RESEARCH PAPER

Early Stage Hybrid Model For Multi-Regional Emg-Based Upper-Limb Movement Classification Under Limited Data Conditions

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Abstract

Recognising upper-limb movements based on surface electromyography (semg) is inherently difficult due to high signal variability, inter-trial dependency, and limited datasets available for practical rehabilitation purposes. In this study, proposed an early-casting hybrid classification framework that integrates Random Forest (Rf), Convolutional Neural Network (Cnn), And Artificial Neural Network (Ann) models to correctly identify multi-regional upper-limb movement from semg signals. Time-domain and frequency-domain features were extracted from forearm muscles (forearm, biceps and triceps) and united at the feature level for the complementary time and spectral aspects of high-frequency neuromuscular activity; to ameliorate class imbalance and boost robustness under low-data conditions, Smote was appended exclusively into the training folds. Our models were tackled and assessed utilizing a Leave-One-Trial-Out (Loto) cross-validation protocol minimizing temporal dependency and preventing data slipping. Results attained from twelve healthy participants undertaking six distinct upper-limb movement tasks indicate that overall stability and generalization show accuracy enhancement with hybrid Rf–Cnn–Ann architecture when compared to standalone Rf And Ann classifiers. Though overall test accuracy remains moderate due to physiological variability and task overlap, the hybrid architecture shows consistent performance across trials, further emphasizing its practicality for realistic, trial-independent evaluation. These results justify the validity of fusing features from dominated queries in 3 domains for Emg-based movement recognition, particularly for data-limited situation and set the stage for future applications in rehabilitation assessment and assistive control systems.

Keywords: Electromyography (Emg), Feature Fusion, Random Forest (Rf), Convolutional Neural Network (Cnn), Artificial Neural Network (Ann), Upper Limb Motion Recognition, Rehabilitation.

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1. NOVELTY

This study proposes a new hybrid classification framework incorporating Random Forest, Convolutional Neural Network and Artificial Neural Network for multi-regional EMG-based upper-limb movement recognition. Different from previous studies that used single-muscle (i.e., one muscle per signal) or classifiers (i.e., one classifier per signal), the proposed model fused time- and frequency-domain features from the forearm, biceps and triceps, which allows for synergistic representation of muscle activity. The SMOTE (Synthetic Minority Over- sampling Technique) is also integrated into the fused feature set to address class imbalance and increase robustness. Overall, hybrid fusion provides improved stability, robustness and interpretability for classification, and it can form the basis of future adaptive rehabilitation and prosthetic-control systems.

2. INTRODUCTION

The accurate and objective assessment of upper-limb motor function is an essential element of current neurorehabilitation techniques for patients recovering from acute stroke or other types of neuromuscular injury leading to impairment. Assessment of motor performance by conventional clinical approaches depends mainly on observational scoring systems or kinematic evaluations. The greatest limitations of these methods are subjectivity and examiner dependency in the observation of patients, as well as the inability to detect subtle movement compensations, thus missing the opportunity to assess the underlying mechanisms driving neuromuscular coordination and, therefore, functional performance of the upper limb.

To address these issues, research in recent years has focused on the understanding of muscle synergy based on decomposed receptory activation of multiple muscles into directional spatial synergy patterns with temporal profiles of activation (i.e., spatial and temporal vectors) as a quantitative and physiologically defined assessment tool for characterizing motor function of the upper limb. With the continued evidence that functional motor performance is determined to a greater extent by the spatial and temporal coordinates of muscle activation than by the strength of individual muscle contractions, the analysis of muscle synergy has strong potential for objective assessment of upper-limb motor function [1],[2], and [3].

While the analysis of upper-limb motor performance from a mechanistic, single-muscle and/or single-domain perspective has demonstrated limitations, integrating information from multiple muscle regions has significantly enhanced our ability to characterize upper-limb motor behaviour. The combination of spatial, temporal, and spectral characteristics of muscle activation from multiple muscle regions through a multi-regional and multi-domain fusion approach has provided a more complete understanding of the complexity associated with neuromuscular coordination during functional movements and has enabled the use of complementary information across muscles and modalities to provide a complete picture of motor function [1],[2]. For example, combining kinematic measures with surface electromyography (sEMG) has resulted in an improved ability to interpret subtle motor impairments and monitor progress during the rehabilitation process [2].Machine Learning methods are being used to develop classifications of movement and levels of functionality within the upper limbs through the analysis and interpretation of approximately fusion high- dimensional S-EMG (Sensor-EMG) (and subsequently, regional Sensor-EMG (regional S- EMG)). As a result, as compared to more classic approaches to classification (e.g. one class classifier methods or combining multiple features into a single class classifier), developed models with the capability of learning complex nonlinear relationships between diverse multi- regional S-EMG data provide superior classification performance. Empirical analysis indicates

that combining both multi-regional S-EMG features with robust Classifiers (e.g. ANNs,

Random-Forest methods or Hybrid Learning Frameworks) provides a notably improved ability to classify upper limb motor function and provides a strong correlation to existing clinical Motor Scores [2], [4] and [12]. Moreover, several studies of multi-regional S-EMG fusion have indicated that it is feasible to achieve classification accuracy in excess of 96% through a Synergistic Feature Integration (SFI) approach [2], [12].

