Guest Editorial AI-Empowered Internet of Things for Data-Driven Psychophysiological Computing and Patient Monitoring

AS THE cornerstone of human health, physical and mental well-being are intricately linked, influencing both an individual's physical condition and their emotional state [1]. Chronic diseases such as hypertension and diabetes can have a significant impact on mental health, leading to anxiety and depression [2]. Similarly, psychological problems such as stress, anxiety, and depression can weaken the immune system, making individuals more susceptible to physical illnesses. In recent years, the rapid development of technology has brought exciting new possibilities to the field of physical and psychological health. The Internet of Things (IoT) and artificial intelligence (AI) have shown great potential in building a comprehensive health management system that empowers individuals to take a more proactive role in their well-being.

Smart wearables and sensor technology empower users with convenient, real-time monitoring of physiological parameters like heart rate, respiratory rate, and body temperature. This data seamlessly transmits to the cloud via the IoT for processing. These devices go beyond simple vitals, also capturing a wider range of user behavior patterns and activity levels, such as sleep patterns, stress levels, and even gait analysis. Leveraging AI, systems can analyze this data in real-time, potentially identifying signs of both physical and psychological concerns by reflecting the user's emotional state and mood fluctuations[3]. This allows for early intervention and preventative measures, empowering individuals to make informed decisions about their health [4]. AI algorithms can be used to analyze various biomedical data, such as ECGs, EEGs, and genetic data, to aid doctors in diagnosing diseases, and to develop personalized health management plans to help users improve their health. Additionally, AI can be used to provide real-time health monitoring, allowing doctors to track patients' progress and intervene early if necessary.

Internet of Things (IoT) technology utilizes various sensors and devices to collect key health data [5], thereby comprehensively assessing an individual's physiological and psychological status. Physiological data, such as heart rate, blood pressure, respiratory rate, blood oxygen saturation, and body temperature, can reflect the individual's cardiac function, blood circulation, respiratory system status, and temperature regulation. Motion data, including activity level and posture movement patterns collected through sensors like accelerometers or gyroscopes, help assess physical activity levels and exercise habits. Sleep tracking devices provide essential sleep data, such as duration, depth, and stages, crucial for assessing sleep quality. Biochemical data, such as blood sugar and cholesterol levels, are critical indicators for managing and preventing related health issues. Psychological status can be assessed through indicators such as heart rate variability (HRV) and skin conductance activity, revealing stress levels, emotional states, and autonomic nervous system activity. Additionally, environmental data, such as air quality and temperature-humidity, provide important information about the impact of environmental factors on health. After integrating this data, IoT systems not only provide comprehensive physiological and psychological health assessments but also assist healthcare professionals in formulating diagnosis and treatment plans while helping individuals manage their health more effectively [6].

The integration of deep learning technology enables the realization of multimodal health data-driven physiological and psychological health diagnostics This integrated approach plays a crucial role in improving diagnostic accuracy, personalized treatment, and predictive health management. By extracting deep correlations and patterns from various health data sources, such as physiological parameters, psychological indicators, motion data, sleep quality, and biochemical markers [7], deep learning models can handle complex and large-scale datasets. This capability reveals subtle and nonlinear patterns of health status, providing a scientific basis for early disease detection and personalized treatment planning. Additionally, these advanced technologies can automate health monitoring and diagnostic processes, enhancing healthcare service efficiency, particularly in resource-limited environments. They can also support remote healthcare services and alleviate burdens on traditional healthcare systems. By making health diagnostics more precise, efficient, and predictive, the application of deep learning not only promotes the development of personalized medicine but also holds promise for improving public health outcomes and enhancing individual health results.

The use of perceptual psychological parameters and AI-powered emotional care offers tremendous potential for improving human health. However, the development of this field still faces multiple challenges. Processing and analyzing psychological data are hindered by the complexity and subjectivity

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of emotional states. This necessitates the development of advanced technological methods capable of accurately capturing and parsing subtle emotional changes [8]. When implementing AI-based emotion monitoring and care, the technical challenges lie primarily in the need for highly advanced algorithms that can accurately understand and predict human emotions. These algorithms must also handle and analyze large amounts of unstructured emotional data, such as facial expressions, vocal tones, and body language [9].

With all this in mind, this special issue is meant to provide just a snapshot of some of the latest research advances at the intersection of artificial intelligence and the Internet of Things (IoT) for data-driven psychophysiological computing.

The first paper by Hu W et al. [10] focuses on measures of emotion in the peripheral nervous system. In this study, a body surface potential mapping (BSPM) system was constructed, and an experiment was designed to induce emotions and obtain high-density body surface potential information under negative and non-negative emotions. Then, by constructing and analyzing the functional connectivity network of BSPs, the high-density electrophysiological characteristics are obtained and visualized as bodily emotion maps.

The second paper by Jin H et al. [11] addresses two-way emotional development. It proposes a multimodal domain adaptive method based on EEG and music called the DAST, which uses spatio-temporal adaptive attention (STA-attention) to globally model the EEG and dynamically maps all embeddings into high-dimensional space by an adaptive space encoder (ASE). Then, adversarial training is performed with a domain discriminator and ASE to learn invariant emotion representations.

The third paper by He P et al. [12] addresses the safe and efficient processing of physiological signals. In this work, they designed a novel scheme named Heterogeneous Compression and Encryption Neural Network (HCEN), which aims to protect signal security and reduce the resources required for processing heterogeneous physiological signals. The proposed HCEN is designed as an integrated structure that introduces the adversarial properties of Generative Adversarial Networks (GAN) and the feature extraction functionality of an Autoencoder (AE). Moreover, it conducts simulations to validate the performance of HCEN using the MIMIC-III waveform dataset. Electrocardiogram (ECG) and Photoplethysmography (PPG) signals are extracted in the simulation.

