

Emerging Trends in Deep Learning and Signal Processing for Wearable Biomedical Signal Analysis

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Abstract

Deep learning for biomedical signal analysis is revolutionizing the analysis of complex physiological signals through the extraction of intricate patterns from physiological and wearable sensor data. This Special Issue brings together five articles that address cardiac, neural, muscular, and motion signals using complementary approaches across signal processing, machine learning, deep representation learning, and wearable sensing. Two contributions focus on ECG: one introduces a constraint-based method to suppress false positives in P/R/T peak detection, and the other one presents an interactive GUI for rapid R-peak correction. In the third study, an EEG biometrics system was developed that uses 3D brain mapping and autoencoder features, and the fourth study compares machine classifiers for athlete movement recognition from EMG. In the final study, wearable IMUs were used to improve jump height estimation via optimal sensor placement. We summarize these works and highlight themes such as physiological prior integration, human–AI interaction, and multi-sensor fusion. This Editorial concludes with the identification of future directions, including multi-modal modeling and adaptive learning in real-world settings.

Keywords: deep learning; physiological signals; ECG analysis; EEG biometrics; EMG recognition; inertial sensors; wearable computing

1. Introduction

The accurate processing of physiological signals—such as ECG (heart), EEG (brain), EMG (muscle), and inertial motion data—is essential for medical monitoring and human performance analysis. Recent advances in deep learning have made it a promising approach for identifying and representing complex patterns in biomedical signals. At the same time, effective biomedical signal analysis does not necessarily depend on increasingly complex models; physiological knowledge, appropriate signal-processing strategies, sensor configuration, and human oversight can also play important roles in achieving reliable and interpretable results. This Special Issue brings together five studies spanning cardiac, neural, muscular, and biomechanical signals, illustrating complementary approaches to these challenges.

2. Summaries of Contributions

ECG signal analysis: Two articles address complementary challenges in ECG analysis, focusing on automated peak detection and human-assisted correction. Yoshida and



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Yokoyama [1] propose a *sample-wise false-positive reduction* framework for ECG peak detection. Their method imposes physiological constraints (e.g., refractory periods) on lightweight binary classifiers, jointly detecting P-, R-, and T-peaks within appropriate windows, thereby obtaining very high sensitivity while greatly suppressing spurious detections. In a companion paper [2], the same authors introduce an *interactive ECG viewer* that enables manual R-peak editing. Users can add or remove R-wave detections through a GUI, with R–R intervals and related heart rate variability metrics updating instantly. The tool was tested on synthetic and MIT-BIH arrhythmia ECG data and achieved near-perfect agreement with reference R–R intervals. Together, these works balance automated detection with intuitive human-in-the-loop correction, improving practical ECG analysis.

EEG biometrics: Öztemel and Soysal [3] investigated person identification from brainwaves by extracting 3D topographic ‘cubes’ from multi-channel EEG. They used a convolutional autoencoder to obtain compact representations of these spatial–temporal patterns. The resulting latent features were then evaluated using conventional classifiers for subject identification. On a publicly available EEG dataset, the method achieved high accuracy in identifying subjects based on their brain activity. This highlights how deep feature learning can capture distinctive neural patterns, suggesting potential for secure biometric applications based on EEG signals.

EMG movement recognition: Zohirov et al. [4] compare classification techniques for lower-limb movements using surface EMG in athletes and evaluate actions such as running and jumping, extracting both time- and frequency-domain features from EMG recordings. They tested multiple machine learning models, and the top performer was a random forest method that uses well-engineered EMG features. The article discusses practical factors like optimal electrode placement and training dataset design, and the results indicate that relatively simple models, given good features, can reliably distinguish athletic movements, which is promising for wearable motion analysis systems.

Inertial sensor jump analysis: Althouse et al. [5] examine counter-movement jumping using wearable IMUs. They placed multiple IMUs at anthropometric centers (trunk, thighs, shanks) and compared vertical acceleration measurements to a force-plate reference. Various sensor configurations were tested to estimate jump height. They found that multi-segment IMU setups significantly reduce acceleration errors compared with single-sensor setups. In particular, a two-segment configuration (trunk plus shanks) and a three-segment setup (trunk, thighs, feet) yielded a much lower RMSE in jump dynamics. This work confirms that placing inertial sensors to approximate body segment centers of mass markedly improves measurement validity for biomechanical analysis.

3. Conclusions and Future Directions

The collected articles illustrate powerful synergy between machine learning and physiological signal analysis. Each study applied intelligent algorithms in a context-aware manner, for example, by embedding physiological timing rules in ECG peak detection, by designing user-friendly correction tools, by leveraging spatial EEG structure for biometrics, and by matching sensor placement to biomechanics. Common themes among the studies include the importance of interpretability (aligning models with physiological insights), user interaction (facilitating human review of automated results), and multi-sensor integration.

Future research opportunities include multimodal fusion, potentially combining ECG, EEG, EMG, and inertial data to support more comprehensive physiological and human performance monitoring. Adaptive algorithms that become personalized to an individual’s signal patterns over time may enhance long-term robustness. Another promising direction is the use of reinforcement learning from human feedback (RLHF) to incorporate domain-expert or clinician feedback into the development and refinement of biomedical

deep learning models. Such feedback could help align model outputs with physiologically meaningful patterns, application-specific requirements, and expert interpretation. In biomedical settings, where accuracy alone may not fully capture clinical or physiological relevance, human-guided model adaptation may provide an additional mechanism for improving reliability, interpretability, and practical usability. Addressing real-world challenges—such as noise, motion artifacts, and sensor variability—remains critical; techniques like transfer learning, noise-aware training, and sensor calibration will be important. Developing lightweight, real-time implementations of these methods for embedded and wearable devices is also a key goal.

Taken together, the contributions in this Special Issue illustrate how biomedical signal analysis can benefit from the complementary integration of signal processing, physiological knowledge, machine learning, deep representation learning, wearable sensing, and human interaction. Rather than point to a single methodological solution, the collected works highlight the importance of combining data-driven approaches with domain knowledge and practical considerations. These perspectives may help guide the continued development of reliable, interpretable, and deployable technologies for physiological and wearable signal analysis.

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