Affect-Learn: An IoT-based Affective Learning Framework for Special Education

Ghazal Yadav Researcher Frisco, Texas, USA. Email: ghazalsuhani@gmail.com Prabha Sundaravadivel
Dept. of Electrical Engineering
The University of Texas at Tyler, USA.
Email: psundaravadivel@uttyler.edu

Lokeshwar Kesavan Independent Researcher Dallas, Texas, USA.

Email: lokeshwarkesavan@gmail.com

Abstract—A learning disorder is associated with the ability of the child to process the information effectively. The purpose of special education is to provide equal access to education for all children to help them succeed in the regular curriculum through specialized services. Children with anxiety, hyperactive, or attention-deficit disorders require special assistance to help them stay at their normal level and thus effectively suit in a classroom setting. With the advancement in technology, the landscape of special education is rapidly changing. The motivation for this research is to develop an Internet of Things-based affective computing framework, Affect-learn, that can help teachers in identifying the hyperactivity or inattentiveness in children, and help them improve the overall learning outcomes. The proposed research is validated with the help of commercially available off the shelf components. The measure of success in this research is the response time of the proposed framework and the efficiency of emotion elicitation.

Index terms— Internet of Medical Things (IoMT), Affective computing, Smart Education, Smart healthcare, Internet of Things (IoT) Immersive environment, Virtual Reality

I. INTRODUCTION

During early childhood days, a child witnesses several rapid changes in their cognitive, social, emotional, and language development in addition to the physical changes. These advancements can be characterized and analyzed by their ability to learn new languages, communicate with coherent sentences, hand-eye coordination, responding to parents and caregivers. Researchers and Psychologists have set definitive milestones that can help in analyzing the growth and development of children in these significant years.

In these early years of childhood, some children have difficulty staying focused or attentive in a closed classroom setting, which leads to hyperactivity in the person. This kind of disproportionality in the mood of the person can lead to Attention Deficit Hyperactivity Disorder (ADHD). Though ADHD is not classified as a learning disability, it can make learning extremely challenging. As per the reports of the Learning Disabilities Association of America (LDA), approximately 2 million children in the United States are affected by this disorder. The primary characteristics of ADHD are hyperactivity, inattention, and impulsivity. There are other kinds of disorders such as conduct disorder, anxiety disorder, depression, and bipolar disorder that can accompany ADHD at times.

This research focusses on applying technology to help and

improve the learning outcomes of students with ADHD. Artificial Intelligence (AI) helps in designing machines that have cognitive abilities. AI-based applications have been used in several consumer platforms for decades. Affective computing, known as artificial emotional intelligence that can help the frameworks to recognize, interpret, and stimulate human emotions [1]. The computing effort in these frameworks involves recognizing an emotion with the help of intelligent frameworks and eliciting the emotion to bring it back to the normal baseline as recorded by the user [2]. Hence, affective computing based frameworks can help in closing the loop of monitoring frameworks by providing affective feedback. A network of interconnected devices, known as the Internet of Things (IoT), helps in storing the processed information in the cloud instead of the device. This helps in developing cost-efficient, portable devices that can be used at ease by the consumer [3], [4]. In order to develop a smart framework for special education, we propose a novel IoT-based affective framework. Affectlearn, that can help Educators and Parents to monitor hyperactivity in children and provide customized learning approaches to improve their overall learning outcomes. The thematic picture of the proposed framework is given in figure 1. The proposed framework utilizes the frontiers of advanced research fields such as affective computing and IoT, to develop a framework which can help in stimulating certain human emotion based on the features obtained using heart rate changes, activity data, along with the ambient data such as temperature, and humidity.

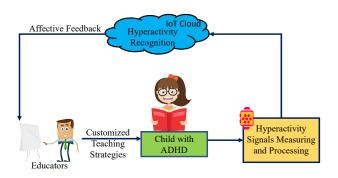


Fig. 1. Thematic Picture of the proposed Affect-learn system

This paper is organized as follows: The novel contributions of the proposed Affect-learn framework is described in Section II. A broader perspective of the proposed Affect-learn framework is presented in III. Some literature on existing research work on modeling IoT-based special education systems and applications of affective computing is discussed in Section IV. An overview of the system-level modeling of the proposed framework is given in V. The implementation of the designed blocks along with simulation results are discussed in VI.