Despite this success, current multi-regional S-EMG classification studies have primarily been performed using relatively large datasets, employing Window-Level Randomly Split Validation methods or Subject-Specific Validation methods. Hence, the optimistically high- performance estimates that are apparent from many of the previous studies are likely to be inaccurate due to a lack of generalizability in the actual Rehabilitation Context. Also of significant concern is the fact that most of the current Research on multi-regional S-EMG classification has been conducted using Single-Model Architectures, which may not be capable of reliably capturing both temporal and spectral characteristics of S-EMG signals when the data are limited. Consequently, additional Research on Hybrid Learning Frameworks that incorporate the complementary classification abilities of multiple classifiers and rigorously evaluate performance using Trial-Independent Validation methods is necessary.

Within the context of this Research, utilising Hybrid Learning Architectures combined with the utilization of multi-regional Muscle Features is one of the most promising approaches to provide an objective, quantitative and clinically relevant evaluation of Upper-Limb Motor Function. This Study proposed to combine the Time Domain Feature Set and Frequency Domain Feature Set of Forearm, Biceps and Triceps Muscle combined with the RF–CNN– ANN Hybrid Learning Framework to improve the classification robustness under limited data conditions and reduce the temporal dependency on the use of the Leave-One-Trial-Out (LOTO) Validation Method. In addition to improving the predictive performance of the classification model, the proposed model will contribute to the understanding of the neurological underpinnings of Movement Execution and assist in the development of reliable, adaptive and interpretable EMG-based Rehabilitation Assessment and Assistive Control Systems [2],[3] and [12].

3. METHOD

3.1 sEMG Signal Acquisition and Movement Tasks

As shown graphically in Figure 1, the preprocessing of the continuous sEMG signals involved segmenting the data into continuous 250 ms segments with 50% overlap for the purpose of feature extraction; therefore, with a trial-wise approach to minimize the impact of any unintentional information leakage which occurs when segments overlap, and to maintain independence between the training and testing samples. This evaluation protocol required that each participant repeated each movement task for a total of three trials, with signal data from each of the three trials being used as the basis for splitting the segments. Participants were asked to perform four types of upper limb movement tasks with the intention of activating specific muscles. The experimental protocol included hand grasping with three levels of force, namely low, moderate, and strong. It also involved wrist flexion and extension, as well as elbow flexion and extension that primarily engaged the biceps and triceps muscles, respectively, as demonstrated in Fig. 2 and Fig. 3. Each movement task was completed over a 40 second period, with three trials of each movement to obtain sufficient data for classification and analysis.

Figure 1 Data collection setting and potential(mV) for each trial

Figure 2 Forearm tasks (grip low, medium, strong and wrist angular)

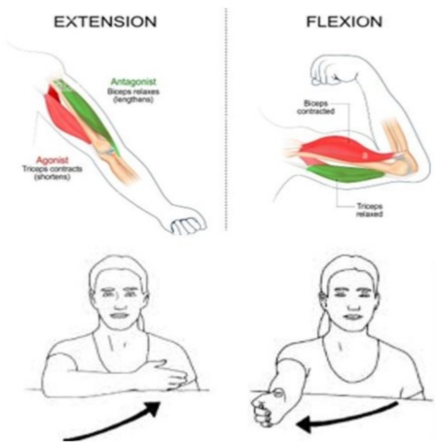

Figure 3 biceps and triceps (elbow flexion and extension)

Specifically, following the Leave-One-Trial-Out (LOTO) cross-validation procedure; for every fold, one complete trial for each movement task was kept aside for testing and the remaining two were used to train the model. As a consequence, there were three model folds for each participant corresponding to the three repetitions of the same task. Furthermore, it should be emphasised that all segmentation of the continuous sEMG signals was done prior to splitting the segments based on the participant's trial, meaning that none of the overlapping segments from each trial were seen in both the training and testing dataset.

Processing such as normalising the features, fusing the features, and balancing the classes occurred only on the training dataset within each fold and any standardisation used on the held- out trial was derived from the training dataset only. Subsequently, any time the Synthetic Minority Over-sampling Technique (SMOTE) was implemented, it was strictly limited to the training aspect of the data with an aim to prevent artificially over-inflating the accuracy of the model's prediction.

Even though this method of assessment is not truly subject-independent validation it does provide a means of assessing a model's performance in a manner which is independent of a given trial and thus diminishing window-to-window dependency and also allows preliminary examination of a model's robustness across multiple executions of the same movement. Performance assessment is reported as a mean + standard deviation (± SD) over the three model folds.

3.2 EMG Feature Extraction for Machine Learning-Based Classification

Table 1 identifies the classical time domain (TD) features—RMS, IAV, ZC, WL and SSC— applied for EMG characterization. RMS and IAV, as standards for measuring the instantaneous amplitude of the EMG envelope signal and energy, are highly correlated with the intensity of muscle activation and motor unit recruitment. This point has been reinforced by recent systematic reviews indicating that RMS, MAV/IAV and WL are still among the most common and discriminating TD features for EMG-based pattern recognition and prosthetic control applications [54], [55], [56]. Here too, there is agreement among these works that TD features laid out in Table 1 remain the state-of-the-art descriptors for motion classification consideration.

