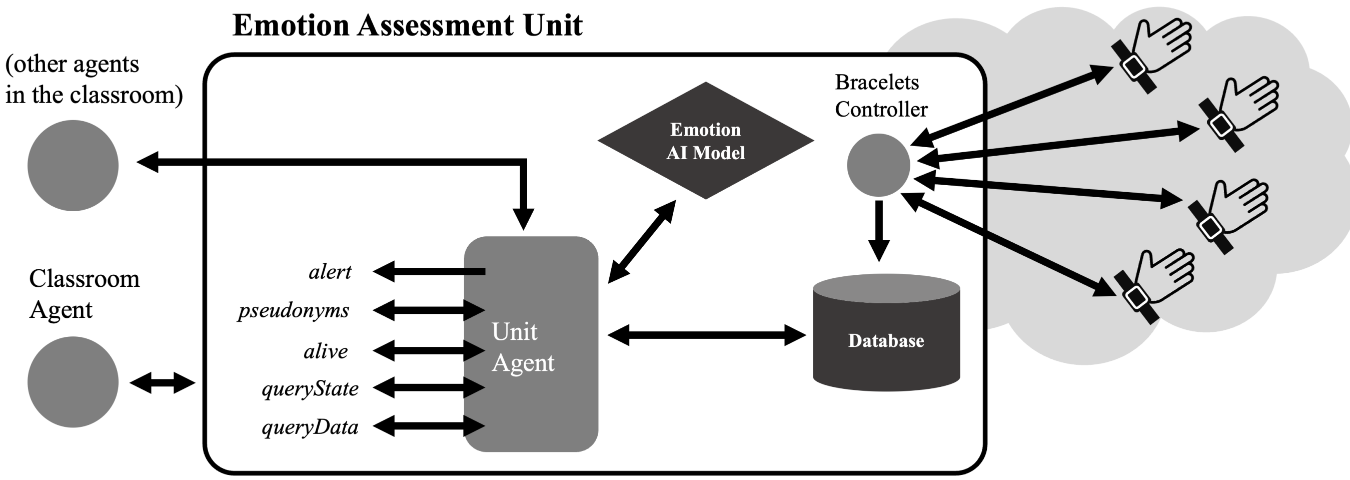

Figure 1. High-level diagram of the proposed Emotion Assessment Unit.

proprietary applications to collect and visualise the data. In contrast, open-source devices, such as EmotiBit [13][14], facilitate the wireless, real-time transmission of scientifically validated data from a variety of integrated sensors.

In this paper, we present a first approach to a real-time emotion assessment system for both students and teachers within smart classrooms. Our proposal involves real-time data collection gathered from EmotiBit devices and employs an AI model that might be used for emotion assessment. Additionally, this system is equipped with capabilities to interact with other distributed systems within the smart classroom ecosystem. The remainder of the paper is organised as follows: Section II describes the architecture of our proposal, Section III elaborates on the implementation and testing of the system, Section IV discusses the results and, finally, Section V concludes the article and provides further research lines.

II. Our Proposal

This section describes the design of the Emotion Assessment Unit, aiming to identify, track, and respond to the emotional states of the classroom population. The unit collects data from bracelets, which are then processed by an AI model. Moreover, the unit responds to request from the Classroom Agent, which can ultimately inform teachers in a timely manner. The architecture of our proposal is illustrated in Figure 1.

A. Components

Our system comprises the following components:

- **Bracelets Controller:** Responsible for interacting with all the bracelet devices within the smart classroom through a specific communication protocol.
- **Database:** Responsible for storing the data collected from the bracelet devices.
- **Emotion AI model:** This subsystem assesses the emotional states of the classroom population based on specific data, including physiological parameters, such as EDA, HR, and SKT, but also contextual data, such as ambient noise and air temperature, obtained from other agents in the smart classroom. In this first approach, this component only addresses the variability of physiological parameters that indicate emotional changes.
- **Unit Agent:** Core component of the unit consisting of a software agent that interacts with the other components in the unit and with other agents in the smart classroom. It takes decisions about the emotional states of students and teachers, and responds to request from the Classroom Agent.