II. NOVEL CONTRIBUTION

In an affective computing system, the system helps in recognizing the target emotion based on features obtained from the sensors and actuators in the wearables and helps in maintaining the person's normal emotional baseline through feedback systems. As this research focuses on detecting emotions in a person, in a classroom setting, the following are the main contributions of this research:

- A novel hyperactivity and anxiety emotion recognition model based on multi-class features has been proposed.
- Validation of the proposed hyperactivity emotion recognition algorithm is done with the help of a custom-built framework based on an accelerated single board computer.
- A novel affective feedback system with strategies to improve the overall student learning outcomes has been proposed.
- A novel customized feedback system to help students be aware of the learning environment and engage in the classroom setting has been proposed.

III. AFFECT-LEARN FOR SMART EDUCATION: A BROAD PERSPECTIVE

The level of inattentiveness and hyperactivity in children diagnosed with ADHD can vary amongst each other and, to a great extent, from non-ADHD children of the same age group. Based on the pattern of behavior in such children, there can be three main classifications of ADHD: the hyperactive type where the child is physically hyperactive, the inattentive type where the child has difficulty in paying attention or concentrating on something, and the combined type where the child is hyperactive and inattentive [5].

The underlying disorder of any mental health is the disproportionate levels of emotion, which leads to a certain mental health disorder [6]. Every person responds to events in their way, which can particularly be a trigger that can range from a piece of disturbing news to repetitive noise or events. The way the person responds to the same is their trait, whereas the particular emotional state is their state anxiety. Helping students understand their disproportionality in perceiving a particular emotion can further help them be conscious of their surroundings. The goal of this research is to develop the proposed Affect-learn framework to monitor the hyperactivity of a student in accordance with the ambient values. Additionally, Affect-learn helps students to be aware of their state and trait anxiety by providing them appropriate

feedback as required. Figure 2 shows an overview of the proposed approach in the Affect-learn framework.

In the proposed Affect-learn framework, hyperactivity recognition is implemented by monitoring the heart rate, and daily activity, with respect to the ambient temperature and humidity sensing. Through this IoT-based framework, an affective feedback is given to the educator which helps them understand the emotional state of the student and helps them devise a customized teaching plan for students in need. Additionally, the student and parents are given feedback that can help them in achieving their learning objectives. By monitoring these features the vision for the proposed system is to find a correlation between state and trait anxiety through IoT-based framework with respect to a person's ambiance.

IV. RELATED PRIOR RESEARCH

One of the research dimensions in ADHD is to use advanced machine learning and deep learning algorithms to identify the abnormalities in datasets such as ADHD-200, fMRI and so on. A combination of deep belief network and Bayesian classifier for structured learning is given in [7]. Kuang et al. [8] have developed a deep-learning model to classify the fMRI data into control, combined, inattentive or hyperactive classes. Eloyan et al. [9] used the decomposition method to build a deep network for classifying ADHD. Mobile health and the Internet of Medical Things are significant subsets of e-health which helps in monitoring our health daily [10], [11]. Pandria et al. [12] have advocated their mobile application WHAAM as an assistive application for ADHD. In their review, they have discussed 6 other existing mobile health technologies that are available for assisting students with ADHD [13]. A self-assessment tool for ADHD has been proposed in [14].

Affective computing platforms are built by analyzing various parameters for emotion recognition and stimulating the human emotions in different emotion elicitation methodologies. Research in emotion recognition part of the affective computing framework has been mainly focussed on visual, speech, gestures and pupil dilation [15], [16], [17]. Traditionally the emotion elicitation strategies are either passive methods or fully immersive methods such as virtual reality headsets [18], [19]. Researchers have also used affective computing to treat specific disorders [20], [21]. Similarly, IoT-based frameworks have been developed as application-specific architectures for various applications ranging from activity monitoring [22], [23] to monitoring women's health [24], [25].