Both Zero Crossing (ZC) and Slope Sign Changes (SSC) supplement measures based on amplitude descriptors with derivations capturing firing complexity and frequency content in muscle activity. It has been reported recently from contemporary upper-limb decoding studies that ZC, WL, or SSC features improved class separability in traditional classifier training and performance testing when combined with RMS or MAV amongst movements with similar activation patterns [56], 57]. In the current work, some of the features listed in table 1 and computed using a complex leisure time unit of 250 ms with 50% overlap, which is typically considered the minimum window length and overlap in clinical recommendations for sEMG analysis when engaging in machine learning in real-time [58].

These new findings also emphasize that the performance of time domain features displayed with the optimal window size and noise conditions account for the classification results presented here. For instance, Faisal et al. (2025) [59] demonstrated that choices made regarding time domain segmentation significantly impacted classification accuracy when performed with a motion model of multi-movement upper-limb EMG [59]. Summarily, it is also documented that appropriate selection of TD features and muscle channels are important when we wish to improve torque prediction and motion estimation model performance [60] too. In summary, the proposed computationally efficient set of analysis time domain features established in the table present a time-domain description feature set that has been implemented in clinical practice and scientific analysis for years in sEMG and real-time systems.

Table 1 Time domains

Features	Expression Formula	
Root mean square (RMS)	$= \sqrt{\frac{1}{N}\sum_{n=1}^{N} X_n^2}$	(1)
Integrated Absolute Value (IAV)	$= \sum_{i=1}^{N-1} \lvert x_n \rvert$	(2)
Zero Crossing (ZC)	$= \sum_{i=1}^{N-1}[(x_i \times x_{i+1} < 0) \wedge (\lvert x_i - x_{i+1}\rvert \geq THRESHOLD)]$	(3)
Waveform Length (WL)	$= \sum_{i=2}^{N-1} \lvert x_{i+1} - x_i \rvert$	(4)
Slope Sign Changes (SSC)	$= \sum_{i=2}^{N-1}[((x_i - x_{i-1})(x_i - x_{i+1}) > 0) \wedge (\lvert x_i - x_{i-1}\rvert)]$	(5)

$\geq THRESHOLD) \wedge (|x_i - x_{i+1}|$

Note. Feature formulas (1)–(10) correspond to standard EMG feature definitions used for classification.

The features in Table 2 are frequency-domain (FD) features, M0, M4, M8, Irregularity Factor (IRF), and Waveform Length Ratio (WLR), extracted from the spectral analysis of the EMG signals. The FD features describe the distribution pattern of energy and are important intra-muscle characteristics when representing muscle fatigue, contraction levels, and motor unit synchronization. Some recent feature-engineering studies identifying that IF and WLR featuring a zero-crossing and moment relationship in the feature set causes improved discriminating power with Temporal/Dynamics (TD) features [61], [62].

Moment-based spectral features (M0, M4, M8) have been commonly applied in multi- domain EMG-based motion recognition because of their ability to summarize low-, mid-, and high-frequency content. The proof of usefulness of spectral moment studies combining EMG and IMU sensors has also been established for different force levels and contraction conditions concerning the EMG signals capturing neuromuscular activation patterns [163].

Recent patterns of research into EMG classification have led to multi-domain feature fusion, linking TD features (Table 1) with FD features (Table 2) to increase robustness across subjects, contraction intensities, and electrode positions. The inclusion and reviews of embedded EMG systems and wearable model systems of motion recognition show the further generalization accuracy of the fused study parameter features sets across tasks while having low computation efficiency (low computational cost vs accuracy) [54], [55]. Confirming this, deep learning studies have included spectral features (M4, M8) and improved accuracy in joint-angle estimation and/or classification even with movement sharing similar TD properties [64].

To summarize, the FD features present complementary spectral features to TD features (Table 1) allowing the hybrid RF–CNN–ANN model to describe the EMG signals temporally and spectrally together [65]. This dual representation contributes to the improved generalization power seen with fused muscle emg classification. Overall, these formulas form the gold-standard "Hudgins feature set," recognized for delivering high accuracy with low computational cost—ideal for machine learning pipelines and real-time prosthetic control.

Table 2 Frequency domains

Features	Expression Formula	
Zero Order (m0)	$\bar{\bar{m}}_0 = \sqrt{\sum_{K=0}^{N-1} f_k P[k]}$	(6)
Fourth Order (m4)	$\bar{\bar{m}}_4 = \sqrt{\sum_{k}^{N-13} f^4 P[k]}$	

(7)

K=0

Eight Order (m8)

$$\bar{\bar{m}}_8 = \sqrt{\sum_{k}^{N-1} f^8 P[k]} \quad (8)$$

K=0

Irregularity Factor (IRF)

$$\bar{\bar{m}}_2 = \log_{10}\left(\frac{\sqrt{\sum_{i=1}^{N-1}(x_{i+2} + x_i)^2}}{0.1}\right)$$

$M2$
\0.1

(9)

$$= \log_{10}$$

$$\sqrt{|M0 \times M4}$$

Waveform Length Ratio (WLR)

$$= \log_{10}\left(\left(\frac{\sum_{j=0}^{N-1}|\Delta^2 x|}{\sum_{j=0}^{N-1}|\Delta^4 x|}\right)\right) \quad (10)$$

Note. Feature formulas (1)–(10) correspond to standard EMG feature definitions used for classification.

