Guest Editorial
Emerging IoT-Driven Smart Health: From Cloud to Edge

RECENT advances in healthcare can be experienced with the development of smart sensorial things, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), edge computing, Edge AI, 6G, cloud computing, and connected healthcare have attracted a great deal of attention and a wide range of views. However, the need to deliver real-time and accurate healthcare services to patients, while reducing costs is a challenging issue [1]. Especially, COVID-19 has recently demonstrated the importance of fast, comprehensive, and accurate intelligent healthcare involving different types of medical, physiological, and epidemiological investigation data to diagnose the virus.

Smart health is a real-time, intelligent, ubiquitous healthcare service based on Internet of bioMedical Things (IoMT). With the rapid development of related technologies such as deep learning, edge computing and IoT, smart health is playing vital role in healthcare industry to increase the accuracy, reliability, and productivity of mobile sensory devices. To meet the computational requirements of deep learning, a common approach is to leverage cloud computing. To use cloud resources, data must be moved from the data source location on the network edge (e.g., from smartphones and IoT sensors) to a centralized location in the cloud. This potential solution of transferring the data from the source to the cloud brings about several challenges: latency, bandwidth, and privacy. A large amount of biomedical data is difficult to tolerate network latency and needs to be processed in real time, which poses challenges for cloud computing. Edge-computing capabilities are the most promising approaches for enabling smart healthcare that can provide quick and cost-effective patient remote monitoring [2]. Therefore, there are many studies that do not perform the computation and processing of biomedical and health data in cloud center, but migrate tasks to edge end, through edge computing to effectively improve the real-time service, to meet the real-time needs of smart health services.

However, the IoMT data analysis and managing still represent the main trend due to a huge number of devices that connect to the server environments, which generate a significant amount of biomedical data. Besides, many challenges remain in deploying deep learning on the edge, not only on end devices but also on the edge servers and on a combination of end devices, edge servers, and the cloud. Therefore, there is a necessity for providing real-time, efficient, and scalable intelligent algorithms that lead to additional sophisticated solutions and that can make operative decisions in emerging IoT-driven smart health.

This special issue focuses on smart sensors challenges in IoMT, and solutions that leverage techniques and insights from the domains of artificial intelligence, edge computing, and IoT. Specifically, it also solicits high quality contributions that investigate the usage of biometric signals in the context of IoMT for continuous monitoring for patient-centric healthcare. After a careful review process, only 5 high quality and interesting articles were selected for publication.

The first paper by Zhang *et al.* [A1] addresses challenges of Human activities recognition (HAR) based on multimodality sensor data in an incremental learning way. A multi-modality incremental learning model called HarMI is proposed, which first adopts an attention mechanism to align sensor data with very different frequencies to eliminate heterogeneity of different sensors. Then, as catastrophic forgetting is common yet challenging in incremental learning, it overcomes catastrophic forgetting from a multi-modality perspective based on an elastic weight consolidation (EWC) framework by introducing the EWC regularization term and the correlation regularization term to preserve knowledge in previous activities. As demonstrated in the experiments, the proposed model HarMI outperformed the state-of-the-art baselines on two public datasets.

The second paper by Kang *et al.* [A2] tackles challenges on hand gesture recognition during dynamic walking and a transfer learning method. It develops and validates a signal decomposition approach via empirical mode decomposition to accurately segment target gestures from coupled raw signals during dynamic walking and a transfer learning method based on distribution adaptation to enable gesture recognition through domain transfer between dynamic walking and static standing scenarios. Ten healthy subjects perform seven hand gestures during both walking and standing experiments, while wearing an IMU wrist-worn device. The extensive experimental results demonstrate that the signal decomposition approach reduces the gesture detection error by 83.8%, and the transfer learning approach (20% transfer rate) improves hand gesture recognition accuracy by 15.1%.

The third paper by Dibiasi *et al.* [A3] contributes to two essential aspects of melanoma detection research. The first aspect is how a simple modification of the parameters in the dataset determines a change of the accuracy of classifiers. In this case, it investigates the transfer learning issues. Following the results of the investigation, this work suggests that continuous

Date of current version March 7, 2022.
Digital Object Identifier 10.1109/JBHI.2022.3149040

training-test iterations are needed to provide robust prediction models. The second aspect is the need to have a more flexible system architecture that can handle changes in the training datasets. In this context, it proposes the development and implementation of a hybrid architecture based on Cloud, Fog and Edge Computing to provide a Melanoma Detection service based on clinical and dermoscopic images. At the same time, this architecture must cope with the amount of data to be analyzed by reducing the run-time of the continuous retraining process.

