Volume 1, Issue 1
September/October 2021

IEEE Bio-inspired Computing STC Newsletter Volume 1, Issue 1

Technical Articles

- Parker Wilmoth, Prosenjit Ghosh, Damien Stephens, and Prabha Sundaravadivel, "*Towards Bio-inspired Edge Intelligent Wearables*"
- Mojtaba Taherisadr, Berken Utku Demirel, Mohammed Al Faruque, and Salma Elmalaki, "*Future of Smart Classroom in the Era of Wearable Neurotechnology*"

Technical Activities

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Volume 1, Issue 1
September/October 2021

Bio-inspired Computing in Edge Intelligent Wearables

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***Abstract* –** In an era of Internet of Things (IoT) based monitoring devices integrated as part of multiple applications in day-to-day life, it is essential to have intelligent sensing nodes, networks, algorithms, and infrastructures, that are robust and resilient. The emergence of bio-inspired computing and bio-inspired algorithms has become the area of significant research in the past few decades due to their potential to solve problems introduced with traditional systems design and data analytic techniques. This article is a technical review on the current trends of bio-inspired computing in designing IoT-based wearables and robots, as well as their significance in data analytics. In this article, we present an edge-intelligent emotion monitoring wearable that integrates bio-inspired algorithms for real-time anxiety monitoring. The proposed edge-intelligent wearable combines bio-inspired techniques to monitor human emotions in real-time.

CURRENT TRENDS IN BIO-INSPIRED COMPUTING:

Bio-inspired Wearables:

Often the best solutions to problems already exist hidden in nature, especially when it comes to devices made to monitor or emulate biological processes in humans. Bio-inspired wearable devices look to our biology to find the best way to solve a problem. This way of problem-solving has been around forever, but with advancements in technology in recent years, it's applications have significantly increased. One example of this trend is with devices used to measure heart rate. Most wearable heart rate monitors use photoplethysmography (PPG), which is the measurement of the reflection of infrared light off blood cells as it moves through veins [1]. However, these devices for measuring heart rate have been found to be unreliable and inaccurate [2]. Taking a bio-inspired approach, researchers decided to measure heart rate in a different way [3]. They built their device based on how humans check their pulse by applying pressure to the skin over a vein and counting the palpitations using their finger. By using a solution based on the properties of a human finger, which is known for being accurate, researchers were able to create a much more reliable solution than the preexisting arterial pulse waveform measurement. Another way that bio-inspired wearables are evolving is how they conform to the user's body. By studying the surface of human skin, wearables that come in contact with the skin's surface have been engineered to be easily applied and removed multiple times without causing discomfort [4]. Using this new technology, devices such as Holter monitors can be reduced in size and won't cause severe itching as generic adhesives do over time. Wearable devices can perform tasks other than simply recording biometrics. For instance, researchers can artificially recreate the sensation of touch using a wearable device by studying how a nerve functions. Sensors on the skin detect pressure from touch and send signals to the nerve endings to simulate the sensation of a touch. The functionality of a damaged nerve can be restored using this wearable tactile sensor which stimulates neuroreceptors [5]. These can be used for people with third-degree burns where nerve function was lost. Researchers arrived at this elegant solution by basing their device on how a natural nerve functions, rather than trying to make it up from scratch. As we continue to create new and improved wearables, we find ourselves constantly looking back at the way nature does things.

Bio-inspired Robots:

With the development of modern control and technology, robots have been used for versatile fields where high accuracy, combinability and stability is required. Many researches are focusing on how to make an alignment between machine and human that makes a neoteric machine class. Soft robots make this possible by connecting the technological gaps among humans [6]. Soft robots show promise for multiple applications, including wearable systems [7] and surgical devices. For instance, a fabricated humanoid robotic arm driven by cables can function and perform on par with the human muscles. Bio-inspired robotics is moving forward due to its structures with sensory-motor coordination, in which learning often plays a pivotal role in gaining multi-adaptation. A bio-inspired soft robotic device is designed using soft sensors and actuators for ankle-foot rehabilitation. It has demonstrated the capability for feedback control of ankle joint angle using an identified LTI model of the system and optimized walking motion using a precise whole-body dynamic model [8].