For the sake of brevity, we only focus on the Classroom Agent, which is considered the central component of the smart classroom. Other agents, responsible for monitoring other aspects of the smart classroom, such as the air quality or the noise, are also integral to this ecosystem but are not discussed.

B. Functionalities

Functionalities are categorised into three groups: (i) bracelet operational functionalities, (ii) Classroom Agent coordination functionalities, and (iii) management functionalities.

The first group, managed by the Bracelets Controller, ensures the proper management of wearables in the smart classroom:

- **Bracelets discovery:** Detection of all bracelet devices in the smart classroom network, *i.e.,* identifying each device's IP/MAC address.
- **Bracelet assignment:** Temporal assignment of each bracelet device to its wearer.
- **Start/Stop monitoring:** After assignment, the Bracelets Controller starts collecting data from the devices and stores them in the database until the functionality is deactivated.

The second group includes actions performed by the Unit Agent upon requests from the Classroom Agent:

- **alive:** Verifies whether the Emotion Assessment Unit is up and running.
- **pseudonyms(*pseudonyms*):** To protect individuals' privacy, the system uses pseudonyms instead of real identi-

fiers. This function updates the pseudonym list whenever the Classroom Agent generates a new set.

- **queryState(*pseudonyms*):** As the Classroom Agent may request the emotional states of students and teachers specified in the *pseudonyms* list, the Unit Agent retrieves the latest data from the database, sends them to the Emotion AI model, and returns the resulting emotional state assessments.
- **queryData(*tsInitial, tsFinal*):** As the Classroom Agent may retrieve data for further analysis, the Unit Agent queries the database to retrieve information stored between the specified timestamps.

The third group comprises proactive functionalities conducted by the Unit Agent to manage the system effectively:

- **Emotion update:** Periodical assessment of the emotional states of the smart classroom population using the AI model with the latest data stored in the database. Upon detecting significant changes (*e.g.,* increased number of stressed students), the Classroom Agent is alerted.
- **Battery alert:** Regular checking of the battery levels of the bracelet devices, alerting the Classroom Agent of low battery levels.
- **Database reduction:** To maintain optimal database performance, a maximum number of records in the database is limited. If it is exceeded, the oldest records are deleted. Note that the queryData functionality can be used if the Classroom Agent intends to store raw data values.

C. Emotion AI Model

In this first approach, our model processes an array of data representing a succession of physiological values for a specific parameter within a *t*-seconds timeframe (where *t* is a parameter). The model analyses these values to identify distinct patterns: *peaks* (characterised by a sudden increase followed by a decrease within a short period), *valleys* (a sudden decrease followed by an increase within a short period), *increases* (a steady rise over time), *decreases* (a steady decline over time), and *constant behaviour* (a stable state with no significant variations). Consequently, the model returns a 5-item array, each of them representing the significance of these patterns occurring in the input array.

III. Development

This section elaborates on the development of a prototype of the proposed system to evaluate its feasibility in real-world classrooms.

A. Sensors

In our implementation, EmotiBit bracelets were employed for data collection (see Figure 2). These devices provide real-time physiological data, including EDA, HR, HRV, SKT, and oxygen saturation, among others, which have been scientifically validated [15]. Each EmotiBit is equipped with a battery and wireless connectivity capabilities. To manage the collected data effectively, a dedicated tool called Oscilloscope is provided to identify all EmotiBits within a network and select a specific device for data capture. Once selected, the Oscilloscope begins capturing the transmitted data in real-time and displays them graphically [16]. Unfortunately, since the Oscilloscope can only capture data from a single device at a time, and our goal is to process data from multiple devices, we opted to develop a software that emulates the Oscilloscope functionality, *i.e.,* the Bracelets Controller. This required analysing the open-source documentation and using Wireshark to understand the communication protocol between the EmotiBits and the Oscilloscope. Specifically, the EmotiBit ecosystem operates on three different network channels through Transmission Control Protocol (TCP) and User Datagram Protocol (UDP):

