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Introduction

Electroarthrography is a new and novel non-invasive technique that detects load-generated bioelectric potentials from joint cartilage using surface electrodes. Although bioelectric signals during dynamic activities are difficult to discern, they may contain distinct patterns reflecting different loading conditions. This study evaluated a deep neural network model for classifying bioelectric signals during various dynamic knee joint activities to establish a foundation for future rehabilitation applications.

Methods

Bioelectric signals were recorded from 20 knees of 20 healthy subjects (age: 25.00 ± 2.20 years, 75% male) using 8 surface electrodes during three activities: active knee extension, restricted squat, and passive range of motion. Signals were sampled at 250 Hz, low-pass filtered at 5 Hz, downsampled to 10 Hz, and Z-score normalized. The model consisted of a convolutional neural network (CNN) combining 2D and 1D layers: two Conv2D layers (16 and 32 filters, 3×3 kernel, ReLU activation), followed by two Conv1D layers (32 and 64 filters, kernel size 3), with MaxPooling, Flatten, Dense, and Dropout layers, culminating in a softmax output layer with 8 neurons. The model was trained using the Adam optimizer (learning rate: 0.001) with sparse categorical crossentropy loss for 1,000 epochs. Input data shape was (201, 8, 1) (Figure 1). Performance was evaluated using 5-fold cross-validation (8:2 split). No data augmentation was employed. Eight classes were defined based on activity type and movement direction.