Meanwhile, a lot of research has been to investigate the application of Bio-inspired robots such as in the field of industries, medical technology, animal and species, and human rehabilitation [9]. The observance of Bio-inspired robotics is attractive predominantly due to it’s flexibility and versatility. The system architecture precisely takes part in the surroundings making it safe, comfortable and easy to use. Wearable robotic devices made from soft compliant materials gained momentum in both the academic and commercial settings over the past decade [10]. At present, wearable soft robot are being designed for stroke survivors which can assist the patients during exercise and help restore their range of movement [11]. Another proposed soft robotic device perfectly aligns with the user’s joints or the object with which a connection needs to be created [12]. Bio-inspired robots are usually fabricated using soft materials which are very flexible, deformable and can deftly mimic the biological systems.

Bio-inspired Data-Analytics:

With an increasing trend in the volume of data being collected, transmitted, stored, and processed, it is more important than ever to introduce new and improved algorithms that meet the modern big data analysis demands, particularly in IoT applications, where system performance is highly important. A variety of systems have grown to volumes in excess of 500 MB/second [13]and in order to address this, researchers have been introducing new algorithms and technologies for big data analytics. One such solution is the introduction of an alternative paradigm with a focus on bio-inspired algorithms for big data analytics [14]. New bio-inspired efficient approaches to clustering and transmitting data in wireless sensing networks have been introduced, which optimizes system performance and energy efficiency [15]. Such an approach has been applied to both relatively small-scale networks such as the agriculture industry, and to large scale projects including smart cities. Newly realized bio-inspired machine learning techniques have been growing in popularity due to their ability to improve big data analysis speed. These models have proven effective at reducing ML algorithm training time significantly while maintaining prediction accuracy [16]. The field of bio-inspired data analytics has seen significant prevalence as of late, but much research is still needed to address key problems in established techniques [17]. With nearly no limit to the fields, bio-inspired data analytic models can be used to detect and protect systems against denial of service (DoS) attacks [18].

Meanwhile, due to the increasingly prevalent importance of cyber security, bio-inspired data analysis models are being explored and tested to remain proactive in the areas of remote monitoring and information security. From relatively simple classification tasks to current research being pursued in hyper-complex cyber security analysis, bio-inspired data analytic techniques are moving forward due to their proven performance and efficiency. There exist several evolutionary algorithms such as the genetic algorithm (GA), genetic programming (GP), differential evolution (DE), evolutionary strategy (ES), and simulated annealing (SA), each with their own techniques, strengths, and limitations. Additional algorithms have been proposed which take a hybrid approach such as the SAFS and FSOSAH techniques. Several of the evolutionary algorithms have shown notable performance in the fields of big data analysis and computer vision. In addition to the proposed evolutionary algorithms, numerous swarm-based algorithms have also been explored. One such evolutionary algorithm is the artificial bee colony (ABC) algorithm, which has been used to identify clusters and perform optimization for different dataset sizes [19]. Ecological algorithms, such as the invasive weed optimization (IWO) algorithm, have been applied to big data optimization tasks in order to resolve multi-objective portfolio optimization tasks. All three bio-inspired algorithm structures: evolutionary, swarm-based, and ecological, have been primarily applied to the five fields of data analytics: predictive analytics, social media analytics, video analytics, audio analytics, and text analytics. Ongoing and future research in the scope of bio-inspired data analytics has been well received and is continuing to address certain challenges such as resource management, elasticity, interconnected clouds, energy efficiency, sustainability, privacy, edge computing, and security.

