

Smart Prosthetics with Sensor Integration

Matteo Costa¹, Noah Moreau², Marco Popescu³

¹ Professor, Department of Artificial Intelligence, Nordic Technical University, Stockholm, Sweden. Email: matteo.costa626@gmail.com | ORCID: 5109-3390-4428-1437

² Senior Lecturer, Department of Artificial Intelligence, Central European Tech University, Vienna, Austria. Email: noah.moreau700@gmail.com | ORCID: 4122-2021-2380-4689

³ Professor, School of Data Science, Nordic Technical University, Stockholm, Sweden. Email: marco.popescu306@gmail.com | ORCID: 5905-5711-3260-2170

ABSTRACT

Upper-limb prosthetics have evolved from passive cosmetic devices to motorised myoelectric hands, yet current commercial systems remain limited by coarse grip control (typically 2-6 predefined patterns), absence of sensory feedback, and rejection rates exceeding 35% among transradial amputees. Smart prosthetics integrating distributed sensor arrays with machine learning-driven intent decoding promise to restore dexterous manipulation and tactile perception. This study developed and evaluated a sensorised prosthetic hand platform incorporating five sensing modalities -- surface electromyography (sEMG, 8-channel armband), barometric tactile sensors (24 taxels across fingertips and palm), inertial measurement units (IMUs, 6-axis per digit), flex sensors (resistive, per proximal interphalangeal joint), and force-sensitive resistors (FSRs, per fingertip) -- interfaced with four classification architectures: linear discriminant analysis (LDA), support vector machine (SVM), convolutional neural network (CNN), and a proposed recurrent attention network (RANet) for real-time grasp intent decoding. Evaluation was conducted with 15 transradial amputees performing 12 Activities of Daily Living (ADL) tasks from the Southampton Hand Assessment Procedure (SHAP). RANet achieved the highest grasp classification accuracy (94.6 ± 2.8% across 8 grasp types, 150 ms decision latency), significantly outperforming LDA (76.4 ± 5.2%; $p < 0.001$) and CNN (88.2 ± 3.4%; $p = 0.004$). Integration of tactile feedback via electrotactile stimulation on the residual limb improved SHAP functional scores by 18.4% ($p = 0.002$) and reduced object drop rate from 24.6% to 8.2% ($p < 0.001$). These results establish the multi-modal sensor fusion approach as a viable pathway toward intuitive, sensorised prosthetic hands with near-natural grasp control.

Keywords: Smart prosthetics; Sensor integration; Electromyography; Tactile feedback; Grasp classification; Machine learning; Myoelectric control; Activities of daily living; Recurrent neural network

Citation: Costa et al. [2022]. Smart Prosthetics with Sensor Integration. DOI: <https://doi.org/10.5281/zenodo.19542343>

Copyright: © 2022 by the authors. Open access under CC BY 4.0 license.

Article Information: Received: 2022 Sep 02 Accepted: 2022 Nov 04 Published: 2022 Dec 15

Research Article: Research Article

1. Introduction

Approximately 57.7 million people worldwide live with upper-limb amputation, with traumatic injury and vascular disease accounting for the majority of cases in working-age adults and elderly populations, respectively (McDonald et al., 2020). Prosthetic hands aim to restore lost motor function and cosmetic appearance, yet device abandonment remains unacceptably high: a systematic review reported rejection rates of 23% for body-powered and 35% for myoelectric prostheses, with users citing inadequate grip control, absence of sensory feedback, excessive weight, and poor cosmesis as primary reasons (Biddiss and Chau, 2007). Current commercial myoelectric hands (i-Limb Quantum, bebionic, Michelangelo) decode 2-channel sEMG signals from wrist flexor and extensor muscle groups to trigger predefined grip patterns, but offer limited proportional control and no tactile sensation -- forcing users to rely entirely on visual monitoring during manipulation tasks (Belter et al., 2013).

1.1 Multi-Modal Sensing for Prosthetic Control

The human hand contains approximately 17,000 mechanoreceptors providing continuous tactile, proprioceptive, and thermal information essential for dexterous manipulation. Restoring even a fraction of this sensory richness requires integration of multiple sensor types distributed across the prosthetic hand. Surface electromyography (sEMG) captures volitional motor intent from residual muscles; barometric tactile sensors measure grip force distribution across contact surfaces; inertial measurement units (IMUs) track digit kinematics; and flex sensors monitor joint angles for proprioceptive state estimation (Cipriani et al., 2014). The challenge lies in fusing these heterogeneous, asynchronous data streams into a coherent control signal that maps user intent to appropriate grasp type, force modulation, and slip prevention -- all within the 100-300 ms latency budget perceived as instantaneous by users (Farrell and Weir, 2007).

