# Learning Neuromuscular Phase Transitions in Yoga Postures from Multi-Muscle EMG Signals Using Deep Temporal Latent Representations

Suvitti Suvitti
Department of Artificial Intelligence
Indian Institute of Technology, Hyderabad
Hyderabad, India
suvitti08@gmail.com,
ai21resch11005@iith.ac.in

Kousik Sarathy Sridharan
Department of Biomedical Engineering
Indian Institute of Technology, Hyderabad
Hyderabad, India
ks@bme.iith.ac.in

Mohan Raghavan
Department of Artificial Intelligence,
Department of Biomedical Engineering
Indian Institute of Technology, Hyderabad
Hyderabad, India
mohanr@bme.iith.ac.in

***Abstract*—Understanding the temporal organisation of neuromuscular activity during complex human movement remains a fundamental challenge in EMG analysis. While EMG is widely used for classification, the intrinsic temporal structure of coordinated multi-muscle activity is rarely modelled. We propose an unsupervised framework that combines temporal convolutional representation learning with change-point detection to identify neuromuscular phase-transition boundaries directly from EMG trajectories. The method learns a compact latent representation that captures coordinated muscle dynamics, enabling phase analysis without manual annotations. Experiments involving 595 EMG trajectories across seven yoga postures yield a consistent four-phase neuromuscular representation comprising initiation, transition, stabilisation, and recovery. The results demonstrate that meaningful temporal structure can be inferred directly from EMG signals, enabling data-driven analysis of simple to complex human movements.**

***Index Terms*—Surface electromyography (sEMG), Deep Learning, Temporal Representation, Latent Space, Phase Detection, Yoga Postures.**

## I. Introduction

Understanding the temporal organisation of muscle activity during human movement is an important problem in signal processing, biomechanics, and motor neuroscience. Surface electromyography (EMG) provides a direct measure of muscle activation and is widely used to study coordination during complex motor tasks. However, extracting meaningful temporal patterns from multi-muscle EMG remains challenging. A key challenge is identifying movement phase transitions directly from EMG data. Unlike gait analysis, where phase definitions are predefined, many real-world movements such as yoga postures involve continuous transitions without clear phase markers. In such cases, phase boundaries must be inferred directly from the underlying muscle activity. This problem is difficult for several reasons. First, EMG signals are noisy and highly variable across subjects, trials, and muscle groups. Second, recording multiple muscles introduces complexity and redundancy. Third, movement phases are often characterised by subtle changes in coordinated muscle activity that are difficult to capture in raw EMG signals. As a result, direct segmentation of EMG trajectories is often unstable and noise-sensitive. Most current methods rely on predefined phase definitions or supervised learning frameworks that require labelled data and do not adapt well to unconstrained movements. Consequently, there is limited work on learning phase structure directly from EMG signals in an unsupervised manner. We address this challenge using a data-driven framework that learns a compact representation of multi-muscle EMG trajectories and identifies phase transitions within this representation. The main idea is that a compact representation can reveal underlying muscle coordination and enable reliable detection of temporal transitions. The main contributions of this work are as follows:

i) A deep representation framework capturing the temporal coordination of multi-muscle EMG in a latent space.
ii) An unsupervised method for identifying neuromuscular phase-transition boundaries directly from EMG without manual phase annotations.
iii) Identification of a four-phase neuromuscular representation comprising initiation, transition, stabilisation, and recovery.
iv) Analysis of posture-specific phase timing reveals distinct stabilisation dynamics and coordination strategies.

The proposed framework provides a scalable approach for analysing complex human movement using EMG, with applications in movement assessment, rehabilitation, and smart training systems.

## II. Related Work

Existing work on EMG-based movement analysis can be broadly categorised into three themes: (i) multi-muscle EMG analysis for studying coordination patterns, (ii) temporal and phase-based modelling of human movement, and (iii) representation learning approaches for physiological signals. **EMG-Based Muscle Analysis**: Prior works have extensively used surface EMG to study muscle activation patterns and neuromuscular coordination during human movement. Traditional approaches focus on extracting time-domain and frequency-domain features, such as RMS amplitude and spectral characteristics, to quantify muscle activity [1], [2].