Bio-inspired Edge-intelligent Wearable:

Edge-intelligence refers to integrating artificial-intelligence (AI) based applications and services at the computing edge of the IoT applications. In short, this means bringing the cloud computing to the "Things" in the IoT network. Though this has the advantage of reducing the data traffic to the cloud, it has some limitations because these devices have specific hardware requirements. The existing edge-intelligent applications are not completely cloud-independent as some amount of data is uploaded in the cloud for deeper learning models. For instance, devices that use voice assistants such as Apple’s Siri, Google assistant and Microsoft's Cortana would not function without network connectivity.

Bio-inspired algorithms have been used for medical data mining for the classification and monitoring of various chronic diseases. Examples of such implementations include lung cancer classification using neural networks and support vector machines (SVM) [20]; implementing fuzzy rules in an evolutionary learning of ant/bee colony for monitoring and managing diabetics [21]; building a heart disease prediction system using Naiive Bayes algorithm [22]. Edge computing largely refers to edge caching, edge training, inference, and edge offloading. Hence the edge-intelligent wearables need to use at least some hybrid techniques that can help in process the data at the end device, instead of just uploading them to the cloud.

In this paper, we propose an edge-intelligent wearable for monitoring anxiety and negative emotions through physiological signals of the user. The proposed custom-built wearable uses an accelerometer and a microphone connected to a microcontroller, which helps monitor the person’s daily activity. The microphone helps in tracking the user interactions and for collecting the user input as required. The data collected through this wearable is uploaded to the cloud where deep learning models perform speech analysis. At the monitoring edge, the activity variability and the interaction variability is analyzed based on the accelerometer and microphone data. Currently this analysis is implemented with the help of local search algorithm with simple if-then fuzzy rules at the edge. Future research includes integrating a personal base station at the sensing edge that can help in building a deep learning model at the edge.

Figure 1 shows the proposed emotion monitoring framework with the edge intelligence. Here the proposed algorithms for emotion monitoring, i.e. the simple if-then constructs, are deployed at the emotion monitoring edge or at the personal base station. The data acquired through these wearables are stored in the cloud for long term valence-arousal analysis, which indicates quantifying the emotion data as a two-dimensional graph. Based on the thresholds obtained, the quantified emotion data is classified

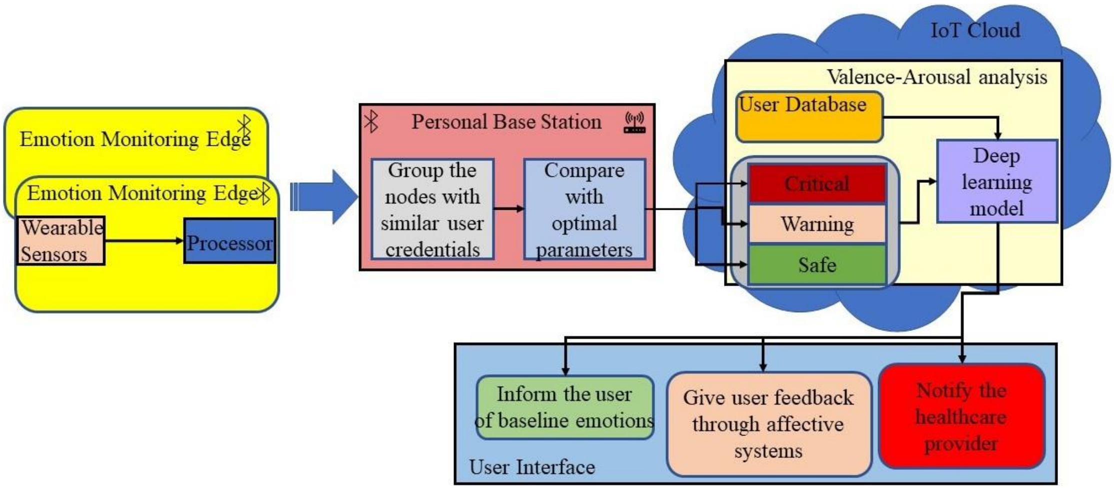

Fig. 1: Overview of the proposed edge-intelligent emotion monitoring wearable.

as "critical", "warning" and "safe" depending on how close the acquired data is to the baseline emotion. With the flexibility to add more sensors to the emotion monitoring edge, the proposed framework can help in designing a scalable real-time emotion monitoring wearable.