The fourth paper by Shao S et al. [13] aims at the identification of mental workload remotely based on human physiological signals. In this paper, a method based on the spatial and time–frequency domains of electroencephalography (EEG) signals is proposed to improve the classification accuracy of mental workload. Moreover, a hybrid deep learning model is presented. First, the spatial domain features of different brain regions are proposed. Simultaneously, EEG time–frequency domain information is obtained based on wavelet transform. The spatial and time–frequency domain features are input into two types of deep learning models for mental workload classification.

The fifth paper by Huang W et al. [14] aims to difficulties in emotional expression in Parkinson's patients. Based on this, they propose an auto PD diagnosis method based on mixed emotional facial expressions in the paper. Specifically, the proposed method is cast into four steps: Firstly, they synthesize virtual face images containing six basic expressions (i.e., anger, disgust, fear, happiness, sadness, and surprise) via generative adversarial learning, in order to approximate the premorbid expressions of PD patients; Secondly, they design an effective screening scheme to assess the quality of the above synthesized facial expression images and then shortlist the high-quality ones; Thirdly, they train a deep feature extractor accompanied with a facial expression classifier based on the mixture of the original facial expression images of the PD patients, the high-quality synthesized facial expression images of PD patients, and the normal facial expression images from other public face datasets; Finally, with the well-trained deep feature extractor, they thus adopt it to extract the latent expression features for six facial expression images of a potential PD patient to conduct PD/non-PD prediction.

The sixth paper by Gao D et al. [15] aims to an effective fatigue detection method, which can intuitively reflect the drivers' mental state. This paper proposes a novel multidimensional feature fusion network, CSF-GTNet, based on time and space-frequency domains for fatigue detection. Specifically, it comprises Gaussian Time Domain Network (GTNet) and Pure Convolutional Spatial Frequency Domain Network (CSFNet). The experimental results show that the proposed method effectively distinguishes between alert and fatigue states.

The seventh paper by Shi F et al. [16] addresses the automatic detection of APs. In this paper, they realize the skin conductance-based APs and non-APs recognition with machine learning, which could assist in APs detection and localization in clinical practice. Firstly, they collect skin conductance of traditional Five-Shu Point and their corresponding non-APs with wearable sensors, establishing a dataset containing over 36000 samples of 12 different AP types. Then, electrical features are extracted from the time domain, frequency domain, and nonlinear perspective respectively, following which typical machine learning algorithms (SVM, RF, KNN, NB, and XGBoost) are demonstrated to recognize APs and non-APs. Moreover, thry also quantify the impacts of the differences among AP types and individuals, and propose a pairwise feature generation method to weaken the impacts on recognition precision.

The eighth paper by Ahmed U et al. [17] addresses depression recognition. This paper introduces a Graph Attention Network (GAT) model for the classification of depression from online media. The model is based on masked self-attention layers, which assign different weights to each node in a neighbourhood without costly matrix operations. In addition, an emotion lexicon is extended by using hypernyms to improve the performance of the model. Furthermore, the embedding of the model is used to illustrate the contribution of the activated words to each symptom and to obtain qualitative agreement from psychiatrists. This technique is used to detect depressive symptoms in online forums with an improved detection rate. This technique uses previously learned embedding to illustrate the contribution of activated words to depressive symptoms in online forums.

The ninth paper by Lu H et al. [18] addresses capture the higher-order relationship between emotion and gait. In this paper, they utilize a range of research, including psychophysiological computing and artificial intelligence, to propose an integrated emotion perception framework called EPIC, which can find novel joint topology and generate thousands of synthetic gaits by spatio-temporal interaction context. First, they analyze the joint coupling among non-adjacent joints by calculating Phase Lag Index (PLI), which can discover the latent connection among body joints. Second, to synthesize more sophisticated and accurate gait sequences, they explore the effect of spatio-temporal constraints, and propose a new loss function that utilizes the Dynamic Time Warping (DTW) algorithm and pseudo-velocity curve to constrain the output of Gated Recurrent Units (GRU). Finally, Spatial Temporal Graph Convolution Networks (ST-GCN) is used to classify emotions using the generation and the real data.

The final paper by Hu Y et al. [19] addresses the problem of missing data faced by wearable devices during data collection. To address these issues, they propose a systematic ensemble classification model for depression (ECD). For the missing data problem of wearable devices, they design an improved GAIN method to further control the generation range of interpolated values, which can achieve a more reasonable treatment of missing values. Compared with the original GAIN approach, the improved method shows a 28.56% improvement when using MAE as the metric. For depression recognition, they use ensemble learning to construct a depression classification model which combines five classification models, including SVM, KNN, LR, CBR, and DT. Ensemble learning can improve the model's robustness and generalization. The voting mechanism is used in several places to improve noise immunity.

All ten papers explore different but extremely relevant domain vectors of AI-enabled IoT based on data-driven psychophysiological computing. We believe that this special issue will raise awareness in the scientific community by presenting and highlighting advances and the latest novel emerging technologies, implementations, and applications regarding AI-enabled IoT. Finally, we would like to thank all the authors who submitted their research results to this special issue. We would also like to thank the many experts in the field who participated in the review process and provided helpful suggestions to the authors to improve the content and presentation of the articles. We would in particular like to thank Professor Dimitrios I. Fotiadis, the Editor-in-Chief, and the publishing team for their support and very helpful suggestions and comments during the delicate stages of concluding the special issue.

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