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Editorial

AI-Based Biomedical Signal Processing

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Motivated by the numerous studies working towards innovative processing of biomedical signals, especially exploiting Artificial Intelligence (AI)-based methodologies, this Special Issue was proposed in 2022. This initiative aims to provide a comprehensive overview of the most recent advancements in the field, highlighting both theoretical contributions and practical implementations.

As well-depicted by Wei et al. [1], the learning ability of AI techniques is being leveraged to aid diagnoses and improve prediction accuracy while considering proper raw data processing and/or feature extraction. These advancements are made possible through careful preprocessing of raw biomedical data, as well as through the extraction of informative and discriminative features that feed into AI models. Moreover, the literature confirms this research trend, particularly applied to heart-related data, such as electrocardiographic (ECG) [2–8], electromyographic (EMG) [2,9], and electroencephalographic (EEG) signals [2,10,11]. Furthermore, AI techniques are also being successfully applied to the analysis and interpretation of biomedical imaging data [12], opening new frontiers in diagnostic imaging and computer-aided detection.

This Special Issue thus serves as a timely platform for the dissemination of novel AI-driven solutions in biomedical data processing, fostering interdisciplinary collaboration among engineers, computer scientists, and healthcare professionals.

Notice that a total of 14 contributions were collected, focusing mainly on (i) feature engineering, (ii) deep-learning applications, and (iii) model explainability, interpretability, and personalization, as per the previously cited papers. These aspects will be briefly presented, and a general overview of the Special Issue studies provided.

Two key aspects of biomedical signal processing are feature extraction and selection [13,14] and their use to evaluate the physiology of the systems or their clinical use. This process was recently named feature engineering and is fundamental to provide a correct data characterization as well as reduce signal dimensionality [14]. Many AI-based algorithms have aimed to use feature engineering as a biomedical signal-processing step.

For this purpose, the Authors of this SI have proposed different strategies, spanning from the use of a combination of decomposition transforms for signal analysis and least-squares support vector machines to reliably detect atrial fibrillation to the extraction of RR-interval-related features in ECG as inputs to artificial neural networks and adaptive neuro-fuzzy interference systems. Other ECG feature types were investigated in the context of COVID-19 mortality risk detection or extracted through the use of convolutional neural networks (CNNs).

Another case lies in seizure detection on EEG data. Spontaneous alpha and beta rhythms are selected by exploiting the discrete wavelet transform and features extracted from these rhythms by employing the Mallat algorithm.

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An interesting approach is the one by Alonso-Hernández et al. [15], who propose an innovative detection and monitoring of Alzheimer's disease by using automatic speech analysis, exploiting voice features related to the concept of emotional temperature. Particularly, they work with the 2019 Cross-Sectional Alzheimer Prognosis database containing spontaneous and induced voice samples and thus analyzing the differences between emotional temperature features derived from a human or an automatic interview process. The automatic speech analysis is conducted through (i) emotional temperature calculation with a voice activity detector providing features that (ii) undergo a statistical and (iii) univariate analysis. Afterwards, (iv) a multivariate analysis using a linear discriminant analysis, logistic regression, and k-nearest neighbor to detect if there is Alzheimer's disease or not and its severity (mild, moderate, or healthy control). Notice that a feature selection step is also conducted through a neighborhood component analysis. The results show that the investigation of an automated process to detect and monitor Alzheimer's disease may improve speech-based remote healthcare.

Moving to the next main topic, deep learning methods are continuously gaining interest from the biomedical research community [16–18], considering their ability to capture patterns exploitable for data augmentation and information transfer, and provide temporal and frequency information from different data types.

In this Special Issue, very different approaches in a variety of biomedical domains have been proposed.