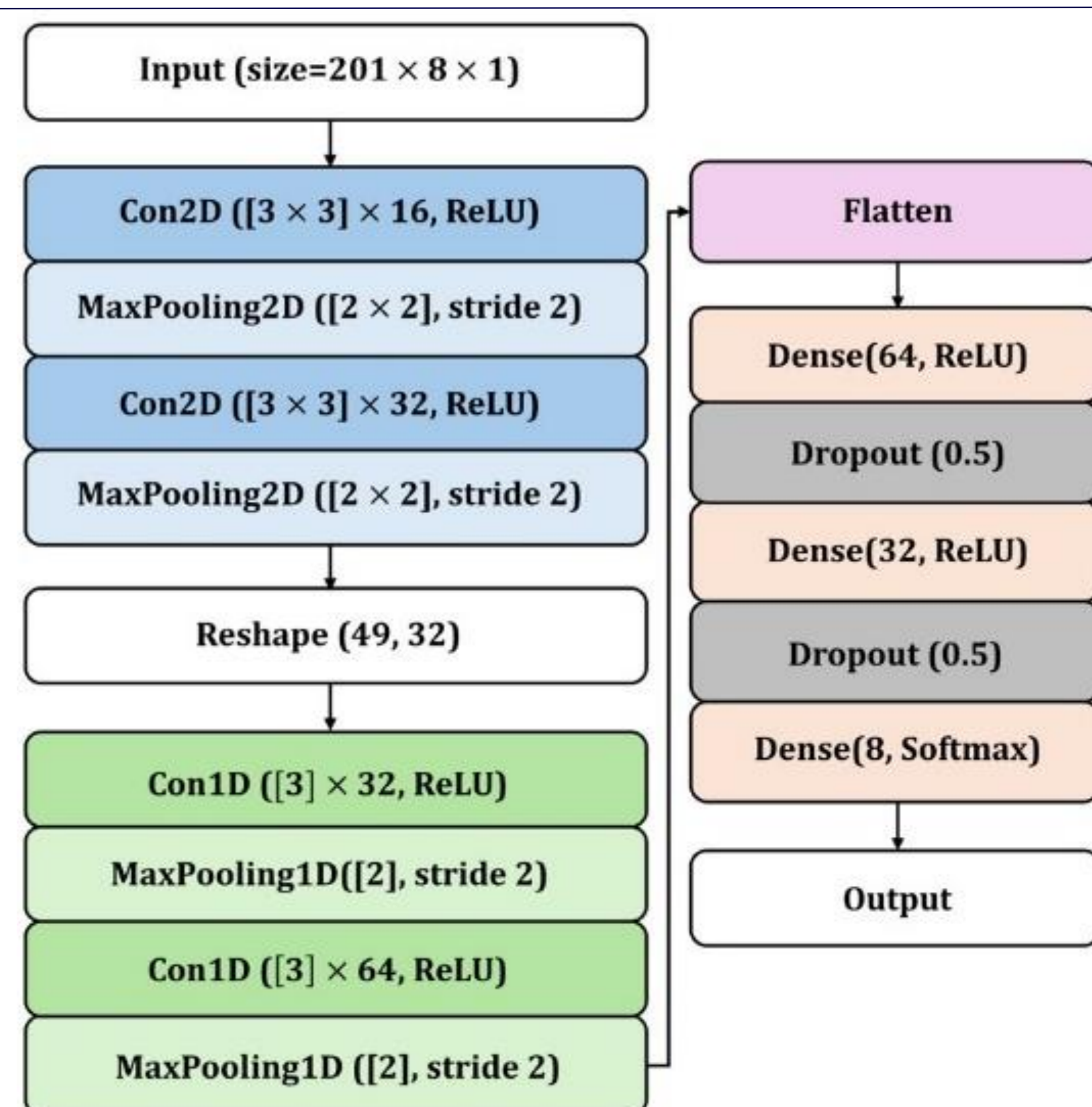


Fig 1. Hybrid 2D-1D convolutional neural network (CNN) architecture for bioelectrical signal classification

Results

The mean accuracy was 98.77% ($\pm 0.65\%$) across 5-fold cross-validation (97.7–99.44%). Mean precision, recall, and F1 score were 0.9547 (± 0.0488), 0.9649 (± 0.0347), and 0.9597 (± 0.0417), respectively. Perfect classification (F1 = 1.0000) was achieved in several activity-direction combinations for active knee extension ($90^\circ \rightarrow 0^\circ$) and passive ROM ($90^\circ \rightarrow$ full flexion; full flexion $\rightarrow 90^\circ$). Only 11 misclassifications occurred, most commonly squats ($0 \rightarrow 90^\circ$) misclassified as active knee extension ($90^\circ \rightarrow 0^\circ$) (5 cases), which can be explained by similar mechanical transitions toward peak cartilage loading. Training and validation loss curves demonstrated stable convergence without evidence of overfitting (Figure 3).