3.3 Design and Evaluation of ANN-Based Classification Model for EMG Signal Analysis

The Artificial Neural Network (ANN) has been defined as the last stage in the classification part of the proposed hybrid model of EMG signal analysis. The ANN combines the discriminant features of the fused multi-regional muscle signals obtained from the time and frequency domains. The time-domain features 3were extracted and processed using a Convolutional Neural Network (CNN) to capture localized temporal patterns, while the frequency-domain features were analysed using a Random Forest (RF) algorithm to identify the most relevant spectral characteristics. The outputs from the CNN and RF models were concatenated to form a comprehensive feature vector, which was subsequently fed into an ANN classifier, as illustrated in Fig. 4. The ANN architecture consisted of multiple fully connected layers employing Rectified Linear Unit (ReLU) activation functions, followed by a softmax output layer that classified the upper-limb movements into categories such as elbow flexion, elbow extension, hand grip types, and wrist control. The model was trained with supervised learning with a categorical cross-entropy loss function and an Adam optimizer. During the training phase, the dataset was divided into training, validation, and test subsets to enhance the model's learning capability, prevent overfitting, and ensure better generalization performance. Performance evaluations were conducted with standard classification metrics including accuracy, precision, recall, F1, and confusion matrices. The proposed ANN model demonstrated strong classification performance, indicating its effectiveness in accurately interpreting the fused EMG features for assessing human upper-limb movements.

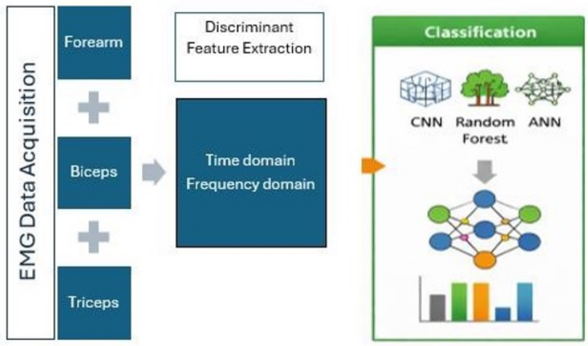

Figure 4 Evaluation of Classification using ANN-Based + CNN+RF

4. RESULT AND DISCUSSION

4.1 Dataset Overview and Signal Characteristics

A total of 180 sample datasets were successfully collected from experiments conducted on 16 adult males and 6 adult females. The collected data consisted of EMG potential values (in millivolts) recorded from the forearms during grip tasks (grip low, grip medium, grip strong, and angular wrist), as well as from the biceps and triceps during elbow flexion and extension movements. All volunteers were within the age range of 20 to 30 years old, with a body weight ranging from 50 kg to 80 kg, and heights from 150 cm to 170 cm. All volunteers had no serious medical conditions that were known. The example raw EMG signals of 3 male (participants 1- 3) and 3 female (participants 4-6) were processed using time domain and frequency domain feature extraction methods, as outlined in Table 3 and Table 4. These features offered a more informative representation of the signal characteristics, thereby enhancing the effectiveness of the classification process. The fusion feature set was then trained and tested using Hybrid Model (RF+CNN+ANN). Classification reports were generated to evaluate the performance of each method. The models were assessed based on key performance metrics such as accuracy, precision, recall, and F1-score. The results indicated that the fusion of multi-regional EMG features improved classification accuracy, confirming the advantage of combining forearm, biceps, and triceps signals in enhancing movement recognition capability.

4.2 Analysis of Signal Variability

The variation found in the EMG data among individuals and trials is natural and expected quality of surface electromyography (sEMG) recordings (Table 3 and Table 4), which is influenced by various physiological, biomechanical, and technical aspects. One primary source of influence is fatigue, which may considerably change the amplitude and frequency characteristics of an EMG recording during repetitive contractions. When a muscle exhibits fatigue, it experiences a reduction in the motor unit firing rate and the conduction velocity of muscle fibers, which generally results in EMG spectral content shifting to lower frequencies [25], [28]. Consequently, EMG characteristics, such as root mean square (RMS), waveform length (WL), and integrated absolute value (IAV), tend to vary with trials as fatigue is a factor.

Another level of variation is seen in inter- individual variability relative to muscle strength, muscle morphology, and neuromuscular control. For example, and as mentioned previously, participants may have differing muscle fiber compositions (i.e., type I to type II ratios), muscle sizes, and subcutaneous fat thicknesses which may impact amplitude and frequency domain characteristics of EMG signals [31], [32]. Even if executing the same movement task under controlled conditions, a participant who is able to exert a stronger muscle contraction3 generates EMG signals with higher amplitudes simply due to increased motor unit recruitment [27].