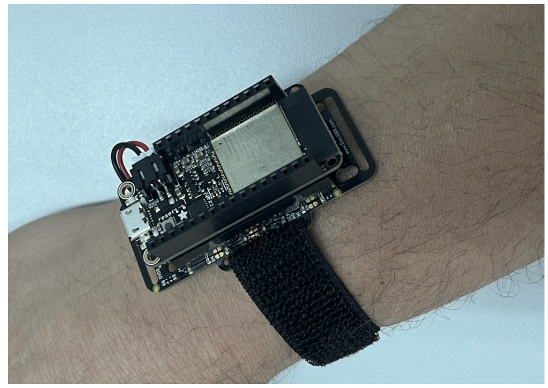

Figure 2. An EmotiBit sensor placed as a wearable bracelet.

- **Advertising channel (via UDP):** This channel is used for device discovery through the so-called *Discovery Protocol*. In a nutshell, the Bracelets Controller broadcasts a ‘Hello EmotiBit’ message across the network and awaits ‘Hello Host’ responses from the devices. These responses contain a unique EmotiBit identifier for each device.
- **Data channel (via UDP):** This channel facilitates the transfer of data from the EmotiBit to the Bracelets Controller.
- **Control channel (via TCP):** This channel manages various operational aspects of the EmotiBit, such as initiating and terminating data exchange. To initiate data collection, the Bracelets Controller sends an ‘EmotiBit Connect’ message to each of the detected devices to specify the ports used for data collection.

The data messages sent by the EmotiBit contain the timestamp, the packet number, and the number of data points encapsulated in the payload. Indeed, each packet can contain up to sixteen different variables. Data acquisition occurs at different times depending on the variable: for instance, the sampling frequency is 15 Hz for EDA and 7.5 Hz for SKT [15]. Finally, the packets also contain the version and a reliability tag reserved for future updates.

B. Emotion Assessment Unit

All components of the Emotion Assessment Unit, namely the Bracelets Controller, the Unit Agent, the database, and the Emotion AI model, run on a Raspberry Pi 4 Model B

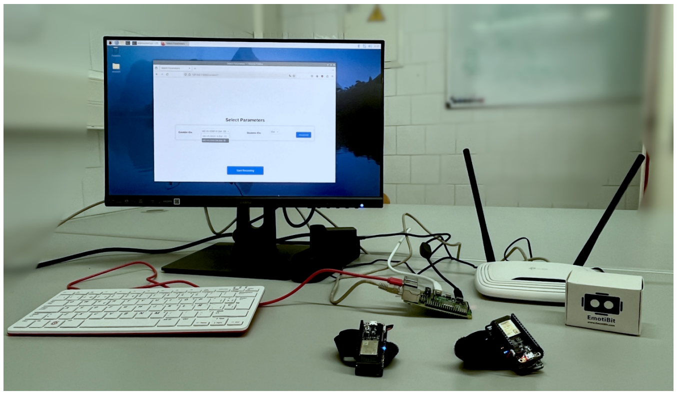

Figure 3. Prototype implementation of the solution with the Raspberry Pi, two EmotiBit bracelets, an access point, and the front-end web application.

board. The EmotiBits and the Emotion Assessment Unit are connected to the same network using a wireless LAN (WLAN) enabled by an access point. Hence, the Raspberry Pi board and each EmotiBit obtain their IP addresses via classical Dynamic Host Configuration Protocol (DHCP). Once connected, the Bracelets Controller can then initiate the Discovery Protocol to the broadcast address of the WLAN and awaits responses from the devices to launch the complete system. A picture of the prototype implementation is shown in Figure 3.