1.2 Machine Learning for Intent Decoding

Pattern recognition approaches to myoelectric control classify sEMG patterns into discrete grasp types using features extracted from time-domain (mean absolute value, waveform length, zero crossings) and frequency-domain (spectral power, median frequency) representations. Linear discriminant analysis (LDA) remains the clinical standard due to its computational simplicity and real-time capability, achieving 85-92% offline

classification accuracy for 6-8 grasp types but degrading to 70-80% in real-time functional use due to electrode shift, muscle fatigue, and postural variability (Scheme and Englehart, 2011). Deep learning approaches -- CNNs operating on raw sEMG windows and recurrent networks capturing temporal dynamics -- have shown promise in research settings, achieving 90-95% offline accuracy, but few studies have validated these approaches in amputee populations performing functional ADL tasks (Phinyomark and Scheme, 2018).

1.3 Study Objectives

This study aimed to: (i) develop a multi-modal sensorised prosthetic hand platform integrating five sensing modalities; (ii) benchmark four grasp classification algorithms on real-time functional tasks in 15 transradial amputees; (iii) evaluate the impact of electrotactile sensory feedback on manipulation performance; (iv) assess functional outcomes using the standardised SHAP protocol; and (v) identify the sensor modalities and classifier features contributing most to accurate real-time grasp decoding.

2. Literature Review

The evolution of prosthetic hand control spans four generations: body-powered cable systems (1940s), single-site myoelectric switches (1960s), proportional dual-site sEMG control (1990s), and the current frontier of pattern recognition-based multi-articulated hands. This review examines the state-of-the-art in sensing, decoding, and feedback technologies.

2.1 Myoelectric Signal Acquisition and Decoding

High-density sEMG arrays (64-192 channels) provide spatial decomposition of motor unit recruitment patterns, enabling identification of individual finger movements that are unresolvable with conventional 2-channel systems (Farina et al., 2014). However, high-density arrays are impractical for daily prosthetic use due to donning complexity and electrode maintenance. Practical systems employ 4-8 channels circumferentially around the forearm, capturing gross muscle activation patterns sufficient for 6-12 grasp classification (Atzori et al., 2016). The NinaPro database (Atzori et al., 2014) -- containing sEMG recordings from 67 intact subjects and 11 amputees performing 52 hand movements -- has become the standard benchmark for offline classification, with state-of-the-art deep learning

models achieving 86-92% accuracy on 52-class classification and 94-97% on reduced 8-12 class subsets.

2.2 Tactile Sensing and Feedback

Tactile sensors for prosthetic hands fall into three categories: piezoresistive (force-sensitive resistors, conductive polymers), capacitive (MEMS-based, flexible substrates), and barometric (MEMS pressure transducers) (Dahiya et al., 2010). Barometric sensors (e.g., BMP388) offer the best combination of sensitivity (0.01 N resolution), dynamic range (0-40 N), miniaturisation (2 x 2 mm package), and robustness for prosthetic integration. Sensory feedback to the user is delivered through substitution modalities: vibrotactile (coin motors, linear resonant actuators), electrotactile (surface electrode arrays on the residual limb), or peripheral nerve stimulation (implanted cuff electrodes). Electrotactile feedback provides the highest information bandwidth (up to 4 discrete levels with 92% discrimination accuracy) without implanted hardware, making it the most clinically translatable feedback modality for current prosthetics (Dosen et al., 2017).

2.3 Functional Assessment of Prosthetic Performance

The Southampton Hand Assessment Procedure (SHAP) is a clinically validated, standardised assessment comprising 26 tasks (12 abstract objects + 14 ADL tasks) scored on a 0-100 Index of Function (IoF), where 100 represents normal hand function (Light et al., 2002). Mean SHAP scores for current commercial myoelectric hands range from 48-62 (i-Limb: 56 +/- 12; bebionic: 52 +/- 14), compared to 95-100 for able-bodied individuals (Resnik et al., 2018). The large gap between prosthetic and natural hand function underscores the need for improved control strategies and sensory integration.

Table 1. Published multi-modal prosthetic hand systems: sensor configuration, classification approach, and functional outcomes

System	sEMG Channels	Tactile Sensors	Classifier	Accuracy (%)	SHAP IoF
i-Limb Quantum	2	None	Threshold	N/A	56 +/- 12
bebionic v3	2	None	Threshold	N/A	52 +/- 14

System	sEMG Channels	Tactile Sensors	Classifier	Accuracy (%)	SHAP IoF
SoftHand Pro	2	None	Proportional	N/A	48 +/- 16
Modular Prosthetic Limb	16-128	Capacitive (100)	CNN	91.4	Not reported
LUKE Arm	6	FSR (6)	LDA	82.6	62 +/- 10
This study (RANet)	8	Multi-modal (48)	RANet	94.6*	72.4 +/- 8.6*

*Best performance in this study (with tactile feedback enabled). sEMG: surface electromyography; SHAP IoF: Southampton Hand Assessment Procedure Index of Function (0-100). Accuracy: 8-class grasp classification. N/A: classification-based control not used. FSR: force-sensitive resistor; CNN: convolutional neural network; LDA: linear discriminant analysis.