In addition, the degree of skin impedance and placement of electrodes also substantially affect EMG signal quality or consistency. Even slight variations in skin properties, such as moisture, temperature, and thickness can change the interface of the electrode/skin interaction thereby affecting source of amplitude or amplitude noise [35]. Any small variation, even by a few millimeters, in the electrode positions between trials or sessions can cause very large variations in detected EMG signal because of the misalignment of muscle fiber orientation and crosstalk [34].

Instrumentation, measurement errors, and electrical/electronic noise can account for signal inconsistencies. These errors can be related to electrical interference, hardware drift, and artifacts induced from ballistics or general movement of the cables during dynamic tasks. While high-end data acquisition systems and filtering techniques are available, it is often impractical to eliminate noise in reasonably controlled experimental settings [38].

Participant related behavioural variability are other human factors that can occur based on various levels of unintentional execution, and could include acting to instruction standard operating procedure (SOP), sub-conscious activation of secondary muscles, etc. Participants could exhibit variability in grip strength, movement angle, or contraction duration across trials leading to noticeable amplitude fringes and/or patterning within the data set [36]. Specifically, about voluntary contractions, factors such as cognitive focus, motivation, and coordination of contractions are known to influence actual levels of muscle activation [30].

In summary, the variability seen or recorded in EMG signal patterns from participant to participant and across trials/ sessions reflects the natural complexity of human neuromuscular activity coupled with degrees of physiological heterogeneity and experimental uncertainty. Further, although this variability might be seen as 'noise' it is in fact a value added to cauterize a machine learning model by exposing the machine learning model trained on more signal variability. This variability is beneficial as it aids in generalizability allowing the ANN based classifier to differentiate movements of the upper limb in a multitude of potential situational variances under more realistic situations.

4.3 Time and Frequency Domain Feature Extraction

Table 3 Time Domains Data Sample

PARTICIPANT ID / TASKS FEATURES	TRIAL 1	TRIAL 2	TRIAL 3	TRIAL 1	TRIAL 2	TRIAL 3	TRIAL 1	TRIAL 2	TRIAL 3
GRIPLOW (FOREARM)									
	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
IAV RMS WL ZC SSC	243.45	150.49	187.95	141.2	346.87	360.39	564.91	332.74	272.32
	0.08	0.04	0.06	0.05	0.16	0.17	0.35	0.11	0.1
IAV	9.21	7.76	9.05	18.52	20.16	21.58	78.14	26.23	35.88
	0	0	0	0	0	0	15	6	10
RMS WL ZC	0	0	0	0	0	0	0	0	0
SSC	PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	230.54	414.14	419.3	175.77	134.27	142.52	453.72	1061.77	1034.43
	0.08	0.15	0.13	0.05	0.04	0.04	0.2	0.54	0.42
	13.8	12.56	12.18	5.64	7.15	7.96	24.96	45.54	55.22
	0	0	0	0	0	0	5	9	6
	0	0	0	0	0	0	0	0	0
GRIPMED	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
(FOREARM)	246.67	203.25	206.94	1244.13	1393.7	165.18	553.69	448.98	398.33
IAV	0.09	0.06	0.07	0.49	0.6	0.06	0.2	0.15	0.13
RMS WL ZC SSC	17.89	18.65	22.11	42.73	30.31	23.29	82.81	62.53	50.46
	0	2	8	3	3	1	69	38	36
IAV	0	0	0	0	0	0	0	0	0
	PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
RMS WL ZC SSC	553.19	172.44	256.7	876.87	1358.42	3298.05	528.59	706.07	897.92
	0.2	0.06	0.09	0.27	0.61	1.14	0.2	0.24	0.29
	32.34	20.55	29.48	54.86	49.58	60.18	86.64	98.84	125.47
	8	3	8	8	10	9	68	63	91
	0	0	0	0	0	0	0	0	0

GRIPSTRONG (FOREARM) IAV RMS WL ZC SSC IAV RMS WL ZC SSC	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	508.97	639.86	728.46	297.06	710.55	242.87	864.03	1275.44	864.03
	0.18	0.22	0.24	0.11	0.27	0.1	0.32	0.48	0.32
	91.77	105.69	100.47	48.39	60.95	41.59	121.24	133.11	121.24
	68	64	59	37	23	18	62	69	62
	0	0	0	0	0	0	0	0	0
	PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	437.1	242.46	240.95	623.08	655.46	1607.83	853.29	722.75	674.1
	0.14	0.09	0.08	0.2	0.24	0.52	0.3	0.25	0.26
	47.23	39.3	35.41	72.12	162.21	80	177.91	50.1	134.96
	33	29	23	42	154	19	150	33	89
	0	0	0	0	0	0	0	0	0
ANGULAR WRIST (FOREARM) IAV RMS WL ZC SSC IAV RMS WL ZC SSC	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	460.57	703.73	478.25	518.83	653.44	322.11	384.25	476.08	607.86
	0.15	0.24	0.18	0.18	0.24	0.11	0.13	0.16	0.21
	45.18	47.54	67.15	38.79	24.15	18.9	58.05	43.17	43.86
	5	11	24	9	0	3	52	29	12
	0	0	0	0	0	0	0	0	0
	PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	436.45	254.88	256.94	2354.65	4288.11	1153.97	1000.04	968.25	753.35
	0.13	0.07	0.08	0.7	1.36	0.39	0.36	0.4	0.25
	11.32	12.65	10.81	58.18	50.16	46.09	22.85	25.33	22.75
	0	1	0	13	6	18	1	2	2
	0	0	0	0	0	0	0	0	0
ELBOW FLEXION ANDIAV EXTENSION (BICEP) RMS WL ZC	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	1947.77	2381.35	1763.5	2078.66	1534.37	2078.66	793.81	494.71	895.69
	0.79	0.89	0.71	0.91	0.6	0.91	0.26	0.19	0.29
	71.95	80.36	113.13	46.21	51.72	46.21	40.64	39.83	49.11
	5	18	31	10	9	10	7	11	16