CONCLUSION:

Bio-inspired computing takes different learning aspects of living organisms and integrates it into machines as algorithms and hardware. With the help of bio-inspired algorithms, optimal solutions for data driven applications are obtained. In the current IoT era, the bio-inspired computing devices can also help with energy optimization of the sensors, increase the security and privacy of the devices, and help in quantifying the decision-making process through multi-dimensional features and constraints. With the identified advantages, these algorithms have a great potential to improve the real-time edge-intelligent wearables.

ACKNOWLEDGEMENT: This material is based upon work supported by the National Science Foundation under Grant No.OAC-1924117. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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Volume 1, Issue 1
September/October 2021

Future of Smart Classroom in the Era of Wearable Neurotechnology

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Abstract **–** Interdisciplinary research among engineering, computer science, and neuroscience to understand and utilize the human brain signals has resulted in advances and widespread applicability of wearable neurotechnology in adaptive human-in-the-loop smart systems. Considering these advances, we envision future education exploiting the advances in wearable neurotechnology and moving towards more personalized smart classrooms where instructions and interactions are tailored to students' individual strengths and needs. In this paper, we discuss the future of the smart classroom and how advances in neuroscience, machine learning, and embedded systems as key enablers will provide the infrastructure for envisioned smart classrooms and personalized education along with open challenges that are required to be addressed.

INTRODUCTION:

The disruption of face-to-face exchanges and the urgent digital transformation of our everyday life activities, abide the COVID-19 hit, have spurred us to shift many working paradigms to incorporate the new reality of the online and remote collaborative environment. In particular, many sectors, including the education and the healthcare systems, had to integrate new technology to assist the continuation of their services even with remote interactions [1], [2]. Nevertheless, this forced digital transformation of many sectors is expected to stay even in the post-COVID-19 era. In particular, in the education sector, the e-learning market worldwide is forecast to surpass 243 billion U.S. dollars by 2022 [3].

While the education sector has already taken technological leaps over the last decades with the introduction of smart classroom concept [4]–[6], efficient teacher-student interaction has to be envisioned especially with the possibility of remote education. In particular, we envision that the future of education using smart classrooms should move from a *one-size-fits-all* approach to a *personalized* process in which instructions and interactions are tailored to students' individual needs. In this paper, we argue that advances in biosciences, machine learning, and embedded systems can play a significant role in realizing the vision of personalized and smart education.

A cornerstone in the envisioned personalized learning is to replace the traditional measures of education (e.g., quizzes, scores in exams, and teacher evaluations) with real-time measurements of the student's state of mind. Such real-time signals can be then used to adapt the instructed materials to maximize the student's performance. The student's stress level, drowsiness level, readiness to learn new knowledge, cognitive load, and learning rate are just examples of such real-time signals that can be used to adapt the instructed materials to enhance the learning performance. Indeed, there is a tremendous opportunity in attaining this vision. In particular, advances in neuroscience and wearable sensor technology have widened the horizon to reveal the fundamental processes of various human mental states [7], [8]. These advancements resulted in tremendous research efforts among interdisciplinary fields, from engineering researchers, computer scientists, and healthcare (neurologists, clinicians) to integrate the brain state (drowsiness, sleep quality, readiness potential, and learning activity) as an additional sensor modality to design adaptive human-in-the-loop smart systems [9]. Using such advances, we envision the future smart classroom as shown in Figure 1. The future smart classrooms will be extended to include physical and remote students. Students' state will be used to adapt the education system through feedback and personalized recommendation to enhance the student's performance. In what follows, we highlight two scientific and technological advances that are key enablers for the envisioned personalized and smart classrooms, along with open challenges that need to be addressed.