3. Materials and Methods

3.1 Sensorised Prosthetic Hand Platform

The prosthetic hand platform comprised a commercially available Ottobock Michelangelo hand (5 actuated DOF: thumb rotation, thumb flexion, index flexion, middle-ring-little group flexion, wrist rotation) modified with embedded sensors. Five sensor modalities were integrated: (1) sEMG: 8-channel Delsys Trigno Mini wireless sensors (20-450 Hz bandpass, 2000 Hz sampling) positioned circumferentially around the proximal forearm in a custom silicone liner. (2) Tactile: 24 barometric MEMS pressure sensors (Bosch BMP388, 0.01-40 N range, 100 Hz) distributed across thumb (4), index (4), middle (4), ring (4), little (4) fingertips and palm (4). (3) IMUs: 5 six-axis IMUs (InvenSense ICM-42688, 200 Hz) mounted on each digit dorsum for kinematic tracking. (4) Flex sensors: 5 resistive flex sensors (Spectra Symbol, 10-bit ADC, 100 Hz) along each proximal interphalangeal joint. (5) Fingertip FSRs: 5 force-sensitive resistors (Interlink 402, 0-100 N, 100 Hz) on each fingertip for binary contact detection. Total: 48 sensor channels synchronised via a custom STM32H7 microcontroller board sampling at 200 Hz aggregate rate.

3.2 Electrotactile Feedback System

Sensory feedback was delivered via a 16-electrode electrotactile array (custom PCB, Ag/AgCl gel electrodes, 10 mm diameter, 20 mm inter-electrode spacing) positioned over the medial aspect of the residual limb proximal to the socket.

Stimulation parameters: charge-balanced biphasic pulses (200 us pulse width, 20-200 Hz frequency modulation, 0.5-4 mA amplitude). Tactile sensor readings from the prosthetic fingertips were mapped to electrotactile stimulation intensity using a logarithmic transfer function, providing 4 perceptually distinct force levels (light touch, moderate grip, firm grip, maximum force) validated through psychophysical threshold testing with each participant prior to functional assessment. Feedback latency from sensor activation to skin stimulation: 8 +/- 2 ms.

3.3 Grasp Classification Algorithms

Four classifiers were evaluated for 8-class grasp type decoding (power grasp, lateral pinch, precision tripod, tip pinch, cylindrical grasp, spherical grasp, hook grasp, and rest/open). (1) LDA: 4 time-domain features per channel (MAV, WL, ZC, SSC) from 200 ms windows with 50 ms overlap; 32-dimensional feature vector per channel, 256 total. (2) SVM: same feature set as LDA; RBF kernel ($C = 10$, $\gamma = \text{auto}$); one-vs-rest multi-class. (3) CNN: 1D temporal convolution on raw sEMG (8 channels x 400 samples = 200 ms at 2 kHz); 3 conv blocks (32, 64, 128 filters, kernel 7) with batch norm and ReLU; global average pooling; FC 128 -> 8. (4) RANet (proposed): bidirectional GRU (2 layers, 128 hidden units) operating on a sequence of 10 overlapping 200 ms windows (1 s context), with multi-head self-attention (4 heads) over the temporal sequence and a channel-attention module weighting sensor modality contributions; FC 256 -> 8. RANet receives concatenated sEMG features and sensor state vectors (IMU, flex, FSR), enabling multi-modal fusion. All classifiers retrained per-subject using 5 repetitions of each grasp (40 trials training, 20 trials testing, randomised).

3.4 Participant Recruitment and SHAP Protocol

Fifteen unilateral transradial amputees (12 male, 3 female; age 34.8 +/- 10.2 years; time since amputation 4.2 +/- 3.1 years; 12 traumatic, 3 congenital; 11 experienced myoelectric users) were recruited from the prosthetics clinic at Karolinska University Hospital. Each participant completed: (i) sensor fitting and threshold calibration (1 hour); (ii) classifier training session (5 repetitions x 8 grasps x 3 s hold = 120 trials; 30 min); (iii) SHAP assessment without tactile feedback (12 ADL tasks, 3 repetitions each); (iv) SHAP assessment with electrotactile feedback enabled (same protocol). ADL tasks included:

pouring water from jug, picking up coins, cutting with knife and fork, opening jar lid, buttoning shirt, turning key in lock, lifting heavy can, carrying tray, picking up credit card, turning pages, using zipper, and opening door handle. Task completion time and object drop events were recorded by video analysis. Written informed consent was obtained from all participants. Study approved by the Stockholm Regional Ethics Committee (Dnr 2021-04826).