The Unit Agent, the Emotion AI Model, and the Bracelets Controller are implemented in Python. The latter uses lightweight process to handle unicast connections with each EmotiBit. Data are stored in an SQLite database to maintain a lightweight structure. All bracelet operational functionalities, explained in Section II-B, are managed using a local web front-end implemented in Flask, a Python web application framework. It is worth noting that, in a real smart classroom scenario, these functionalities would be managed through a front-end agent of the smart classroom. Similarly, the Classroom Agent's requests are handled via web services implemented with Flask. For instance, the list of pseudonyms is received through the *pseudonyms* function, and the association between EmotiBit identifiers and pseudonyms is stored in the database to ensure traceability.

Regarding data collection, the Bracelets Controller stores only the values for EDA, HR, and SKT in the database. Each value is stored as a new record in the database. Table I provides an example of data received in two consecutive packets: the first packet contained several data points, from which the Bracelets Controller retained EDA and HR, resulting in the insertion of two new records into the database, and the second packet contained a single data point on SKT, leading to the insertion of one new record.

C. Testing

Overall, the emotion assessment system works smoothly based on tests conducted in the laboratory with four EmotiBits simultaneously. Data are transmitted at the specific frequencies programmed in the sensors' firmware. The Bracelets Controller filters out values not related to emotions, and relevant records are inserted into the database. Moreover, when the Classroom Agent requests data, the web service processes these requests and retrieves the required information from the database without any performance issues. This agent also receives responses from the Emotion AI model with no noticeable delay for queries performed at a rate of one per minute.

Regarding database size, we observed that collecting all 16 values transmitted by a single EmotiBit per hour results in approximately 25 MB of data. If only EDA, HR, and SKT are stored, the storage requirement decreases significantly to approximately 4 MB per hour. Considering the application of EmotiBits in a typical primary school in Catalonia, where the average student-to-teacher ratio is 20 students per class [17] and each student wears an EmotiBit device for 5 hours per day, the storage requirement for the entire class is around 2 GB per week. Given the vast amount of data, the database reduction functionality described in Section II-B is crucial for maintaining the efficiency and performance of the database. However, having real-time processing in mind, this operation should be requested by the Unit Agent when no data are being collected from the devices, for instance, post-lecture.

Regarding battery life, the EmotiBit device offers two operational modes that significantly impact its duration: (i) a normal mode, where the device operates at full capacity, using all its sensors and transmitting data wirelessly in real-time, and (ii) a low-power mode with no transmission but storage on an SD card. Hence, only the normal battery fits our requirements. Battery performance measurements were repeated three times to ensure reliability and consistency. In normal mode, the device's battery lasts approximately 3.25 hours, which can be impractical for a typical school day. In low-power mode, the battery life extends up to 9 hours.

IV. Discussion

The implementation and testing of the proposed system works adequately in laboratory settings from a technological perspective. However, to fully deploy this solution in a real-world classroom, several aspects should be considered.

A. Computational Capabilities

The current prototype considers four EmotiBit devices, but real-world classroom deployments would necessitate a greater number. This demands managing and processing more data, so requiring increased computational capabilities. Currently, the system operates on a Raspberry Pi, which despite being a cost-effective computer, is constrained by limited resources. To address the demand for increased computational power, the Raspberry Pi could be seamlessly replaced by an Intel NUC,

TABLE I. Sample of data stored in the database.

Timestamp	EmotiBit_Identifier	Data_Type	Value
2024-06-23 18:15:09	MD-V5-000014	EDA	0.030191
2024-06-23 18:15:09	MD-V5-000014	HR	72
2024-06-23 18:15:10	MD-V5-000014	SKT	36.232

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a more powerful computer with a small form factor that could be integrated into a smart classroom.

B. Data Volume

The amount of data stored can grow rapidly unless adopting adequate implementation and maintenance processes. Two optimisations could be applied to reduce the data volume. First, it may not be necessary to insert a new record into the SQLite database for every data packet received by the Bracelets Controller. Instead, a more efficient approach could involve inserting new data entries only after a defined time interval has elapsed since the last insertion. Notwithstanding, the implementation of this enhancement is not trivial, as it must go in hand with the data requirements of the Emotion AI model. And second, data storage could be further optimised by adopting binary format storage. For instance, values like HR could be stored in one byte each, rather than allocating one byte per digit.