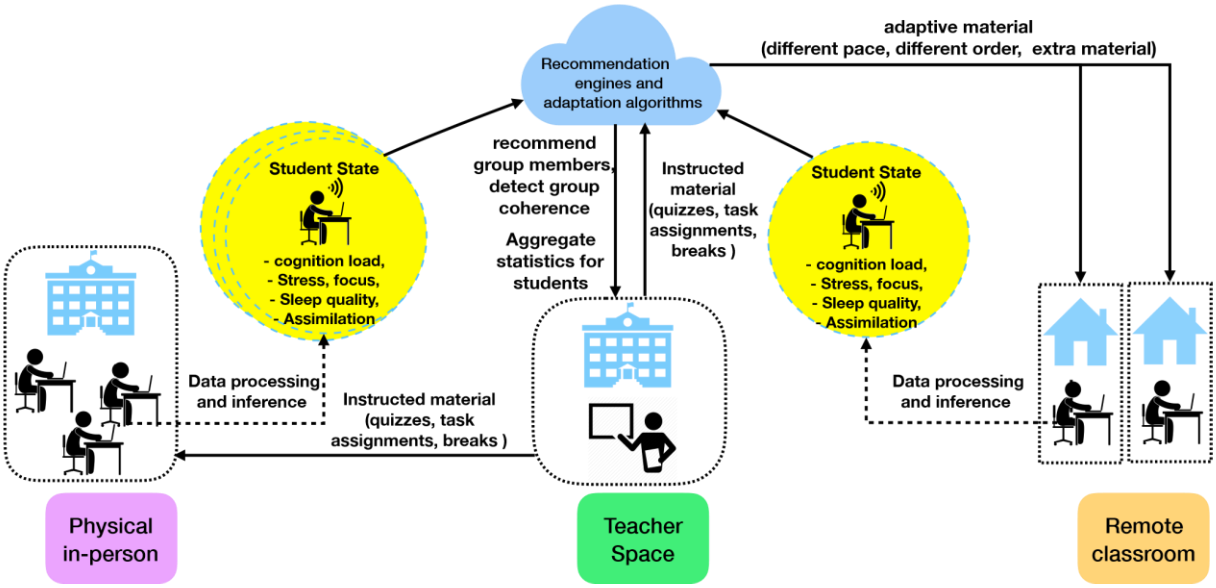

Fig. 1. Future smart classroom in the era of wearable neurotechnology. Student's mental state inferred from wearable sensors is used to provide feedback and recommendation to the student and the teacher for both physical and remote classes.

ADVANCEMENT IN NEUROSCIENCE TO UNDERSTAND COGNITIVE PROCESSING:

As discussed above, a fundamental challenge to achieve the aforementioned vision is to measure the student's mental state in real-time. Indeed, recent advances in neuroscience have opened the gate to unveil fundamental processes in the human brain, such as the ability to generate emotions, memories, and actions [10], [11]. These research efforts have become possible by the ability to record and stimulate the human brain activity in the clinical setup by neurologists with a very high accuracy [12]. Optimal cognitive processing is central to all aspects of human activities. Recent advances in neuroscience have provided critical insights into how the brain accomplishes cognitive processing, spanning single neuron to neural population level resolution [12]. In particular, recent studies using event-related functional magnetic resonance imaging (fMRI) showed that there exists a high correlation between the magnitudes of focal activation in the right prefrontal cortex and the bilateral parahippocampal cortex during visual learning with the memory processing [13]. In addition, recent findings in the literature demonstrating that brain electrophysiological activity observed before stimulus or new concepts presentation profoundly influences subsequent behaviour on fear conditioning [14], motor responses [15], attention [16], and memory tasks [17]. While these studies gave us the fundamentals to measure the ability to memorize visual content, and the specific parts in the brain responsible for cognitive processing, the form factor of the utilized machinery prevents the widespread use of this technology in classroom settings. The next section reviews some technological advances that can provide a solution to such a challenge.