Additionally, muscle synergy analysis methods, including principal component analysis (PCA) and non-negative matrix factorisation (NMF), have been employed to identify low-dimensional structures in multi-muscle activation patterns [3], [4]. These methods effectively capture global coordination patterns and reduce the dimensionality of EMG signals, providing insights into underlying motor control strategies. Recent work has also explored EMG-based analysis for tasks such as gesture recognition and fatigue-invariant modelling using signal processing techniques [5]. However, the existing EMG analysis methods usually assume a rather globally consistent structure throughout the movement and do not clearly model how the coordination patterns evolve over time. As a result, these methods struggle to capture phase transitions in movements where muscle coordination changes dynamically. **Temporal and Phase-Based modelling**: Several studies have explored temporal segmentation of human movement into distinct phases, particularly in structured tasks such as gait analysis. These approaches often rely on external measurements, including kinematic data, joint angles, or ground reaction forces, to define phase boundaries [6], [7]. Probabilistic models (e.g., Hidden Markov Models (HMMs)) and change-point detection techniques have also been widely used for segmenting time-series data [8], [9]. While these approaches work well in structured settings, they mainly depend on strong prior assumptions about the phase structure or on additional sensing modalities, limiting their applicability to complex, unconstrained movements. To better understand the underlying neural control of such tasks, recent in-silico frameworks have been used to investigate spinal feedback phases and motor adaptation [10], [11], [12]. **Representation Learning for EMG Signals**: Recent advances in machine learning have introduced deep learning approaches for EMG analysis, particularly in applications such as gesture recognition, prosthetic control and activity classification [13]. Neural networks (recurrent and convolutional) have been used to learn hierarchical representations from multi-channel EMG signals [14], [15]. These approaches demonstrate that deep models can capture complex patterns in EMG data and learn compact representations of muscle activity. Using deep representation learning with models like convolutional autoencoders has successfully been applied to physiological signals such as electrocardiograms. This highlights the ability of latent representations to capture underlying signal structure [16]. However, most existing approaches are designed for supervised learning tasks and focus on classification or prediction. As a result, they do not explicitly model the intrinsic temporal structure of movement or enable discovery of phase transitions directly from EMG signals. While curated platforms facilitate the development of neuromotor integration models [17], [18], [19], they often require predefined parameters, highlighting the need for data-driven discovery of transitions.

Despite these advances, current methods still do not provide a unified approach for unsupervised discovery of temporal structure in multi-muscle EMG. Traditional EMG analysis approaches capture overall coordination but miss temporal transitions, whereas phase-based approaches rely heavily on external measurements and predefined structures. Similarly, deep learning methods learn strong representations but are mainly focused on supervised tasks, without explicitly modelling phase transitions [20]. In contrast, this work proposes a framework that combines deep representation learning with unsupervised temporal segmentation. By learning a compact latent representation of EMG trajectories and performing change-point detection in latent space, the proposed approach enables data-driven identification of neuromuscular phase-transition boundaries directly from EMG signals, without manual phase annotations or external cues. This unsupervised discovery is crucial for evaluating motor performance where coordination patterns serve as a baseline for rehabilitation protocols [21].