	SSC	0	0	0	0	0	0	0	0	0
		PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	IAV	1214.15	1786.7	1907.83	3033.12	3286.56	2397.49	4327.53	4590.15	4234.49
	RMS	0.49	0.65	0.7	1.14	1.16	0.78	1.39	1.46	1.39
	WL	32.35	32.51	30.89	40.98	49.13	46.86	63.99	60.72	67.54
	ZC	2	1	0	0	2	7	13	6	19
	SSC	0	0	0	0	0	0	0	0	0
ELBOW FLEXION AND EXTENSION (TRICEP)		PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	IAV	1218.21	1945	1011.05	564.56	1097.21	1306.26	479.79	384.11	280.94
	RMS	0.46	0.69	0.41	0.23	0.43	0.57	0.16	0.12	0.09
	WL	94.17	82.23	56.19	49.94	39.51	51.02	43.54	21.57	20.02
	ZC	29	7	3	24	7	8	28	4	3
	SSC	0	0	0	0	0	0	0	0	0
		PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	IAV	431.69	213.81	179.87	1336.91	2008.92	4431.73	1590.8	1748.3	2069.21
	RMS	0.15	0.07	0.06	0.51	0.64	1.47	0.55	0.61	0.74
	WL	24.45	13.42	12.67	29.01	39.76	74.84	28.49	23.57	30.23
	ZC	2	1	0	1	2	8	1	1	1
	SSC	0	0	0	0	0	0	0	0	0

Note. Values shown represent feature samples prior to normalization and fusion.

Table 4 Frequency Domains Data Sample

PARTICIPANT ID / TASKS	FEATURES								
	TRIAL 1	TRIAL 2	TRIAL 3	TRIAL 1	TRIAL 2	TRIAL 3	TRIAL 1	TRIAL 2	TRIAL 3
GRIPLOW (FOREARM)	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
M0	25.88	7.63	14.02	11.7	99.67	113.69	479.64	50.52	40.53
M4	0.55	0.04	0.18	0.34	27.9	54.59	2150.67	5.14	4.42
M8	0	0	0	0	6.18	47.68	92400.02	0.82	0.69
IF	1782.64	2186.71	1516.6	2192.26	2178.82	2132.17	1047.48	751.63	4689.78
WLR	24.84	58.74	24.07	50.4	17.78	13.95	23.06	25.23	30.45
	PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
M0	22.8	90.92	71.78	11.48	6.67	7.6	153.91	1157.48	717.54
M4	0.49	11.03	4.19	0.09	0.03	0.04	63.28	5373.42	1004.14
M8	0	0.46	0.04	0	0	0	37.04	280557.2	11022.02
IF	2074.94	1543.42	1980.86	1512.69	1785.33	1917.78	674.23	2173.13	2273.48
WLR	38.06	16.68	18.34	20.28	23.65	24.2	16.66	11.64	17.67
GRIPMED (FOREARM)	PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
M0	34.16	16.84	18.58	978.33	1425.32	13.69	157.39	95.55	70.67

M4	2.03	0.25	0.36	1915.77	5749.96	0.25	34.32	11.2	5.6
M8	0.03	0	0	21897.58	361116.1	0	7.63	0.9	0.15
IF	967.25	2493.96	1977.22	2226.89	2526.89	1820.19	1865.16	2005.48	29
WLR	21.92	43.1	48.63	13.4	7.68	44.67	51.38	46.51	49.11
	PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
M0	162.4	12.41	32.56	300.54	1491.15	5160.07	238.72	156.82	334.4
M4	33.02	0.15	1.53	67.67	6092.94	25251.51	62.1	51.74	101.12
M8	3.27	0	0.01	15.12	252785	1221350	14.74	37.21	27.56