C. Battery Duration

Battery life is a significant concern when deploying our proposal in real-world classrooms. To address this issue, given the open-source nature of the EmotiBit platform, a viable strategy involves re-configuring the device's firmware to lower the sampling rate or deactivate sensors that are not essential to our objectives. This would effectively reduce the frequency of data transmission packets, thereby extending battery longevity.

D. Data Security

When analysing the network traffic between the EmotiBits and the Oscilloscope, it became evident that the payload of the packets is transmitted without any encryption. Hence, anyone (legitimate or intruder) within the WLAN could potentially access and analyse the transmitted data. More critically, device authentication is not considered. Hence, a malicious intruder could impersonate a fake EmotiBit simply by responding to the 'Hello EmotiBit' message during the Discovery Protocol, and generating data packets with fake values. Overall, there is significant room for improvement in this area to make the system robust against unauthorised access and potential data tampering [18].

E. Emotion AI Model

Assessing emotions and stress involves interpreting complex physiological and psychological signals. Besides the use of non-invasive devices like bracelets, electroencephalography and electrocardiograms can provide valuable data but they require invasive equipment. Moreover, audio analysis can contribute to emotion detection but it might require using individual microphones. In both cases, specialised equipment that is not practical for classroom environments is needed [19]. Although facial recognition could enhance the accuracy of emotion detection, several privacy and ethical concerns arise.

In our first approach to emotion assessment, we have addressed the detection of changes in physiological signals considering the most significant findings from the literature:

- An increase in EDA is related to positive valence and higher arousal and, hence, could be used as a preliminary indicator that students are receptive to learning [11].
- An increase in HR is related to momentary stress, which is an interesting state to monitor in both students and teachers [20][21].
- A decrease in SKT is related to higher arousal. Warmer SKT are hence associated to calm states [22][23].

In our prototype implementation, we have chosen to develop an AI model based on simple heuristics and algorithms. However, since the assessment of emotions is a complex issue, a more sophisticated AI model based on Machine Learning (ML) should be considered in the future. In addition to considering merely physiological parameters, our AI model is expected to also take contextual information into account (such as temperature, humidity, air quality, and noise level) and, to a certain extent, obtain complementary information from video sources.

Notwithstanding, in order to train the ML model, we need a dataset that relates our target predictions (*e.g.,* stress, valence, arousal) to a combination of values of EDA, SKT, air quality, noise level, time of the day, and type of learning activity performed, among others. We searched for databases on emotions that could be used to train a ML model. Despite the availability of databases [24]–[30], they include information from adult subjects (collected in controlled environments not related to learning) and, hence, their suitability to our purposes should be further studied.

V. Conclusion and Future Work

Smart classrooms promote positive learning environments to enhance educational experiences. In this context, students' moods and emotions play a key role to achieve improved academic performance and information retention. In this paper, we have proposed an emotion assessment system able to collect and analyse emotions in real-time across the classroom population. The system builds upon wearable technology in the form of bracelets for physiological data collection, as well as AI models for emotion assessment. Our system, which can be seamlessly integrated into smart classrooms, works autonomously with minimal user intervention. The feasibility of our system has been successfully validated in laboratory settings, and its deployment in real-world classrooms will processed once the identified challenges are addressed.

Future research in this area will concentrate on assessing our proposal in real-world settings using, at least, 20 EmotiBit devices to evaluate the Raspberry Pi's performance. Moreover, EmotiBit devices should be re-programmed to (i) incorporate a data security layer ensuring data confidentiality, integrity, and authentication, and (ii) optimise its firmware to increase battery life. Last but not least, the Emotion AI model should be further refined with comprehensive training datasets. Ideally, this model should be trained using data from different sources, namely physiological data (obtained from the bracelets), video footage (obtained from AI-equipped cameras) and contextual data (air quality, noise level. . .).

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