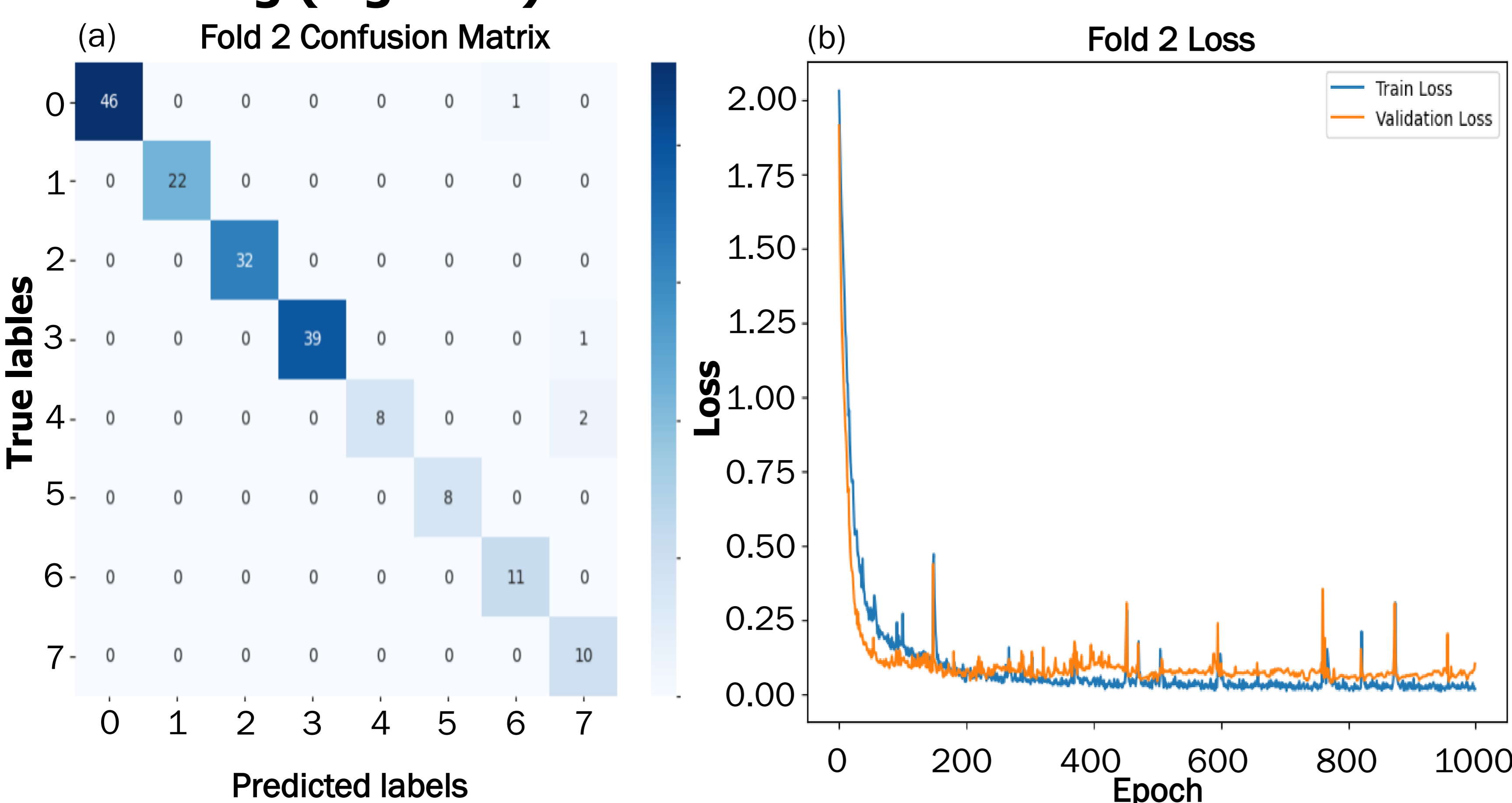


Fig 3. Confusion matrices (a) and Loss curves (b) of the 2nd fold from 5-fold validation