## III. Methodology

### A. Experimental Protocol and Data Preprocessing

The dataset consists of surface electromyography (EMG) recordings from seventeen healthy participants, performing seven basic standing Yoga postures, namely, Mālāsana, Pārśvakoṇāsana I, Tāḍāsana, Trikoṇāsana, Utkaṭkoṇāsana, Vīrabhadrāsana I, and Vṛkṣāsana. These postures were chosen to cover a range of human movements, from strength-based to balance-focused tasks and were performed according to the descriptions in B.K.S. Iyengar's *Light on Yoga*[22]. Each participant performed five trials for each posture, resulting in a total of 595 EMG trajectories. Each trial represented a complete movement cycle, including the movement initiation, posture execution, and return to a neutral position. EMG signals were recorded from sixteen muscles spanning the lower limbs, trunk, and upper body. To ensure accurate and consistent measurements of muscle activity, the SENIAM guidelines [23] were followed when placing the electrodes. Raw EMG signals were processed using a standard pipeline to get stable muscle activation envelopes. Each channel was band-pass filtered (10–200 Hz) to remove motion artefacts and high-frequency noise. This was then followed by full-wave rectification and temporal smoothing with a moving-average window to obtain a clean representation of muscle activation. To allow for consistent comparison, all recorded trials were further interpolated and time-normalised to a fixed duration of 3.585 seconds, corresponding to the shortest valid trial in the dataset. As a result, each trajectory is represented as a matrix $X \in \mathbb{R}^{T \times C}$ where $T = 3585$ denotes the number of time samples and $C = 16$ denotes the number of muscle channels. All trials were then concatenated with associated metadata (subject number, posture, trial number) for downstream analysis.

### B. Deep Temporal Latent Representation

To understand the underlying structure of multi-muscle coordination, we learn a compact representation of the EMG trajectories using a temporal convolutional autoencoder. The

encoder processes the input signal $X$ using three stacked one-dimensional convolutional layers (kernel size 9, stride 2) that operate along the temporal dimension while jointly modelling interactions across muscle channels. This results in a latent representation $Z = f_\theta(X)$, where $Z \in \mathbb{R}^{D \times T'}$. In our implementation, the latent dimensionality is $D = 64$. It maps the original 16 muscle channels to a higher-dimensional feature space that captures coordinated activation patterns. These latent channels do not correspond to individual muscles. Instead, they represent combinations of muscle activations that reflect coordination patterns. The temporal dimension is compressed from $T = 3585$ to $T' = 449$, allowing for a compressed yet organised representation of the trajectory. The model is trained using mean-squared reconstruction loss and the Adam optimiser, enabling the latent representation to preserve temporal structure while reducing noise and redundancy. This learned latent space provides a stable domain for analysing muscle coordination dynamics.

### C. Unsupervised Phase Detection in Latent Space

The main goal of this work is to identify movement phases directly from EMG signals without any manual annotations. Instead of segmenting raw EMG signals, which are often noisy and hard to interpret, we detect phases in the learned latent space. To do so, we apply change-point detection directly to the latent representation using Binary Segmentation with an L2 cost function to identify transitions in the temporal dynamics. For each trajectory, three transition points, $\tau_1$, $\tau_2$, and $\tau_3$, are estimated along the normalised time axis. These transition points divide the movement into four phases: Initiation, Transition, Stabilisation, and Recovery, providing a common representation of the movement cycle across postures. Since all trajectories have been time-normalised to the interval [0,1], each transition point represents a specific proportion of the movement duration (i.e. a boundary at $\tau_1 = 0.31$ indicates that the first phase takes up about 31% of the total movement duration). This formulation allows direct comparison of phase timing across different trials and postures.

### D. Phase-Level Analysis and Interpretation

To interpret the discovered phases, we perform statistical analysis at the phase level for all trajectories. First, we get the durations of each phase from the detected boundaries. We then average these durations across trials to measure specific temporal patterns for each posture and understand how effort is distributed across the identified phases. Second, by aggregating the EMG activity within each phase, we calculate the average muscle activation to identify the most active muscle groups for that phase. We observe that the stabilisation phase shows greater activation of lower-limb and trunk muscles. In contrast, the transition phase features coordinated activation of both upper and lower limb muscles. These observations provide a physiological interpretation of the discovered phases in terms of neuromuscular coordination.

This work combines representation learning and temporal segmentation into a unified framework. Given a multi-muscle EMG trajectory, a compact latent representation is learnt using a temporal convolutional autoencoder. By doing so, the coordination dynamics can be captured while reducing noise. Phase transitions are then identified in this latent space using Binary Segmentation-based change-point detection. This results in an unsupervised segmentation of the movement into well-defined phases. After which, phase-level analysis is performed to characterise temporal structure and muscle activation patterns across all trajectories. This approach allows for data-driven discovery of neuromuscular phase structure directly from EMG signals, without the need for manual labels or external measurements. By integrating deep representation learning with signal processing, the framework provides a robust approach for analysing complex human movement.