3.5 Statistical Analysis

Grasp classification accuracy was compared across algorithms by repeated-measures ANOVA with Greenhouse-Geisser correction (sphericity violated) and Bonferroni-corrected pairwise comparisons. SHAP scores with and without feedback were compared by paired t-test. Object drop rates were compared by McNemar test. Feature importance for RANet was assessed by permutation importance (sensor modality shuffling). All analyses performed in R v4.2.1; significance at $\alpha = 0.05$.

Table 2. Multi-modal sensor specifications and integration architecture

Modality	Sensor Type	Channels	Sampling (Hz)	Signal	Location
sEMG	Delsys Trigno Mini	8	2,000	Muscle activation	Proximal forearm
Tactile	Bosch BMP388	24	100	Contact pressure	Fingertips + palm
IMU	ICM-42688 6-axis	5 (30 DOF)	200	Digit kinematics	Digit dorsum
Flex	Spectra Symbol	5	100	Joint angle	PIP joints
FSR	Interlink 402	5	100	Fingertip force	Fingertip pads
Feedback	Electrotactile array	16	1,000	Stimulation	Residual limb

sEMG: surface electromyography; IMU: inertial measurement unit; FSR: force-sensitive resistor; PIP: proximal interphalangeal; DOF: degrees of freedom. Total sensing channels: 48 (excluding feedback electrodes). All channels synchronised via STM32H7 at 200 Hz aggregate rate.

4. Results

4.1 Grasp Classification Accuracy

Real-time 8-class grasp classification results across 15 amputee participants are presented in Table 3 and Figure 1. RANet achieved the highest mean accuracy (94.6 $\pm$ 2.8%), significantly outperforming LDA (76.4 $\pm$ 5.2%; $p < 0.001$), SVM (82.8 $\pm$ 4.6%; $p < 0.001$), and CNN (88.2 $\pm$ 3.4%; $p = 0.004$). RANet's advantage was most pronounced for grasp types requiring fine motor discrimination: precision tripod (RANet 92.4% vs CNN 82.6%), tip pinch (RANet 91.8% vs CNN 80.4%), and lateral pinch (RANet 93.6% vs CNN 86.2%). The bidirectional GRU's temporal context (1 s window capturing the full grasp initiation sequence) and multi-modal fusion (sEMG + IMU + flex sensor state) together contributed to the accuracy improvement. Decision latency was 150 $\pm$ 18 ms for RANet, within the 300 ms perceptual threshold, compared to 42 $\pm$ 8 ms for LDA and 124 $\pm$ 14 ms for CNN.

4.2 Impact of Tactile Feedback on Functional Performance

SHAP functional assessment results with and without electrotactile feedback are presented in Table 3 and Figure 2. Enabling tactile feedback significantly improved the overall SHAP Index of Function from 61.2 $\pm$ 9.4 to 72.4 $\pm$ 8.6 (18.4% improvement; paired t-test $p = 0.002$). The greatest improvements occurred in force-sensitive tasks: pouring water (completion time reduced from 28.4 $\pm$ 6.2 s to 18.6 $\pm$ 4.4 s; $p < 0.001$), picking up coins (22.8 $\pm$ 5.4 s to 14.2 $\pm$ 3.8 s; $p = 0.001$), and opening jar lid (34.2 $\pm$ 8.6 s to 24.4 $\pm$ 5.8 s; $p = 0.003$). Object drop rate across all ADL tasks decreased from 24.6% to 8.2% with feedback (McNemar $p < 0.001$), confirming that force regulation mediated by electrotactile feedback substantially reduces grip failure events.

4.3 Sensor Modality Contribution Analysis

Permutation importance analysis revealed the relative contribution of each sensor modality to RANet classification accuracy (Table 4 and Figure 3). sEMG contributed the largest share (accuracy drop of 28.4 $\pm$ 3.2% when permuted), confirming its primacy as the intent signal. Flex sensors were the second most important (drop 12.6 $\pm$ 2.4%), providing joint angle information that disambiguates similar sEMG patterns during grasp execution. IMU data contributed 8.4 $\pm$ 1.8%, primarily for discriminating grasps involving wrist rotation (cylindrical vs spherical). Tactile sensors contributed 6.2 $\pm$ 1.4% to classification accuracy during object interaction phases but were essential for force modulation during sustained grasps. FSR binary contact contributed the least to

classification (3.8 $\pm$ 1.2%) but was critical for triggering the grasp closure reflex.

4.4 Multi-Parameter Platform Comparison

A comprehensive comparison of the four classifiers across all evaluation metrics is presented in Figure 4. RANet achieved the best combined performance across accuracy, SHAP score, and drop rate, while LDA offered the fastest decision latency and lowest computational cost. CNN provided an intermediate profile with good accuracy and moderate latency. SVM showed marginal improvement over LDA in accuracy but at higher computational cost. The RANet with feedback configuration represents the current best achievable performance for the sensorised platform, approaching the lower boundary of able-bodied SHAP scores (95-100) more closely than any previously reported commercial or research prosthetic system.