The fourth paper by Kumar *et al.* [A4] addresses medical data stream analytics for Internet of Things-based healthcare systems. A Proportionate Data Analytics (PDA) for heterogeneous healthcare data stream processing is introduced. The analytics method differentiates the data streams based on variations and errors for satisfying the service responses. The classification is streamlined using linear regression for segregating errors from the variations in different time intervals. The time intervals are differentiated recurrently after detecting errors in the stream's variation. This process of differentiation and classification retains a high response ratio for healthcare services through spontaneous regressions. The proposed method's performance is analyzed using the metrics accuracy, identification ratio, delivery, variation factor, and processing time.

The final paper by Sekhar *et al.* [A5] focuses on Brain tumor classification using the fine-tuned GoogLeNet features and machine learning algorithms. Brain tumors are classified into three classes, namely glioma, meningioma, and pituitary, using the transfer learning model. The features of the brain MRI images are extracted using a pre-trained CNN, i.e., GoogLeNet. The features are then classified using classifiers such as softmax, Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN). The proposed model is trained and tested on CE-MRI Figshare dataset. Further, Harvard medical repository dataset images are also considered for the experimental purpose to classify four types of tumors, and the results are compared with the state-of-the-art models. Performance measures such as accuracy, precision, recall, specificity, and F1 score are examined to evaluate the performance of the proposed model.

All five papers tackle different but extremely relevant domains of the emerging IoT-driven smart health and edge computing. We believe this Special Issue will raise awareness in the scientific community that a multidisciplinary (health, data science, engineering, and robotics) research path is therefore in need of a full thrust to meet the expectations for healthcare providers that are currently deposited in this field.

Acknowledgment

The Guest Editors would like to thank Prof. Dimitrios I. Fotiadis and the editorial staff for the opportunity to organize this special issue, and for their constant and prompt support throughout the whole process and also would like to thank all the authors for their valuable contribution to this special issue, and all the volunteer reviewers for their hard work in evaluating the submissions and their helpful comments that certainly contributed to the quality of the published papers.

Shaohua Wan
Shenzhen Institute for Advanced Study,
University of Electronic Science and
Technology of China, Shenzhen 518110
China

Michele Nappi
Department of Computer Science
University of Salerno, 84084, Italy

Chen Chen
Center for Research in Computer Vision
University of Central Florida, 32816-2365,
USA

Stefano Berretti
Department of Information Engineering
University of Florence, 50139, Italy

Appendix: Related Works

[A1] X. Zhang, "HarMI: Human activity recognition via multi-modality incremental learning," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 3, Mar. 2022, doi: 10.1109/JBHI.2021.3085602.

[A2] P. Kang, J. Li, B. Fan, S. Jiang, and P. B. Shull, "Wrist-worn hand gesture recognition while walking via transfer learning," *IEEE J. Biomed. Health Inform.,* vol. 26, no. 3, Mar. 2022, doi: 10.1109/JBHI.2021.3100099.

[A3] L. Dibiasi, M. Risi, G. Tortora, and A. A. Citarella, "A cloud approach for melanoma detection based on deep learning networks," *IEEE J. Biomed. Health Inform.,* vol. 26, no. 3, Mar. 2022, doi: 10.1109/JBHI.2021.3113609.

[A4] P. M. Kumar, "Clouds proportionate medical data stream analytics for internet of things-based healthcare systems," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 3, Mar. 2022, doi: 10.1109/JBHI.2021.3106387.

[A5] A. Sekhar, S. Biswas, R. Hazra, A. K. Sunaniya, A. Mukherjee, and L. Yang, "Brain tumor classification using fine-tuned GoogLeNet features and machine learning algorithms: IoMT enabled CAD system," *IEEE J. Biomed. Health Inform.,* vol. 26, no. 3, Mar. 2022, doi: 10.1109/JBHI.2021.3100758.

References

[1] Kamruzzaman, M. M. New Opportunities, Challenges, and Applications of Edge-AI for Connected Healthcare in Smart Cities. In 2021 IEEE Globecom Workshops (GC Wkshps), pp. 1–6.

[2] A. A. Abdellatif, A. Mohamed, C. F. Chiasserini, M. Tlili, and A. Erbad, "Edge computing for smart health: Context-aware approaches, opportunities, and challenges," *IEEE Netw.*, vol. 33, no. 3, pp. 196–203, May/Jun. 2019.