## IV. Results and Discussions

The proposed framework is built on a simple question: Can meaningful neuromuscular phases be characterised directly from multi-muscle EMG signals without manual phase annotations? The results show that deep temporal representations, together with change-point detection, provide a stable four-phase segmentation of movement trajectories that is temporally consistent and physiologically interpretable.

### A. Latent Representation of EMG Dynamics

The temporal convolutional autoencoder learns a compact latent representation of multi-muscle EMG trajectories. Reconstruction performance for Mālāsana is shown in Fig. 1.

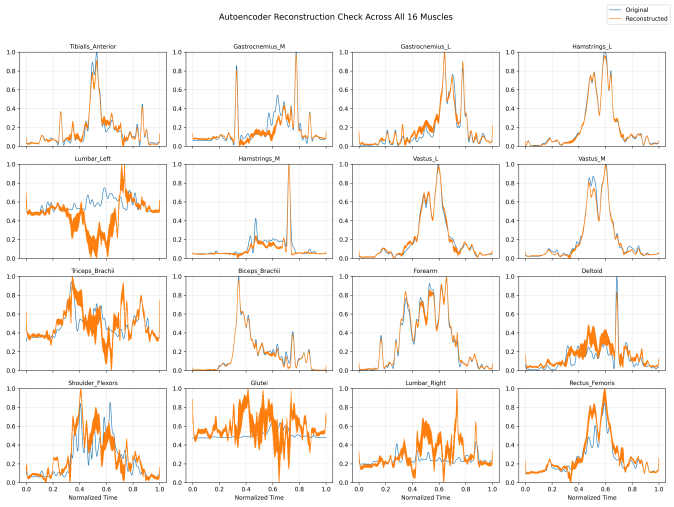


Fig. 1. Autoencoder reconstruction of multi-muscle EMG signals for a trial of Mālāsana

The reconstructed signals closely follow the temporal structure of the original EMG in most muscles, especially in high-activation muscles (e.g., Vastus, Rectus Femoris, and Gastrocnemius). This suggests that the latent embedding preserves the dominant patterns of neuromuscular activation. However, muscles with low amplitude and noisy regions (e.g., lumbar

and Triceps), show lower reconstruction accuracy. This implies that instead of overfitting to noise, the model focuses on coordinated activation patterns relevant for interpreting the movement. The resulting latent representation provides a more compact and stable description of multi-muscle coordination than the original EMG space. Such a representation is well suited for subsequent temporal segmentation, where phase transitions are expected to be identified from coordinated changes across multiple muscles rather than isolated signal fluctuations.

### B. Unsupervised Discovery of Phase Transitions

Phase boundaries are identified using change-point detection on the learned latent representation of each EMG trajectory. The Fig. 2 shows the resulting latent space segmentation for Mālāsana, aggregated across all subjects and trials. The central line indicates the mean EMG pattern and the shaded region represents inter-trial variability. Signals are vertically offset for visualisation and do not represent absolute amplitude scale.

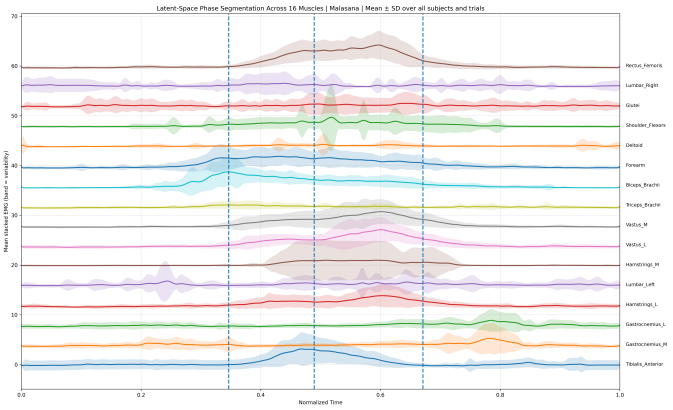


Fig. 2. Latent-space phase segmentation across all muscles for Mālāsana (mean ± variability over all subjects and trials). Vertical lines indicate the mean latent phase boundaries.