A very particular example is the one by Qian, Xiao, and Chongchong [19], who propose a novel Voice Conversion (VC) approach to enhance Mandarin electro-laryngeal speech. This technique is usually prone to producing unnatural and difficult-to-understand speech in the case of tonal languages. Therefore, the Authors propose a CycleGAN-based VC, exploiting a 2D-Conformer–1D-Transformer–2D-Conformer generation to capture both temporal and frequency information characteristic of speech signals. The CycleGAN receives as an input Mel-spectrograms from Electro-laryngeal fixed and variable tone speech signals. Objective and subjective evaluations were used to confirm the efficacy of the approach. Thus, in the objective evaluation, Mel-Cepstral distortion and root mean square error of CodeAP are used to evaluate spectrum features, while speech enhancement was detected with the correlation coefficient of fundamental frequency and error of the logarithmic fundamental frequency. Instead, for the subjective evaluation, 10 Chinese listeners were enrolled to provide a transcription with tones of the audio they heard, and give a mean opinion score of the audio's understandability and naturalness. The results show an enhancement of Mandarin electro-laryngeal speech by improving the tone accuracy and reducing the word error perception rate while considering an increase in intelligibility and naturalness compared to other literature works. Notice that the speech files are available.

Other works have instead focused on (i) the use of bidirectional long-short-term-memory-based models for lower-limb rehabilitation improvement through the combination of extended reality, robotic ankle prosthetic leg, and EMG signals; (ii) the classification of heart sounds to detect cardiovascular diseases through an ensemble of deep learning models using features extracted from phonocardiogram signals; (iii) a novel lightweight encoder–decoder network designed for semantic and instance-level segmentation of human chromosomes in microscopic images; (iv) working on photoacoustic imaging developing YoLov8-MedSAM, specifically designed for precise brain tumor identification and segmentation; and (v) proposing a R-CNN-based system to provide indications on cutting specific regions during thoracoscopic surgery.

The last topic is the one related to model explainability, interpretability, and personalization [13,20]. Debated in the literature, explainability refers to the ability to describe how a model arrives at its predictions, while interpretability focuses on how easily a human can understand the model's decisions and reasoning process. Among the most challenging issues, interpretability and explainability are essential to guarantee reliability and transparency [21]. The so-called "black-box" nature of many high-performing models still hinders their acceptance by medical practitioners, who often need clear, evidence-based justifications for algorithmic decisions, especially when they impact patient care.

In this context, the work of Biskin, Candemir, and Selver [22] is very innovative. The work aimed to correctly detect bipolar disorder and schizophrenia, which are usually studied separately, confused, and diagnosed at advanced stages. Particularly, they propose a ResNet50-based deep learning model intended to work on structural magnetic resonance images. They also exploit gradient-weighted class activation mapping (Grad-CAM) to extract the magnetic resonance imaging regions that are more useful to distinguish between the two disorders. Afterwards, features are extracted in these regions and selected through ElasticNet. The remaining feature set is inputted to a fully connected Bayesian-optimized network. The model efficacy has been evaluated for accuracy, precision, recall, F1-score, area under the curve, and Matthews correlation coefficient. The model interpretability is provided by the use of Grad-CAM, which also contributes to the improvement of the model performance by allowing for the extraction of specific brain regions of interest.

In conclusion, this Special Issue has successfully reached a wide range of high-quality contributions that span across multiple domains of biomedical signal processing, all unified by the common thread of using AI to address complex clinical and technological challenges. The works presented demonstrate the maturity of AI-based methodologies—particularly those based on deep learning architectures—that are beginning to accomplish tasks such as classification, prediction, signal enhancement, and anomaly detection in different biomedical contexts. As technological capabilities continue to evolve rapidly, the potential for implementing even more sophisticated and innovative AI-driven solutions becomes clinically applicable. In particular, the integration of novel deep learning paradigms, such as transformer networks [23], graph neural networks [24], and self-supervised learning [25], opens new ways for advancing the performance and adaptability of biomedical signal analysis. Furthermore, the community continues to face the challenge of finding an optimal balance between the computational complexity of AI models and their practical deployability, particularly in resource-constrained settings such as wearable devices, mobile health platforms, and point-of-care diagnostics. Ensuring sustainability, not only in terms of computational efficiency but also with regard to energy consumption and environmental impact, has become an increasingly relevant consideration in the design of modern AI solutions [26].

Overall, while the contributions collected in this SI mark significant steps forward, they also highlight the need for continued interdisciplinary collaborations aimed at developing AI models that are not only accurate and robust but also interpretable, efficient, and ethically responsible [27]. These elements will be essential to ensure the successful translation of AI-based biomedical signal-processing techniques from research settings to widespread clinical adoption.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CNN	Convolutional Neural Network
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
Grad-CAM	Gradient-weighted Class Activation Mapping
VC	Voice Conversion

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