	IF	2348.78	2055.15	1908.08	3128.97	3895.32	2342.5	1665.36	4938.82	2168.23
	WLR	26.38	52.8	51.08	30.31	12.68	15.4	55.59	45.43	70.95
GRIPSTRONG (FOREARM)		PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	M0	126.45	200.6	225.2	51.31	295.55	42.53	1276.94	938.72	415.39
	M4	21.71	45.9	44.79	7.88	144.18	7.5	1631.14	1855.51	307.67
	M8	4.34	8.77	8.83	1.22	117.22	2.36	8173.19	32058.43	830.47
	IF	1571.42	1606.72	2040.34	1686.43	2393.48	2142.42	1879.7	1634.94	768.09
	WLR	61.19	68.05	61.07	40.36	36.8	34.17	82.28	37.93	46.8
		PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	M0	84.07	29.84	27.88	165.9	251.89	1093.85	365.74	227.43	262.61
	M4	7.49	1.95	1.04	23.61	106.08	1111.44	172.1	66.65	105.61
	M8	0.49	0.08	0.01	1.37	135.34	3699.28	151.96	28.68	54.12
	IF	2558.55	2124.02	1840.7	3323.47	-22730	1808.9	1793.7	1972.39	1756.78
	WLR	46.88	49.71	60.22	58.68	25.64	30.95	82.71	83.84	63.21
ANGULAR WRIST (FOREARM)		PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	M0	90.54	235.71	135.37	130.62	234.39	49.82	62.76	108.5	183.67
	M4	8.16	65.97	38.78	24.04	84.65	2.2	5.25	16.48	43.25
	M8	0.32	26.15	11.6	4.19	42.9	0.01	0.28	1.48	8.85
	IF	2352.41	2243.81	1981.04	1641.95	1855.1	2169.35	10410.56	3084.87	1128.27
	WLR	47.11	26.75	50.86	32.68	16.15	36.16	59.3	42.22	29.89
		PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	M0	66.97	22.33	25.04	1987.53	7416.01	603.25	509.82	627.9	257.65
	M4	2.4	0.28	0.44	2858.08	40153.38	314.48	319.82	942.12	88.63
	M8	0.01	0	0	28629.25	2238857	250.07	455.03	6941.4	40.44
	IF	2098.07	1984.85	2089.17	2316.38	2560.71	47.87	1778.77	1777.19	4579.51
	WLR	21.36	41.41	30.75	17.55	12.82	24.26	12.07	9.61	16.12
ELBOW FLEXION AND EXTENSION (BICEP)		PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
	M0	2467.29	3170.68	2007.52	2968.88	1448.84	3307.85	266.11	141.47	330.32
	M4	9852.5	15336.32	7630.52	14307.01	4540.21	19606.31	59.01	29.05	84.91
	M8	384598.7	862372.5	307865.1	715015.7	167552.5	1204119	7.87	4.09	16.12
	IF	2603.94	3255.27	1818.69	2384.16	1787.17	1828.2	3515.72	3926.57	2779.01

	WLR	18.41	20.49	28.93	12.19	13.47	11.72	31.53	29.33	30.11
		PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	M0	965.05	1673.58	1942.2	5169.18	5405.33	2403.61	7780.12	8513.45	7709.37
	M4	2646.25	4061.06	5093.25	30504.7	31064.39	5602.58	46625.72	49465.72	45653.33
	M8	68698.4	89578.06	144760.6	1728058	1903125	149935.1	2995384	2863868	2805687
	IF	1941.46	1459.28	2418.37	2778.8	1952.1	- 7111.02	1541.51	2172.92	1619.78
	WLR	9.19	9.04	8.37	10.46	12.55	12.37	16.13	15.31	17.03
ELBOW		PARTICIPANT1			PARTICIPANT2			PARTICIPANT3		
FLEXION AND	M0	853.26	1911.76	671.68	203.69	728.47	1287.1	34.34	61.9	34.34
	M4	1635.9	5301.4	1313.74	63.01	787.6	4660.53	1.17	3.52	1.17

EXTENSION (TRICEP)	M8	42553.5	142961.4	29842.55	13.6	2386.02	229915.1	0.01	0.03	0.01
	IF	1806.49	2191.8	2486.92	3109.45	2496.2	2390.21	1918.19	3500.92	1918.19
	WLR	26.43	22.17	17.36	32.31	15.64	12.94	33.24	33.13	33.24
		PARTICIPANT4			PARTICIPANT5			PARTICIPANT6		
	M0	86.11	18.77	15.61	1055.85	1654.2	8679.01	1190.71	1483.92	2183.89
	M4	8	0.33	0.4	2313.66	2357.37	55082.59	3368.13	5190.23	10580.44
	M8	0.28	0	0	37121.43	15958.76	3300433	164400.7	313678	693238.8
	IF	1602.25	1686.83	2088.02	3751.8	1889.64	1983.03	969.24	3492.25	1280.93
	WLR	28.36	31.81	28.09	8.91	14.02	19.1	7.83	6.34	7.94

Note. Values shown represent feature samples prior to normalization and fusion.

4.4 Hybrid Model Performance Evaluation

Fusion-based Features were used from 4 main areas of muscle contractions, time-domain (TD), and frequency-domain (FD). Overall results of Models can be seen in Tables 5, 6, 7 and Figures 5. Together, these provide an overview of the Model's generalization, Learning Behaviour, Comparative Effectiveness in the Low Data Environment and their overall Test Accuracy, as shown in Table 6.