The detected boundaries align with coordinated changes across multiple muscle channels rather than isolated fluctuations in any single muscle, indicating that the latent representation captures global neuromuscular structure. For each trajectory, three transition points are detected along the normalised time axis. These points divide the movement into four phases: initiation, transition, stabilisation, and recovery. Across all trials, the boundary locations remain temporally consistent. Transitions generally occur near one-third, one-half, and two-thirds of the movement duration, although posture-specific variations are observed. This temporal regularity suggests that continuous EMG trajectories exhibit a stable phase organisation that can be characterised directly from coordinated muscle activity. The strong agreement between raw and latent segmentation ($r \approx 0.85$–$0.86$) suggests that the latent representation preserves the essential temporal organisation of the EMG signals while improving robustness to noise and inter-trial variability. The intermediate stabilisation phase consistently occupies the largest portion of the movement cycle, reflecting the sustained neuromuscular control required to maintain posture. Importantly, this process is entirely unsupervised.

### C. Consistency and Variability of Phase Timing

The identified phase boundaries show strong consistency across repeated trials, indicating stable neuromuscular transition patterns. When normalised over movement duration, phase timings remain similar across subjects and repetitions. Table I summarises the mean and standard deviation of the detected phase boundaries for each posture. While all postures exhibit a common four-phase structure, the timing of individual transitions varies according to posture-specific movement demands. At the same time, clear posture-specific differences

TABLE I
MEAN ± SD OF LATENT PHASE BOUNDARIES.

| Posture | $\tau_1$ | $\tau_2$ | $\tau_3$ |
|---|---|---|---|
| Mālāsana | $0.35 \pm 0.08$ | $0.49 \pm 0.09$ | $0.67 \pm 0.06$ |
| Pārśvakoṇāsana I | $0.35 \pm 0.09$ | $0.53 \pm 0.12$ | $0.67 \pm 0.10$ |
| Tāḍāsana | $0.26 \pm 0.18$ | $0.51 \pm 0.18$ | $0.73 \pm 0.15$ |
| Trikoṇāsana | $0.35 \pm 0.11$ | $0.55 \pm 0.15$ | $0.69 \pm 0.13$ |
| Utkaṭkoṇāsana | $0.40 \pm 0.09$ | $0.53 \pm 0.11$ | $0.71 \pm 0.11$ |
| Vīrabhadrāsana I | $0.42 \pm 0.11$ | $0.57 \pm 0.14$ | $0.73 \pm 0.09$ |
| Vṛkṣāsana | $0.24 \pm 0.12$ | $0.43 \pm 0.17$ | $0.69 \pm 0.11$ |

are observed. Fig. 3 shows that stabilisation phase duration varies across postures. For example, balance-intensive postures such as Vṛkṣāsana exhibit longer Phase 3 durations, reflecting increased neuromuscular control demands. The broader spread

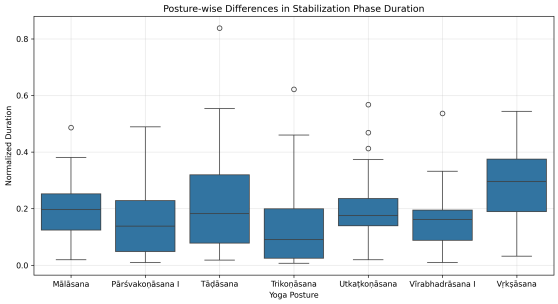


Fig. 3. Distribution of stabilisation phase (Phase 3) duration across different Yoga postures.

observed in some postures further indicates that stabilisation demands are not uniform across movement types. In contrast, postures such as Tāḍāsana show greater variability in stabilisation duration, suggesting increased inter-subject differences in movement execution. These findings demonstrate that the framework captures both common temporal structure and task-dependent variation in motor control.