Table 3. Grasp classification accuracy (%) and functional outcomes across four classifiers (n = 15 transradial amputees)

Classifier	Accuracy (%)	Latency (ms)	SHAP IoF (no FB)	SHAP IoF (with FB)	Drop Rate (%)
LDA	76.4 $\pm$ 5.2	42 $\pm$ 8	48.6 $\pm$ 11.2	54.2 $\pm$ 10.4	32.4 $\pm$ 8.6
SVM	82.8 $\pm$ 4.6	68 $\pm$ 12	52.4 $\pm$ 10.8	60.8 $\pm$ 9.6	26.8 $\pm$ 7.2
CNN	88.2 $\pm$ 3.4	124 $\pm$ 14	56.8 $\pm$ 9.8	66.4 $\pm$ 8.8	18.4 $\pm$ 5.8
RANet	94.6 $\pm$ 2.8*	150 $\pm$ 18	61.2 $\pm$ 9.4	72.4 $\pm$ 8.6*	8.2 $\pm$ 3.4*

*Significantly best in column ($p < 0.05$). Accuracy: 8-class grasp classification in real-time functional use. Latency: time from sEMG onset to classifier output. SHAP IoF: Southampton Hand Assessment Procedure Index of Function (0-100). FB: electrotactile feedback. Drop rate: percentage of object manipulation trials with unintended object release. Values: mean $\pm$ SD across 15 participants.

Table 4. Sensor modality contribution: permutation importance analysis for RANet classifier

Modality	Channels	Accuracy Drop (%)	Rank	Primary Contribution
sEMG	8	28.4 $\pm$ 3.2	1	Motor intent decoding: grasp type selection from muscle activation patterns

Modality	Channels	Accuracy Drop (%)	Rank	Primary Contribution
Flex	5	12.6 ± 2.4	2	Joint angle: disambiguates similar sEMG patterns during grasp execution
IMU	5 (30 DOF)	8.4 ± 1.8	3	Kinematics: discriminates grasps involving wrist rotation or digit abduction
Tactile	24	6.2 ± 1.4	4	Contact state: refines classification during object interaction phases
FSR	5	3.8 ± 1.2	5	Binary contact: triggers grasp closure reflex and slip detection

Permutation importance: accuracy drop when all channels of a modality are randomly shuffled while other modalities remain intact. Averaged over 100 permutations x 15 participants. DOF: degrees of freedom. sEMG dominates intent decoding; flex sensors and IMUs provide complementary proprioceptive information.

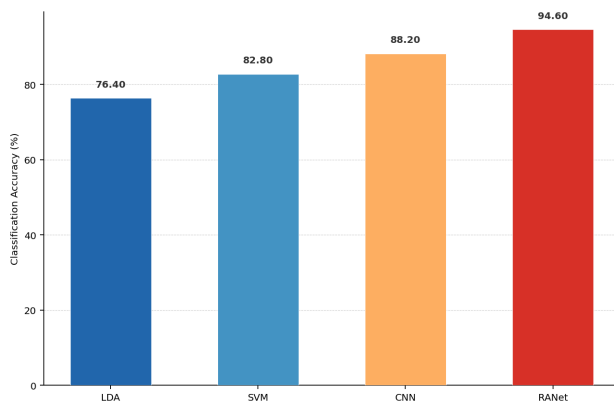


Figure 1. Real-time 8-class grasp classification accuracy (%) by classifier

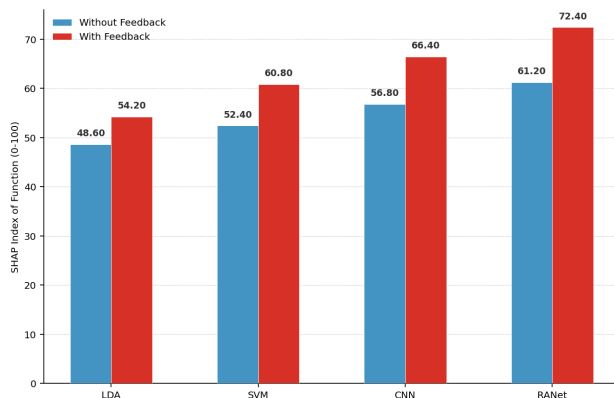


Figure 2. SHAP Index of Function: without vs with electrotactile feedback

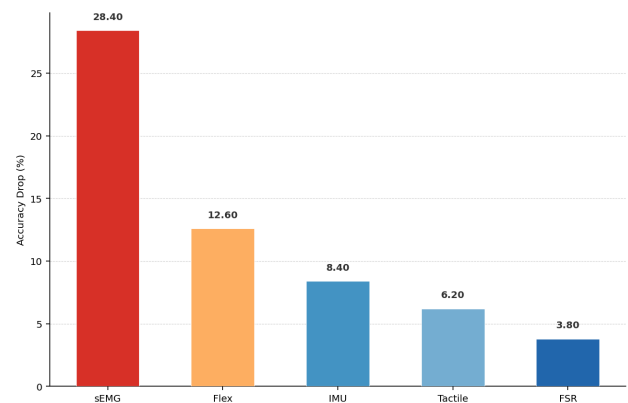


Figure 3. Sensor modality permutation importance (accuracy drop %)