V. SYSTEM LEVEL MODELING OF AFFECT-LEARN

A. Features for monitoring human affects

The key features for emotion recognition in the proposed framework are heart rate variability and activity data variability. The activity data is tracked with the help of the

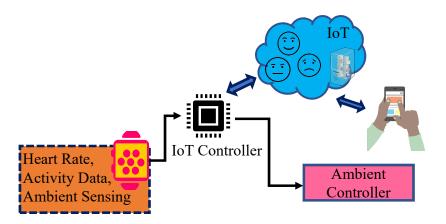


Fig. 2. Overview of the proposed Affect-learn framework

accelerometer sensor that helps in analyzing the position and velocity of the object with respect to the 3 axis namely X, Y and Z-axis, with respect to gravity. The three main variations from accelerometer namely roll, pitch, and yaw helps in monitoring the walking and jogging motions. For the Affect-learn framework, we analyze the activity variability that is how fast the values along X, Y and Z axis change in a given period, which can help in monitoring the hyperactivity. The heart rate sensor helps in tracking the heart rate variability which can be used for tracking how fast the heart rate increases or decreases in a given period. Both the heart rate variability and activity variability helps in analyzing the hyperactivity.

Additionally, the ambient temperature and humidity values are recorded as features for monitoring human affects, to track a pattern of hyperactivity relative to the ambiance. Table I lists the features used for detecting hyperactivity.

TABLE I
FEATURE PROTOCOL FOR DETECTING HYPERACTIVITY IN
AFFECT-LEARN FRAMEWORK

Number	Type of Features
Biosginal Features	
1	Trigger Activity (Accelerometer data)
2	Lifestyle Activity (Accelerometer data)
3	Heart rate variability
Ambient Features	
4	Temperature values
5	Humidity values

B. Proposed Valence-Arousal model for Affect-learn

The valence and arousal graph helps us in analyzing the type of emotions related to particular arousal in a two-dimensional graph. It helps us in interpreting how certain arousal can lead to a negative emotion or a positive emotion in a continuous dimension. Figure 3 shows the valence-arousal graph that was deployed for the Affect-learn framework. Valence is mostly a state of mind, whereas arousal is the measure of the level of excitement caused by the particular emotion. Hence a person will have the same level of arousal when they are in tension, or they are being alerted. However, depending upon the type of

emotion, this arousal can be regarded as "High arousal Positive Affect" or "High arousal Negative Affect." For the proposed Affect-learn framework, any emotion related to high-arousal was taken into account as the primary focus is to monitor hyperactivity.

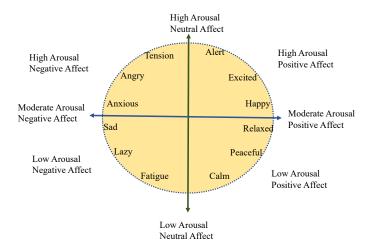


Fig. 3. Proposed Valence-Arousal model for Affect-learn framework

C. Proposed Affect-learn Pattern Recognition methodology

The features obtained with help of the Affect-learn wearable are used to develop a pattern which helps in finding the hyperactivity of the student related to time and ambience. Support Vector machine-based models have proven to provide clear margin of seperation between different classes of data. The hyperplane which is used to find this margin of seperation can be represented by the following equation:

$$f(\mathbf{x}) = \mathbf{x}^T \mathbf{w} + b = \sum_{i=1}^n x_i w_i + b = 0$$

Where w represents the set of weights, one for each feature, X represents the set of (input, output) sample features, and b represents the bias parameter. In the Affect-learn framework,

the main classes to be considered here are "hyperactive," "normal," and "controlled."