### D. Phase-wise Neuromuscular Coordination

The physiological relevance of the identified phases is illustrated by the phase-wise muscle activation heatmap (Fig. 4). Each phase exhibits a distinct muscle activation profile, indicating that the segmentation captures coordinated neuromuscular changes rather than arbitrary temporal partitions.

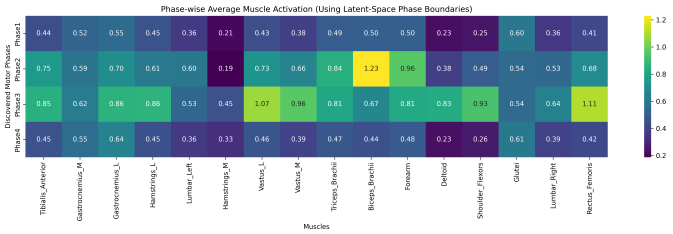


Fig. 4. Average muscle activation across the four identified phases.

A clear progression of motor control can be observed as:

- **Phase 1 (Initiation):** Higher activation of the Glutei and Gastrocnemius muscles, indicating early postural preparation.
- **Phase 2 (Transition):** Increased activation of Biceps, Triceps, Tibialis Anterior, and Vastus muscles during movement execution.
- **Phase 3 (Stabilisation):** Highest activation across Quadriceps, Hamstrings, and Shoulder Flexors, corresponding to posture hold.
- **Phase 4 (Recovery):** Reduced overall activation as the subject returns to a neutral position.

The activation profiles support the physiological interpretation of the identified phases. For unseen trials, the framework automatically estimates three latent-space boundary points ($\tau_1$, $\tau_2$, $\tau_3$), producing a four-phase segmentation of the movement trajectory. The main result is the identification of a consistent four-phase neuromuscular representation across all trajectories without manual phase annotations. This demonstrates that data-driven analysis can reveal meaningful structure in neuromuscular behaviour. By combining deep representation learning with signal processing, the proposed framework bridges machine learning and motor neuroscience while providing an interpretable description of movement dynamics.

## V. Conclusion

In this work, we analysed multi-muscle EMG recordings from seven yoga postures to investigate whether meaningful phase structure can be characterised directly from the signals. Using a temporal convolutional autoencoder and latent-space change-point detection, we obtained a consistent four-phase neuromuscular representation across subjects, postures, and trials. The identified phases exhibited distinct muscle activation patterns and posture-specific timing characteristics, indicating physiologically interpretable coordination dynamics. Overall, the results suggest that EMG signals contain an underlying temporal organisation that can be characterised without manual phase annotations. This framework provides a link between representation learning and signal processing for movement analysis, with potential applications in rehabilitation, motor assessment, and human-centred AI systems.

## Acknowledgment

We sincerely thank all participants for their time and consent in supporting data collection and also acknowledge the Human Gait and Movement Lab team at IIT Hyderabad for their feedback.

## References

[1] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature extraction and reduction of wavelet transform coefficients for EMG pattern classification," *Electronics and Electrical Engineering*, vol. 122, no. 6, pp. 27–32, 2012.

[2] G. R. Naik, D. Kumar, and J. Al-Timemy, "Applications of EMG signal processing in movement analysis," *IEEE Rev. Biomed. Eng.*, vol. 9, pp. 21–38, 2016.

[3] D. D. Lee and H. S. Seung, "Learning the parts of objects by non-negative matrix factorisation," *Nature*, vol. 401, pp. 788–791, 1999.

[4] A. d'Avella, P. Saltiel, and E. Bizzi, "Combinations of muscle synergies in the construction of a natural motor behavior," *Nat. Neurosci.*, vol. 6, pp. 300–308, 2003.

[5] V. Dadape, A. Deshmukh, S. Sharma, and R. R. Sharma, "PSD Information Based Fatigue Invariant Hand Gesture Recognition Using sEMG," in *Proc. IEEE SPCOM*, 2024.