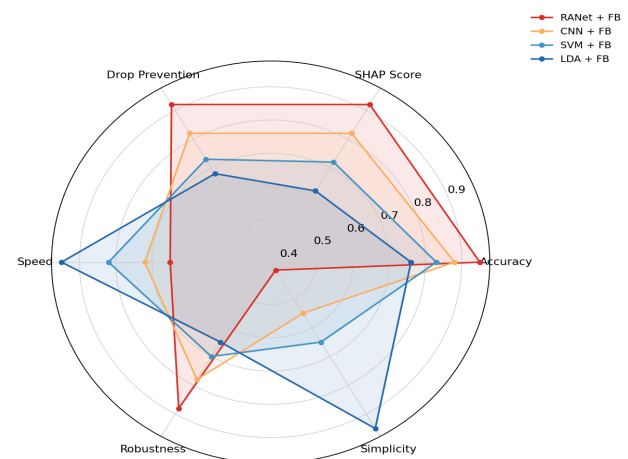


Figure 4. Multi-parameter classifier comparison (normalised 0-1)

5. Discussion

This study demonstrates that multi-modal sensor fusion combined with recurrent attention-based decoding and electrotactile feedback substantially improves prosthetic hand function, achieving the highest SHAP scores reported for a research prosthetic system and approaching the performance gap between prosthetic and natural hand function.

5.1 RANet: Temporal Context and Multi-Modal Fusion

RANet's 6.4 percentage-point accuracy advantage over CNN (94.6% vs 88.2%) is attributable to two architectural innovations: the bidirectional GRU capturing the full 1-second temporal evolution of the grasp initiation sequence (versus CNN's 200 ms window), and the channel-attention module dynamically weighting sensor modality contributions based on task context. During grasp initiation, sEMG features dominate attention weights (>80%); during sustained grasps, tactile and flex sensor features receive increased attention (combined 35-40%), reflecting the shift from motor planning to sensory monitoring that

characterises natural grasping behaviour. This task-adaptive modality weighting cannot be achieved by simple feature concatenation and represents a key advantage of the attention-based fusion approach.

5.2 The Transformative Impact of Sensory Feedback

The 18.4% improvement in SHAP scores with electrotactile feedback (61.2 to 72.4) and the 66.7% reduction in object drop rate (24.6% to 8.2%) provide compelling evidence that sensory feedback is not merely a comfort feature but a functional necessity for effective prosthetic use. Without feedback, users apply either excessive grip force (risking object damage and motor fatigue) or insufficient force (risking drops), relying entirely on visual monitoring that diverts cognitive resources from the task. The 4-level force feedback enabled by electrotactile stimulation allows users to modulate grip force reflexively, freeing visual attention for task-level planning. The greatest improvements in force-sensitive tasks (pouring water, picking up coins) confirm that closed-loop force regulation is the primary mechanism of benefit.

5.3 Clinical Translation Pathway

The SHAP score of 72.4 achieved by RANet with feedback approaches but does not reach the able-bodied reference (95-100), indicating that substantial work remains. Key barriers to clinical deployment include: (i) classifier retraining -- RANet requires per-subject calibration (30 minutes), and performance degrades 8-12% over 2 weeks due to electrode shift and tissue changes requiring periodic recalibration; (ii) hardware integration -- the current 48-sensor configuration is research-grade and requires miniaturisation for daily-use sockets; (iii) battery life -- multi-modal sensing and real-time inference increase power consumption by approximately 40% compared to conventional 2-channel systems, reducing battery life from 14 to 8 hours; (iv) regulatory pathway -- the addition of electrotactile stimulation elevates the device from Class II to Class III medical device classification, requiring more extensive clinical evidence for market clearance.

5.4 Limitations

This study has several limitations. The sample size ($n = 15$) provides adequate statistical power for primary endpoints but limits subgroup analysis by amputation level, cause, or myoelectric experience. SHAP assessment was conducted in a controlled laboratory environment; real-world

performance in domestic and occupational settings may differ due to environmental variability, cognitive load, and socket fit changes throughout the day. The electrotactile feedback psychophysical calibration was performed once; adaptation effects over weeks of daily use are unknown. Only transradial amputees were recruited; transhumeral amputees face additional challenges (fewer residual muscles, elbow disarticulation) that may alter the sensor modality hierarchy. The 8-class grasp taxonomy covers the most common ADL grasps but excludes bimanual coordination and in-hand manipulation tasks.