ADVANCEMENT IN WEARABLE NEUROTECHNOLOGY:

With the development of efficient, intelligent sensing technology, detecting small changes in electric signals becomes plausible. This technology paved the way for developing and producing devices that are capable of monitoring the brain's electrical activity non-invasively with enough resolution and low cost compared to the clinical setups. Although the traditional brain activity monitoring systems suffer from motion artifacts, long preparation time due to conductive gels or pastes, and large equipment (metal electrodes, long wires), the advances in sensor technology allow a fully portable, wireless, long-term, flexible scalp electronic system, incorporating a set of dry electrodes [18]. Moreover, the importance of wearable brain activity monitoring devices is that they are feasible for envisioning a real-time human-in-the-loop education system thanks to their portability, comfortability, and wireless data transfer system.

A study by Dikker et al. [19] proves that using a portable electroencephalogram (EEG) device for recording brain activity from a class of 12 high school students over a semester during regular activities, analyzing the group-based neural coherence is possible where the brain activity is synchronized across students in both student class engagement and social dynamics. Another study by Babini et al. [20] comparatively measured the learning of the students in a virtual reality (VR) environment for using a wearable electroencephalogram (EEG) [21]. They compared the brain engagement level of a group of students while learning through a VR environment compared to the regular two-dimensional environment. Their study showed that the higher the brain engagement, the higher the attention level of the students which led to better learning performance. Moreover, the developments in wearable neurotechnology devices can enable complex applications to be integrated to understand and predict cognitive processing. For example, sleep has a pivotal role in cognitive functions, and their relationship has been a topic of interest for over a century. Extensive research on sleep studies has shown that better sleep is associated with a myriad of superior cognitive functions in healthy adults [22], [23], including better learning and memory [24]. Although the exact mechanisms behind the relationship between sleep, memory, and learning are still research topics, the general agreement is those specific synaptic connections that were active during awake periods are strengthened during sleep, allowing for the consolidation of memory and inactive synaptic connections are weakened [25]. Consequently, sleep provides an essential function for memory consolidation; in other words, it will enable us to remember the topics that have been studied before [25]. It is now well established from a variety of studies that sleep monitoring can be used to associate with the students' performances. Moreover, sleep monitoring should be long-term rather than a single night or particular event recordings. Therefore, the recent developments on low-power wearable devices have crucial importance in monitoring students' sleep or emotional situations in the long term to create the future smart classroom environments [26].

PERSONALIZED FEEDBACK FOR THE FUTURE SMART CLASSROOM:

When these advancements in neuroscience and sensor technology combined with the current evolution in machine learning and signal processing, classification, and analysis of the massive amount of data streaming from wearable devices have become practicable. The resourcefulness of machine learning models provides the ability to analyze the complex recurring patterns of neural activity and detect hidden patterns. However, there are several challenges that need to be addressed to use these advancements to provide personalized feedback to the students and adapt the teaching environment for future smart classrooms.

- **<u>Challenge 1:</u>** Decision making in the face of system variability: Even if we are able to decode the brain activity in real-time to estimate the cognitive processing, addressing the students' individual needs to achieve personalized feedback has a lot of challenges. In particular, there are intrinsic variations that humans exhibit that can complicate the idea of a personalized smart classroom. As discussed in one of our recent works, the same human's preferences and responses may change over time. Even for a small period of time, the same human may produce different responses based on unmodeled external effects (intra-human variability). Similarly, different humans may have different responses under similar conditions (inter-human variability) [27]. For example, adapting the pace of the teaching material or the time of a quiz based on the cognitive load and the sleep quality of the student may not be the same for a different student and even for the same student across time. Moreover, when multiple humans interact in the same environment, their preferences differ based on the number of people they interact with and the type of this interaction. Moreover, when the education system adapts to one student in a multi-student classroom (e.g., changing the

pace of the presented material), it directly affects the other students in the same classroom. In addition
to that, multiple students may require different feedback adaptation actions based on their different preferences (multi-human variability), which can raise a question of fairness of adaptation in future smart classrooms [28], [29]. Hence, these human variations have to be considered an integral part of the design process of the adaptation algorithms for the future of the smart classroom.