[6] C. M. O'Connor, S. K. Thorpe, M. J. O'Malley, and C. L. Vaughan, "Automatic detection of gait events using kinematic data," *Gait & Posture*, vol. 25, no. 3, pp. 469–474, 2007.

[7] J. A. Zeni, J. G. Richards, and J. S. Higginson, "Two simple methods for determining gait events during treadmill walking," *Gait & Posture*, vol. 27, no. 4, pp. 710–714, 2008.

[8] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proc. IEEE*, vol. 77, no. 2, pp. 257–286, 1989.

[9] C. Truong, L. Oudre, and N. Vayatis, "Selective review of offline change point detection methods," *Signal Processing*, vol. 167, 2020.

[10] K. Mallampalli, K. Sarathy, R. Balasubramanian, and M. Raghavan, "Studying spinal feedback loops post tendon transfer surgery using the pincer grasp task: A Neuro-Musculoskeletal study using NEUROiD," in *Proc. IEEE-EMBS Conf. Biomed. Eng. Sci. (IECBES)*, 2022.

[11] W. Li, P. Shi, and H. Yu, "Gesture recognition using surface electromyography and deep learning for prostheses hand: State-of-the-art, challenges, and future," *Frontiers in Neuroscience*, 2021.

[12] M. Atzori et al., "Deep learning with convolutional neural networks applied to electromyography data," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 4, pp. 357–366, 2016.

[13] U. Côté-Allard et al., "Deep learning for electromyographic hand gesture signal classification using transfer learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 4, pp. 760–771, 2019.

[14] A. Jaiswal, P. S. Choudhary, S. Dandapat, and P. K. Bora, "Leveraging Convolutional Autoencoders for Bundle Branch Block Detection in Electrocardiograms," in *Proc. IEEE SPCOM*, 2024.

[15] R. S. Iyengar, M. V. Pithapuram, A. K. Singh, and M. Raghavan, "Curated Model Development Using NEUROiD: A Web-Based NEUROmotor Integration and Design Platform," *Front. Neurorobot.*, vol. 16, p. 833073, 2022.

[16] R. S. Iyengar, K. Mallampalli, A. K. Singh, A. Koppula, K. S. Sridharan, and M. Raghavan, "Chapter 8 - The NEUROiD neuromusculoskeletal movement simulation platform," in *Neuromusculoskeletal Modeling*, ScienceDirect, 2022.

[17] R. S. Iyengar and M. Raghavan, "MPI Parallelization of NEUROiD Models Using Docker Swarm," in *Proc. IEEE*, 2021.

[18] R. S. Iyengar, K. Mallampalli, and M. Raghavan, "A Deep Reinforcement Learning based approach for movement training of neuromusculoskeletal systems," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, 2023.

[19] A. K. Singh, K. S. Sridharan, S. Wu, O. Tirosh, and M. Raghavan, "In-silico neuro-musculoskeletal model demonstrates spasticity progression with descending motor tracts loss in simulated clinical triage," *Comput. Biol. Med.*, vol. 148, p. 105844, 2022.

[20] A. K. Singh, K. S. Sridharan, S. Wu, O. Tirosh, and M. Raghavan, "Simulated Clinical Triage of Modified Tardieu Test for Lower Limb Spasticity," *IEEE*, 2024.

[21] S. C. Prakash, S. Ganguly, P. K. Yadav, M. Raghavan, and K. S. Sridharan, "Evaluation of a gamified upper-arm bimanual trainer for stroke patients - A healthy cohort study," in *Proc. IEEE-EMBS Int. Conf. Biomed. Health Informat. (BHI)*, 2022.

[22] B. K. S. Iyengar, *Light on Yoga*. New York, NY, USA: Schocken Books, 1966.

[23] SENIAM Project, "Surface Electromyography for the Non-Invasive Assessment of Muscles," Online: `http://www.seniam.org`, accessed 2022.