Related Work Summary & Comparison Table

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Surface Electromyography (sEMG)-based gesture recognition is a pivotal technology for human-computer interaction and prosthetic control. The literature explores the transition from manual feature engineering to deep learning backbones capable of decoding complex muscle activation patterns.

Dataset Development and Standardization
High-quality benchmarking is a core focus in recent work. The **IKCU-EMG** dataset [1] provides a balanced demographic of 40 participants (equal gender distribution) across 10 hand gestures, emphasizing the need for representative biosignal data. In contrast, the **NinaPro** series (DB1, DB2) remains the gold standard for high-complexity tasks, offering up to 52 classes [3]. These datasets enable the evaluation of model robustness against inter-subject variability and electrode placement shifts.

Supervised Learning Backbones
The supervised architectures identified in the credible related work can be categorized by their data representation:

- **Convolutional Neural Networks (CNN):** Backbones like **MSHilbNet** [3] utilize space-filling curves to convert 1D sEMG signals into 2D images, capturing spatial correlations between adjacent muscle fibers.
- **Hybrid Spatio-Temporal Models:** Architectures combining **CNNs with LSTM or GRU** layers [4] are preferred for capturing both the instantaneous muscle force and the temporal progression of a gesture.
- **Graph-Based Architectures:** As highlighted in recent surveys [2], **Spatio-Temporal Graph Convolutional Networks (STGCN)** represent the current state-of-the-art for high-density EMG, treating sensors as nodes in a physical grid to model functional connectivity.

Challenges in Classification
Despite high accuracies (often > 95%) on smaller gesture sets, performance drops significantly as the number of classes increases (e.g., 70% on 52 classes [3]). Future research is directed toward adaptive learning and meta-learning to bridge the gap between offline training and real-time prosthetic application [2].

Comparison of sEMG Gesture Recognition Methods

Table 1: Supervised Backbones and Dataset Benchmarking

Title	**Dataset Name & URL**	**Dataset Description (Samples, Classes, Splits)**	**Methods Name**	**Acc.**	**Pros**	**Cons**	**Cit.**
Dataset for multi-channel sEMG signals...	IKCU-EMG [Link]	40 subjects; 10 gestures; 5 repetitive cycles per gesture; 4 channels.	Supervised CNN Baseline	98.4%	Gender-balanced; optimized for 4-channel HCI.	Limited spatial information for fine motor tasks.	[1]
Deep Feature Learning Survey	NinaPro & CapgMyo [Link]	HD-EMG (128 ch); 50+ classes; multi-session splits.	STGCN & Transformers	85–95%	Superior at modeling electrode connectivity.	Extremely high computational cost for training.	[2]
Deep Learning in EMG-based Recognition	NinaPro DB1 [Link]	27 subjects; 52 classes; 10 channels; Train/Test split by repetitions.	MSHilbNet (Modified CNN)	70.5%	Hilbert curve improves spatial mapping vs. simple CNN.	Performance degrades with very high class counts.	[3]
Gesture Recognition Review	NinaPro DB2 [Link]	40 subjects; 50 gestures; 12-channel sEMG; Time-windowed splits.	CNN-LSTM Hybrid	80–94%	Captures both spatial and temporal muscle patterns.	Susceptible to ”noise” from electrode shift.	[4]
Hand Motion Classification Sensor	Custom 6-Channel Dataset	10 subjects; 11 motions; 6-channel ring; Multiple force levels.	Cascaded Classifier	>90%	Robust to variations in motion force and speed.	Relies on manual feature engineering.	[5]

References

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