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DESIGN OF A HEALTHCARE MONITORING AND COMMUNICATION SYSTEM FOR LOCKED-IN PATIENTS USING MACHINE LEARNING, IOTS, AND BRAIN-COMPUTER INTERFACE TECHNOLOGIES

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ABSTRACT

Machine learning (ML) models have shown great promise in advancing brain-computer interface (BCI) signal processing and in enhancing the capabilities of Internet of Things (IoT) mobile devices. By combining these advancements into a comprehensive healthcare monitoring and communication system, we may significantly improve the quality of life for patients living with locked-in syndrome. To that effect, we present a three-tiered approach to systems design using known ML models: data collection, local integrated system deployed on IoT hardware, and administrative management. The first tier focuses on IoT sensors and non-invasive recording of brain signals, their calibration and data collection, and data processing. The second tier focuses on aggregating and directing the data, an alert system for caregivers, and a BCI for personalized communication. The last tier focuses on accountability and essential management tools. This research-in-progress demonstrates the feasibility of integrating current technologies to improve care for locked-in patients.

KEYWORDS

Machine learning, IoT devices, locked-in syndrome, brain-computer interface, signal processing, healthcare system, neurotech.

INTRODUCTION

Imagine a person with full mental capacity who lived an active lifestyle who is now unable to communicate or interact with the world around them due to a severe motor disability to the point they are locked-in to their body. Now, imagine that person is unable to alert their caregiver when uncomfortable or in distress. Currently, caregivers working with locked-in patients must use their intuition, troubleshooting, and standard procedures to provide the best care possible. Even with these mitigations in place, patients still suffer from unnecessary rashes, infections, and preventable deaths. Modern technologies could significantly change this outcome and are being under-utilized in such healthcare environments.

Machine learning models have shown great promise in advancing brain-computer interface (BCI) signal processing and in enhancing the capabilities of Internet of Things (IoT) mobile devices. By combining these advancements into a comprehensive healthcare monitoring and communication system, we may significantly improve the quality of life for patients living with locked-in syndrome. The system will provide up-to-date, relevant telemetry to the caregivers allowing for faster intervention in case of an emergency or distress. It will allow for better data collection for care innovations and more accurate accountability. More importantly, the system will enable the locked-in patent to communicate with the caregiver using a primary interface of essential word choices.

Researchers have been working to bridge the communication chasm with BCI technology which allows for non-muscular control of technologies and devices [3]. Research in non-invasive BCI is widely used, which allows the patient to express distress and some essential communication (yes/no) in many scenarios. However, non-invasive BCI still has its drawbacks[5], such as expensive equipment, uncomfortable long time wearing, and limited mobility.

In recent years, another trend is to take advantage of IoT devices, which are more portable and affordable, to improve healthcare service and help patients recovering. For instance, researchers are currently using IoT devices with ML models in the fight against COVID-19[23]. Scientists deployed image recognition models on Raspberry Pi4s and IR cameras to identify humans with a fever, which significantly enhances the case identification efforts. Besides, engineers are adding more to the already long list of accessories multiplying IoT devices' capabilities. This research proposes to combine the non-invasive BCI signal and IoT devices with ML models to enhance caregiver capabilities by bridging the communicative chasm and allowing dynamic responses to patient needs.

On the one hand, the BCI provides accurate medical signal and intuition information. On the other hand, for comfort reasons, the patient will not wear the BCI device perpetually. Thus, the IoT devices with numerous sensors and ML models can overcome the mobility and provide flexible support and 24/7 data monitor as well as abnormal condition early detection.

RELATED WORK

Many researchers have revealed that the poor performance of healthcare suffered from inefficiency and high cost inside the health system. Therefore, several studies have proposed solutions to optimize problems along the process using IoTs, including interoperability improvement [7], collaborative perception [22], and auto-triggered management [4]. Different from the work improving the traditional healthcare system, our work focuses on optimizing the efficiency and reducing the cost by explicitly using non-invasive BCI signals and IoT real-time data. In addition to taking advantage of newer technology, others proposed lightweight and customized cloud-based remote health services to improve healthcare performance [4, 12, 14, 15, 19, 20, 21]. For example, Griggs et al. [12] proposed utilizing blockchain-based smart contracts to facilitate secure analysis and management of medical sensors. Bibani et al. [15] show a hybrid cloud and fog platform to provide remote healthcare. However, such designs require data transferred and shared on the public or private cloud. In this work, we strive to process the data locally to support the healthcare system while maintaining privacy efficiently.