- **Challenge 2:** Restructuring the pedagogical materials: Prior to applying the vision of personalized feedback in the future smart classroom, the pedagogical materials have to be reconstructed to be adaptable. For example, teaching materials have to be redesigned into small modules that are self-contained to enable quizzes and breaks at any time. Moreover, the same teaching materials themselves have to be designed into different modalities, such as project-based learning with a small group of peers, independent work to complete complex tasks, using immersive technology (VR) to increase the engagement of some students, and even recordings of the material to be watched at a different pace. Quizzes have to redesigned be automated based on the time they are taken and the student's strengths. Projects and group assignments have to take into account the group coherency and the average learning performance of the group members. Even teachers have to be trained to keep an up-to-date record from real-time data that provides a deep understanding of each student's individual strengths, needs, motivations, progress and goals [30].
- **Challenge 3:** Internet-of-Things (IoT) design and robustness to errors: Infusing technology into pedagogy to attain the vision of the future smart classroom requires careful design of the enabling technology to ensure high accuracy of real-time data and robustness to errors. Albeit the wide-ranging adaptation of the Internet-of-Things (IoT) technology in different application domains, low power and low energy design of wearable embedded systems are some of the most critical challenges to realize this new paradigm of future smart classrooms and to ensure its feasibility. Moreover, the need to process EEG data at the edge level with high accuracy (popularly termed as machine learning at the edge) due to privacy, security, and communication latency require new hardware-software design techniques to achieve low cost for accurate real-time local processing [26]. Current research in the area of battery-aware task scheduling for wearables [31], post CMOS technology, and Neuromorphic computing systems [32], [33] will play a significant role in developing such low power, low energy, and high accuracy efficient IoT design for future smart classrooms.

CONCLUSION:

This is an opportune time for smart classrooms. The increased demands of new affordable yet accurate solutions for human-in-the-loop systems lead to rich research areas, especially in human sensing. With the advancement in neuroscience and wearable neurotechnology, new possibilities for improving the quality of the education system by merging both fields have emerged. However, new challenges are yet to be solved in all development phases of future smart classrooms, from more neuroscience insights into the brain circuitry to design phases of accurate sensing to efficient adaptation algorithms. This article highlights the most prominent opportunities for future smart classrooms and recent approaches to tackle them. Nevertheless, this is not an exhaustive list leaving much to be discovered and done.

ACKNOWLEDGMENTS: This research was partially supported by NSF awards CISE CRII 2105084 and CMMI 1739503. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of our funding agency.

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Technical Activities

1. Conferences, Workshops and Special Sessions

- IEEE International Workshop on Artificial Intelligence for Intelligent Network Management (IEEE AINet 2021)
- 7th IEEE International Symposium on Smart Electronic Systems (iSES 2021) Special Session on Secure and Privacy-Aware Cyber Physical-Systems

2. Special Issues in Academic Journals

- Software: Practice and Experience (Wiley Press) Special Issue on Collaborative Edge Computing for Secure and Scalable Internet of Things

Call for Contributions

IEEE Bio-inspired Computing STC publishes two newsletters annually, i.e., one in March/April and the other in September/October. Please find the following to see the deadline to publish your articles in the upcoming newsletter.

- All contributions must be submitted by **January 31, 2022,** to be included in the newsletter's March/April 2022 issue.

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