D. Proposed Emotion Elicitation Methodology in Affect-learn system

Once the Affect-learn emotion detection framework recognizes the high-arousal emotions, it is important to suggest different teaching strategies and methods to the Educator and help the student and parent to analyze a pattern in their behavior. Hence the affective feedback is two-fold in the proposed framework. As part of stimulating human emotions in the Affect-learn framework, the following strategies are to be explored: an IoT framework for changing the temperature and ambiance where the user lives and exploring the semi-immersive environment to change the emotion of the person. This emotion elicitation is achieved by using audio feedback and displaying pictures which were recorded to create a positive affect database.

VI. IMPLEMENTATION AND VALIDATION OF AFFECT-LEARN

The proposed Affect-learn system is modeled with the help of off-the shelf components and accelerated single-board computer. The validation of the proposed framework was analyzed based on its ability to trigger emotion elicitation methodology based on the detected values.

A. Affect-learn Emotion Recognition

1) Affect-learn Sensing Framework Implementation: The proposed wearable for monitoring the heart rate, activity, and ambient sensing was implemented with the help of off-the-shelf components. The proposed wearable was built using MAX030102 heart rate sensor, DHT11 temperature and humidity sensor for measuring the ambient temperature and humidity, and LIS3dh accelerometer, which were integrated to Wi-Fi enabled Arduino Nano ESP32. Figure 4 shows the prototype of the custom-built wearable for Affect-learn framework. This wearable was able to transmit the acquired sensor values to the IoT cloud through the accelerated singleboard computer setup, i.e. Raspberry-Pi integrated with Intel Movidius Neural Computing Stick. The proposed wearable was used to monitor the daily activity data and trigger data for hyperactivity detection. The wearable was designed to be a cost-effective one that can operate in low-power. The operating voltage of the wearable was 3.3 Voltage and it was powered ON with a battery management system for 8 hours. Figure 5 shows a short series of the raw output data obtained from the proposed wearable.

B. Validation of the proposed Affect-learn framework

1) User Input Protocol: The primary aim of the proposed Affect-learn system is to detect biosignals for differentiating state anxiety and trait anxiety. To validate the proposed framework, users were asked to record their current emotion



Fig. 4. Custom-built Prototype of the proposed Affect-learn Framework

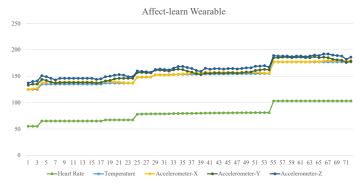


Fig. 5. Raw output data from the proposed Affect-learn sensing framework

whenever there was a change in temperature or activity. Additionally, the users were requested to list 3 favorite images such as dogs, flowers or cats, and 3 favorite songs.

2) Experimental Setup: An analysis for about 30 minutes was performed with the wearable ON and the camera recording 3 volunteers. The temperature was varied in moderation, to check the high arousal negative effect that can be regarded as anxiety triggered by the ambiance. Based on this experimental setup, the data collected showed that there was a direct correlation in the eye-event and temperature variation i.e. when the ambient temperature was higher, there were many blink movements detected. The user's experience validated this as "moderately anxious". The corresponding set of values were grouped under the label "moderately anxious" and "trait anxiety". An SVM network was built using this information, and it was presented to the user through a user interface. A correlation between the user's input and the SVM network results yielded an accuracy of 90.23%.

After this, the user's favorite image was displayed through the accelerated computer setup and a song was being played. The average time required to elicit the emotion was about 3-4 minutes.

VII. CONCLUSIONS AND FUTURE RESEARCH

The proposed research aims in developing an affective computing framework for anxiety disorders using wearable computing. A proof-of-concept of the proposed research was designed with the help of off-the shelf components and a validation of the same was done with the help of user inputs and data gathered from the system. A correlation between the user input and automatic detection yielded an overall accuracy of 90%. Future research involves analyzing alternative methods for eye event detection such as electrooculogram and developing portable semi-immersive environments. Additionally, the outcomes of the experiment will be made available as public datasets in platforms such as Physionet.

VIII. ACKNOWLEDGEMENT

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