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Design and Evaluation of a Compact CNN for EMG-Based Wearable Systems Under Embedded Constraints

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Highlights

What is the current knowledge on the topic?

- EMG-based movement recognition is increasingly used in wearable and cyber–physical systems.
- Embedded deployment requires AI models with low memory footprint and computational complexity.

What are the main findings?

- A compact 1D-CNN (~2000 parameters, ~2 KB after quantization) achieved approximately 91% classification accuracy under embedded constraints.
- The proposed CPS-oriented framework integrates EMG acquisition, preprocessing, and real-time AI inference while maintaining suitability for TinyML deployment.

Abstract

Electromyographic (EMG) signals are increasingly used in wearable cyber–physical systems (CPS), where reliable movement recognition must be achieved under limited computational resources. In this study, we present a compact EMG processing framework that integrates signal acquisition, preprocessing, segmentation, and movement classification within a unified pipeline designed for embedded-oriented applications. The proposed approach combines a multi-channel EMG acquisition system with a lightweight one-dimensional convolutional neural network (1D CNN) developed according to TinyML principles, with-processing input windows of size 32 × 3 and low computational complexity and memory requirements. Experimental evaluation was conducted on a dataset collected from 15 participants performing squat, walking, and running activities under realistic acquisition conditions. The proposed model achieved an accuracy of 0.9135, an F1-score of 0.9124, and a ROC AUC of approximately 0.96, demonstrating reliable classification performance. Following 8-bit quantization, the model size was reduced to approximately 2 KB, supporting deployment on resource-constrained embedded platforms. The results show that compact CNN architectures can effectively classify EMG-based movement patterns while maintaining a small computational footprint, providing a practical foundation for future wearable CPS and TinyML-enabled applications.

Keywords: electromyography (EMG); wearable cyber-physical systems; TinyML; embedded ai; convolutional neural networks; signal classification; neuromuscular signal processing; resource-constrained devices

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