Healthcare data is plentiful and often contains human survival related information. Analyzing healthcare data is of prime importance, particularly considering the immense potential of saving human life and improving quality of life. Sarkar et al. [6] proposed a distributed, interoperable architecture for IoT and presented a unified semantic knowledge base for IoT healthcare data. Many researchers advocated data mining and offered new solutions to mine the vast unstructured biomedical literature to support medical analytics. For instance, Jiang et al. [17] presented a big data healthcare system for older adults, which connects with remote wrist sensors through mobile phones to monitor the wearers' well-being. Hossain et al. [13] propose a healthcare big data framework using voice pathology assessment (VPA) for processing the voice or speech signals and machine learning algorithms in the form of a support vector machine as the classifier. However, none of these techniques are designed to optimize the inefficiency inside IoT devices or edge healthcare system. Instead, our work addresses the data processing inefficiency within the IoT via machine learning to provide a more accurate and privacy-protected solution.

With the increasingly faster pace of life, many physical illnesses and chronic conditions appear across generations of all ages. In recent years, researchers developed new techniques to diagnose ailments early and improve people's lifestyles. These works can be divided into two categories. First, many researchers propose predictive analytics on early disease detection through anomaly detection [18], auto-triggered management [4], transforming sensor data into real-time clinical feedback [9]. Another category of works, including m-IoT for real-time glucose sensing [18], heterogeneous integration [10], and body sensor networks [16], focuses on optimizing early detection through non-invasive methods. However, these works are based on a single model or device to predict abnormal regions. In comparison, our approach attempts to combine both BCIs signals and portable IoT device data to minimize the error in diagnosis, maximize the early detection of diseases, better prognosis, and make healthcare affordable, easy-to-use.

We expect the resulting system will not need extensive tests before reaching the patients and is scalable by adding specific sensors. Imagine a caregiver being able to manage more than one locked-in patient and provide better dynamic care. A medical professional will be able to respond immediately when a patient soils themselves. If a feeding tube accidentally uncouples itself, the system will use an IR camera to identify the rapid spread of temperature changes caused by the liquid, and the humidity sensor will also trigger. The system will alert the caregiver via a monitor or a text message requesting to check the torso of the patient. Overall, for society and the community, this research will contribute to health, safety, and economic well-being by helping improve the state-of-the-art in BCI, IoT, and ML, with an emphasis on practical, systematic infrastructure-level techniques. Government, corporate, and private sector communities all benefit from the development of advanced systems and methods for increased collaboration and flexible communication.

APPROACH

In this project, we will develop a new system to address the challenges in the above discussion. We will also validate our proposed techniques through prototype implementation and evaluation. The project is divided into the following deliverables: IR image recognition, Humidity sensor, BCI Signal processing, Communication app, the controlling system, including behavior recognition and action control. Based on the scrum agile project management philosophy, each deliverable will work independently of one another and will have one set of inputs/outputs (IOs). The team will code a reset input signal and a trigger (including the triggering data) output signal for each deliverable. This research will follow a three-tiered approach as illustrated in Figure 1: data collection, local integrated system deployed on IoT hardware, and administrative management.

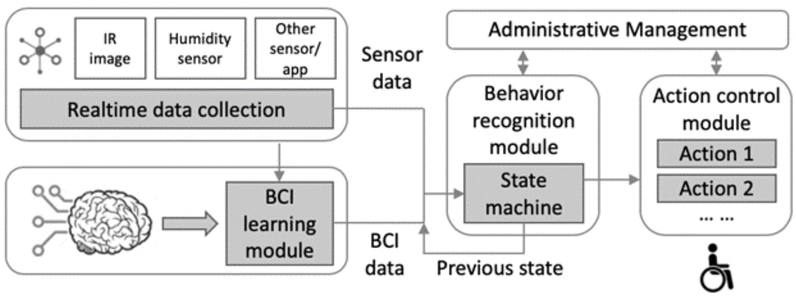

Figure 1: Comprehensive Monitoring and Communication System Diagram

Data Collection

IR image recognition

Researchers will consult with medical professionals to identify the relevant (temperature and viscosity) properties of the feeding liquid administered to the patients. Researchers then select a solution mimicking the feeding liquid's properties. The team will train the model based on the data to trigger when similar properties come through the IR camera.