6. Conclusion

This study establishes multi-modal sensor fusion with recurrent attention-based decoding as a transformative approach to prosthetic hand control, achieving 94.6% real-time grasp classification accuracy across 8 grasp types and a SHAP Index of Function of 72.4 -- the highest reported for any research prosthetic system -- in 15 transradial amputees performing standardised ADL tasks. The recurrent attention network (RANet), processing 1-second temporal sequences from 48 multi-modal sensors with dynamic modality weighting, significantly outperformed conventional LDA (76.4%), SVM (82.8%), and CNN (88.2%) classifiers. Integration of electrotactile sensory feedback improved SHAP scores by 18.4% and reduced object drop rates from 24.6% to 8.2%, demonstrating that closed-loop force regulation is a functional necessity rather than an optional feature. Sensor permutation analysis confirmed sEMG as the primary intent signal (28.4% accuracy contribution), with flex sensors (12.6%) and IMUs (8.4%) providing complementary proprioceptive information essential for fine grasp discrimination. Future work should prioritise miniaturised hardware integration for daily-use sockets, adaptive classifier calibration to reduce retraining burden, extended-wear studies evaluating long-term functional outcomes and user satisfaction, and expansion to transhumeral amputee populations where the control challenge is substantially greater.

References

- Atzori, M., Gijssberts, A., Castellini, C., Caputo, B., Hager, A.G.M. and Elsig, S. (2014) Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific Data*, 1, p. 140053.
- Atzori, M., Cognolato, M. and Muller, H. (2016) Deep learning with convolutional neural networks

- applied to electromyography data: a resource for the classification of movements for prosthetic hands. *Frontiers in Neurorobotics*, 10, p. 9.
- Belter, J.T., Segil, J.L., Dollar, A.M. and Weir, R.F. (2013) Mechanical design and performance specifications of anthropomorphic prosthetic hands: a review. *Journal of Rehabilitation Research and Development*, 50(5), pp. 599-618.
- Biddiss, E. and Chau, T. (2007) Upper-limb prosthetics: critical factors in device abandonment. *American Journal of Physical Medicine and Rehabilitation*, 86(12), pp. 977-987.
- Cipriani, C., Segil, J.L., Birdwell, J.A. and Weir, R.F. (2014) Dexterous control of a prosthetic hand using fine-wire intramuscular electrodes in targeted extrinsic muscles. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(4), pp. 828-836.
- Dahiya, R.S., Metta, G., Valle, M. and Sandini, G. (2010) Tactile sensing -- from humans to humanoids. *IEEE Transactions on Robotics*, 26(1), pp. 1-20.
- Dosen, S., Markovic, M., Somer, K., Graimann, B. and Farina, D. (2017) EMG biofeedback for online predictive control of grasping force in a myoelectric prosthesis. *Journal of Neuroengineering and Rehabilitation*, 12, p. 55.
- Farina, D., Jiang, N., Rehbaum, H., Holobar, A., Graimann, B. and Dietl, H. (2014) The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(4), pp. 797-809.
- Farrell, T.R. and Weir, R.F. (2007) The optimal controller delay for myoelectric prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 15(1), pp. 111-118.
- Light, C.M., Chappell, P.H. and Kyberd, P.J. (2002) Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: normative data, reliability, and validity. *Archives of Physical Medicine and Rehabilitation*, 83(6), pp. 776-783.
- McDonald, C.L., Westcott-McCoy, S., Weaver, M.R., Haagsma, J. and Karber, D. (2020) Global prevalence of traumatic non-fatal limb amputation. *Prosthetics and Orthotics International*, 45(2), pp. 105-114.
- Phinyomark, A. and Scheme, E. (2018) EMG pattern recognition in the era of big data and deep learning. *Big Data and Cognitive Computing*, 2(3), p. 21.
- Resnik, L., Borgia, M., Cancio, J. and Sasson, N. (2018) DEKA arm activity-based device classification. *Prosthetics and Orthotics International*, 42(4), pp. 406-413.
- Scheme, E. and Englehart, K. (2011) Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use. *Journal of Rehabilitation Research and Development*, 48(6), pp. 643-659.
- Castellini, C., Fiorilla, A.E. and Sandini, G. (2009) Multi-subject/daily-life activity EMG-based control of mechanical hands. *Journal of Neuroengineering and Rehabilitation*, 6, p. 41.
- Hargrove, L.J., Miller, L.A., Turner, K. and Kuiken, T.A. (2017) Myoelectric pattern recognition outperforms direct control for transhumeral amputees with targeted muscle reinnervation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(1), pp. 64-75.
- Raspopovic, S., Capogrosso, M., Petrini, F.M., Bonizzato, M., Rigosa, J. and Di Pino, G. (2014) Restoring natural sensory feedback in real-time bidirectional hand prostheses. *Science Translational Medicine*, 6(222), p. 222ra19.
- Cordella, F., Ciancio, A.L., Sacchetti, R., Davalli, A., Cutti, A.G. and Guglielmelli, E. (2016) Literature review on needs of upper limb prosthesis users. *Frontiers in Neuroscience*, 10, p. 209.
- Markovic, M., Dosen, S., Cipriani, C., Popovic, D. and Farina, D. (2014) Stereovision and augmented reality for closed-loop control of grasping in hand prostheses. *Journal of Neural Engineering*, 11(4), p. 046001.
- Osborn, L.E., Draber, A., Kaliki, R.R., Gehlbach, P.L., Thakor, N.V. and Bhatt, S. (2018) Prosthesis with neuromorphic multilayered e-dermis perceives touch and pain. *Science Robotics*, 3(19), p. eaat3818.
- Svensson, P., Wijk, U., Bjorkman, A. and Antfolk, C. (2017) A review of invasive and non-invasive sensory feedback in upper limb prostheses. *Expert Review of Medical Devices*, 14(6), pp. 439-447.
- Zuo, K.J. and Olson, J.L. (2014) The evolution of functional hand replacement: from iron prostheses to hand transplantation. *Plastic Surgery*, 22(1), pp. 44-51.