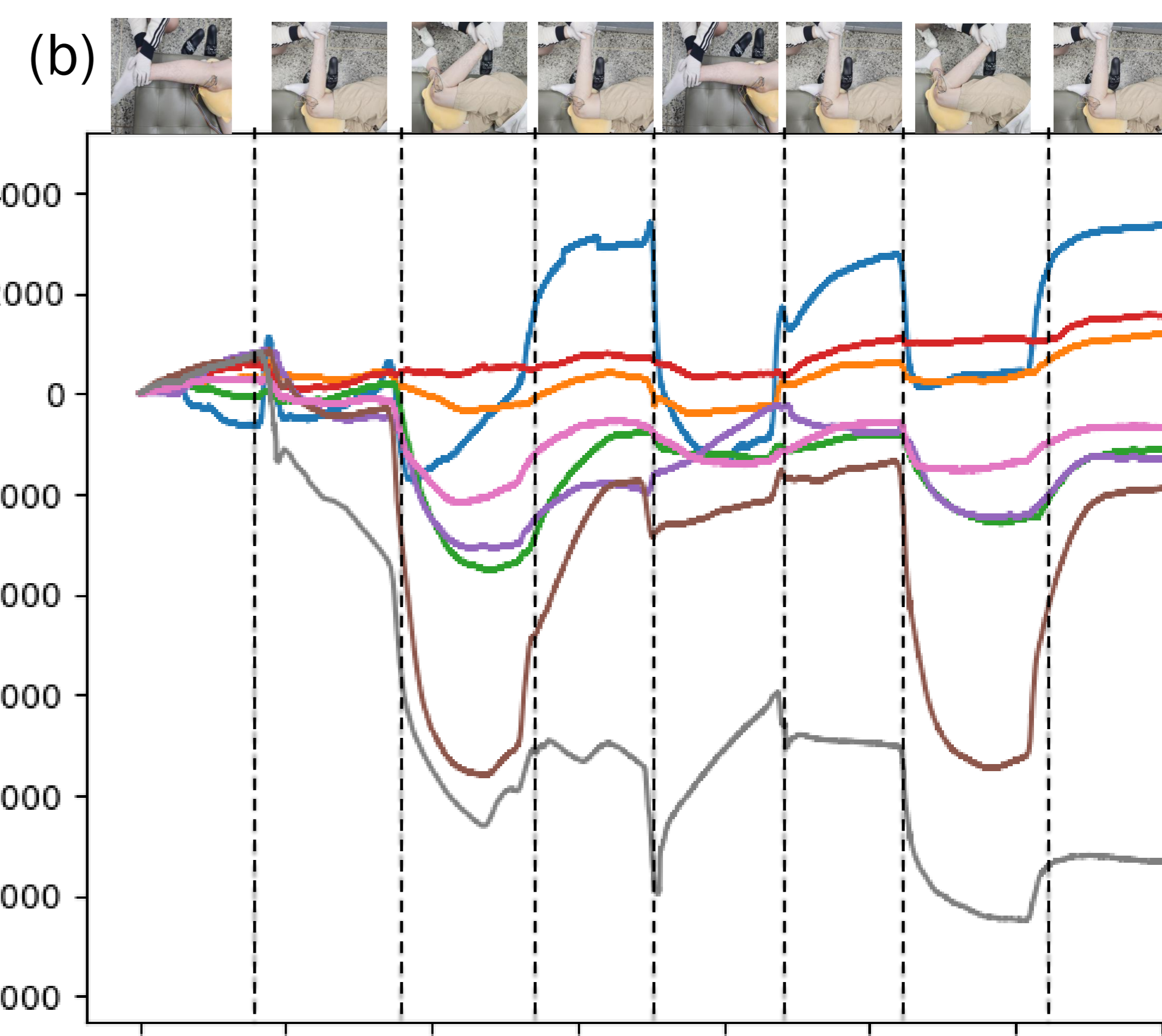
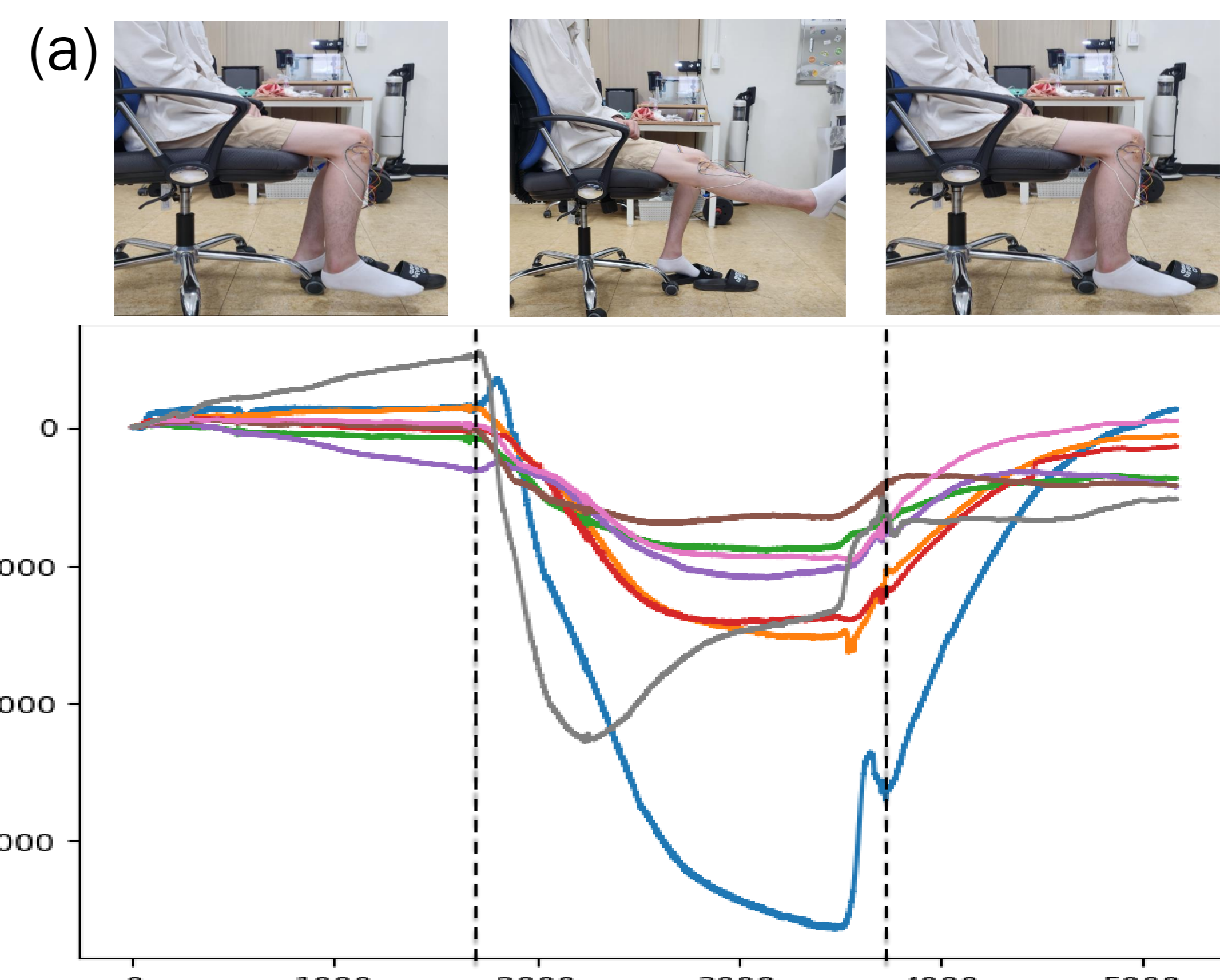


Fig 2. Electrode placement and changes in cartilage-evoked potentials for active (a) and passive (b) knee extension

Conclusion

A deep learning model classified cartilage-generated bioelectric potentials during dynamic knee movements with high accuracy. These findings show that the signals contain not only kinetic information related to biomechanical loading but also kinematic information reflecting movement patterns, which are not readily discernible through physician perception alone. Notably, the model's high accuracy show their potential as a concise, sensor-minimal, and clinically feasible framework for rehabilitation assessment, enabling the classification of physical activities and the estimation of cartilage loading characteristics without additional inertial or electromyographic sensors.