Humidity sensor

Similar to IR image recognition, the researchers will consult with medical professionals to identify the equipment used under the patient to catch excretions. The team will use the above equipment and dyed water to determine the most efficient placement for the humidity sensor. The sensor must detect excretions as soon as possible and trigger while differentiating sweat. The goal is to calibrate the system to prevent false positives.

BCI Signal Processing

This research will work with a medical professional to ascertain a functional list of yes or no questions. The team will program the file into a simple communication interface. The previous will permit the patient to control the interface through the non-invasive BCI. The team will then modify the system's model to interpret the BCI signals. For simplicity, the interface will consist of an up, down, left, and right focus. The team will program the interface to maximize the utilization of the focus points and communication. At a minimum, patients will be able to answer yes or no questions, ask help, request to go outside or watch TV. The system might not restore full communication, but further scientific research will work toward that goal.

Communication App

This project will use an android tablet and app to display the communication interface. The team will use Android Studio, Firebase Authentication API, Firebase Realtime Database, Gradle, Java, and a Jason tree to build the app. Android studio has these tools already integrated. Firebase Authentication API will restrict access to patient data to authorized users. Firebase Realtime Database will synchronize data amongst all connected devices and create a local cache if necessary. Gradle will manage the APIs and SHA keys. This project will use the Java programming language because of its widespread use in the industry. This research will use a Jason tree data structure because of its versatility, modularity, and scalability. The app will take the IO information from the BCI Signal Processor and triggers to the System via Bluetooth.

Local Integrated System

This project will integrate everything from Module 1 into a portable and scalable system. A Raspberry Pi4 will take in all the triggers from the sections and analyze them per the recommendations of a health professional. We will design a behavior recognition module to detect the current state of the patient based on the IoT sensor and BCI processing data. The action control module can flexibly change corresponding action, including sending alarms, asking for help, requesting resources, and notifying the caregivers, etc., based on specific system states. The team will code this using Java. The Local Integrated System will receive the outputs from module 1 and send its outputs to module 2 and the caregiver's device.

Administrative Management

Module 2 will cache all messages and trackable interactions locally until connected via WIFI. The local integrated System, at that time, will sync all cached data with the Firebase Realtime Database. This research project's result will function in the medical field, and oversight is necessary. The team will set up the Firebase Realtime Database and the Jason data tree structure. Firebase makes it easy to incorporate this System into any medical information system. Also, this module maintains a website which will access the information to help relevant personnel make related decisions. For example, managers can use the data for performance reviews, or the company can use the data for audits or as a tool to help with legal disputes. The team will build a website with enough functionality to access the data and present it in an intelligible manner. The team will encode basic filters and relevant reports.

ANTICIPATED OUTCOMES AND EVALUATION

The expected outcomes are improved performance, cost-effectiveness, and predictability of a healthcare system for locked-in patients and their caregivers. The team will measure performance improvements as the gain compared to that in the current state-of-the-art healthcare system as well as in some representative approaches. This research will measure cost-effectiveness as the overall equipment and staff expenditure at a similar level of performance. Predictability will be measured by whether the system can provide in-time service for the patients and detect their early symptoms and needs.

With the implementation of this system, this team hopes to modernize the caregiving environment, reduce the numbers of unnecessary deaths and injuries, provide the locked-in patient a bridge to the outside world, and increase accountability without compromising privacy and security. The system will scale to meet hospitals', group-homes', and care agencies' needs while still deployable in a private residence. The current global availability of the Internet and IoT devices are the perfect foundation for a system of this scope, purpose, and requirements. For future research, this team will investigate improvements on the BCI signal processing to increase the communication capabilities of the system, a module allowing the patient to control their environment through BCI, and the integration of new non-invasive monitoring technologies.

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