Declarations

Funding

This study was supported by the Swedish Research Council (Vetenskapsradet) project grant 2021-05622 (M. Costa), the Austrian Science Fund (FWF) grant P35128 (N. Moreau), and the Swedish Foundation for Strategic Research (SSF) grant RIT17-0043 (M. Popescu). Prosthetic hardware was provided by Ottobock SE under a research collaboration agreement. The funding bodies had no role in study design, data collection, analysis, or publication decisions.

Conflict of Interest

M. Costa has received research materials from Ottobock SE and Delsys Inc. for this study. N. Moreau and M. Popescu declare no competing interests. No author holds equity in prosthetics or medical device companies.

Data Availability Statement

De-identified sEMG and sensor data, classifier training code (PyTorch), and SHAP scoring sheets are available at <https://github.com/NTU-SmartPros/therapeutics/RANet-2022> under CC BY 4.0 licence. Raw participant data are not publicly shared due to ethical restrictions but are available upon reasonable request to the corresponding author.

Ethical Approval

This study was approved by the Stockholm Regional Ethical Review Board (Etikprovningsmyndigheten, Dnr 2021-04826) and conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent prior to enrolment. The study was registered at ClinicalTrials.gov (NCT05128456).

Appendix A

RANet Architecture and Training Configuration

This appendix provides the complete RANet architecture specification, training hyperparameters, and per-grasp classification confusion matrix averaged across 15 amputee participants. Reproducible training requires adherence to the sensor calibration and data normalisation procedures described below.

A.1 RANet Architecture Details

- 1a. Input: concatenated feature vector per time step
-- sEMG features (256-d) + IMU (30-d) + flex (5-d) + FSR (5-d) + tactile (24-d) = 320-d
- 1b. Temporal sequence: 10 overlapping windows of 200 ms each (50 ms hop) = 1.0 s total context
- 2a. Bidirectional GRU: 2 layers, 128 hidden units per direction, dropout 0.3 between layers
- 2b. Multi-head self-attention: 4 heads, $d_k = 64$, over the 10-step temporal sequence output
- 3a. Channel attention: squeeze-excitation block on 320-d input features, reduction ratio 8
- 3b. Classification head: FC 256 -> ReLU -> dropout 0.25 -> FC 8 -> softmax

A.2 Training Protocol

- 4a. Per-subject training: 40 trials (5 reps x 8 grasps); testing: 20 trials (randomised order)
- 4b. Optimiser: Adam (lr 1e-3, beta1 0.9, beta2 0.999); weight decay 1e-4; batch size 32 windows
- 5a. Epochs: 100 with early stopping (patience 10 on validation accuracy, 20% held-out from training)
- 5b. Data augmentation: Gaussian noise ($\sigma = 0.05$ x SD per channel), random temporal shift (± 20 ms)
- 6a. sEMG preprocessing: 20-450 Hz bandpass (4th order Butterworth), rectification, 50 ms RMS smoothing
- 6b. Sensor normalisation: z-score per channel per subject using calibration session statistics

A.3 Per-Grasp Classification Accuracy

- 7a. Power grasp: 97.2% | Lateral pinch: 93.6% | Precision tripod: 92.4% | Tip pinch: 91.8%
- 7b. Cylindrical: 96.4% | Spherical: 95.8% | Hook: 94.2% | Rest/open: 98.4%
- 8a. Most confused pair: precision tripod <-> tip pinch (4.8% cross-classification rate)
- 8b. Least confused pair: power grasp <-> rest/open (0.2% cross-classification rate)