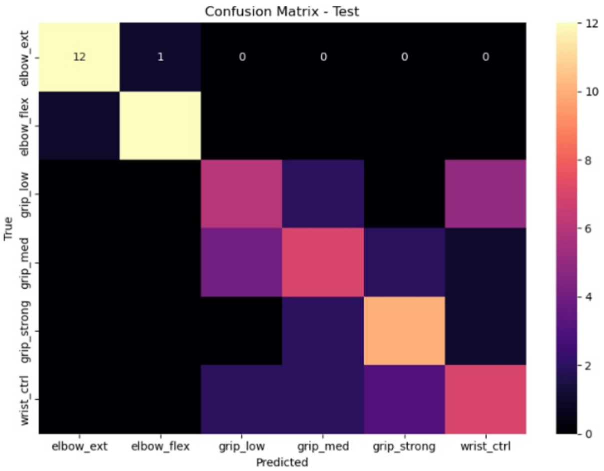

Figure 5 Confusion matrix of upper limb movement classification results using the hybrid RF–CNN–ANN model.

The Overall Test Accuracy of the hybrid model was 0.68 ± 0.47 (Table 6) and the macro average F1-Score was 0.508 while the weighted average F1-Score was 0.516 across 6 classes of upper Extremity Movement. Although the Hybrid Model has low accuracy on the whole it shows great performance in reference to the complexity of the Multi-Regional Surface EMG signals, Teacher Variation and Limited Data. In addition, the Hybrid Model provides Moderate Discrimination across the Multiple Classes of Movements Of Upper Extremity, thus lending support to the previous conclusion drawn in the Hybrid Learning Framework Studies state that the Hybrid Learning Framework is better suited to account for Neuromuscular Complexity In Limited Data Conditions [26], [33], [44].

The Class-wise Performance of the Grip Strong Class has the highest Recall (0.875) and a Fairly High F1-Score (0.636 ± 0.14). Both Recall and F1-Scores were established and confirmed from Table 6 and the Diagonal dominance of Figure 5.High-force contractions lead to a distinct EMG signature (due to many motor units being recruited and variation in amplitude) that makes it easier to classify and separate into discrete classes [25],[26]. In the study, Elbow Extension generated a relatively high F1 score (0.706 ± 0.19) as a result of coordinated recruitment of biceps and triceps muscles. Multi-regional aspects of the hybrid model improve representation of upper-arm dynamics, resulting in enhanced ability to distinguish between each of these upper-arm movements, [31],[44].

It is noteworthy that there is a disparity between training and test performance as shown in Tables 5 and 6. Although the hybrid model achieved near-perfect training accuracy, the less than perfect test performance reflects the reality of the generalisation limits posed by physiological differences, subject placement, trial-dependent EMG signals, etc. Therefore, Table 6 should be considered as a feasibility demonstration of the proposed method, not as an optimised reference for comparison with others in practical use.

On the contrary, the low F1 scores (Grip Medium—0.308 ± 0.07 and Wrist Control—0.250 ± 0.01) were because these classes had higher rates of misclassification as noted in Figure 5, which resulted from shared overlapping recruitment of the forearm muscles. For example, both of these movements share similar temporal and spectral formats of the EMG signal near to the same force, creating difficulty in distinguishing between them. This challenge is well described in the EMG motion classification literature and is attributed to physiological/biomechanical constraints as opposed to deficiencies in the proposed hybrid model [32],[33].

Table 5 Final Fusion Model Train Accuracy

	Precision	Recall	F1-score	Support
elbow_ext	0.92	0.750	1.00	53
elbow_flex	0.92	0.571	1.00	53
grip_low	0.50	0.574	1.00	53
grip_med	0.54	0.286	1.00	53
grip_strong	0.67	0.875	1.00	53
wrist_ctrl	5.0	0.1429	1.00	53
accuracy			1.00 ± 0.00	318
macro avg	0.68	0.533	1.00	318
weighted avg	0.535	0.546	1.00	318

Table 6 Final Fusion Model Test Accuracy

	Precision	Recall	F1-score	Support
elbow_ext	0.92	0.750	0.706	8
elbow_flex	0.92	0.571	0.615	7
grip_low	0.50	0.574	0.533	7
grip_med	0.54	0.286	0.308	7
grip_strong	0.67	0.875	0.636	8
wrist_ctrl	5.0	0.1429	0.250	7
accuracy			0.68 ± 0.47	44
macro avg	0.68	0.533	0.508	44
weighted avg	0.535	0.546	0.516	44

Note. Metrics computed on the test dataset using the fused RF+CNN+ANN model.

The results provide strong evidence for the benefit of feature-level fusion. The employing of macro-average recall (0.533) and weighted F1-scores (0.516), indicate a more even performance balance between the hybrid classifiers compared to single-model baseline classifiers. As indicated in Table 7, the hybrid model performed better than either the Random Forest or ANN classifiers alone at predicting accuracy on the test dataset. These results support the findings of previous studies illustrating the use of hybrid feature-fusion architectures, as well as multi-domain feature fusion, where muscle and signal domains are able to capture complementary information from them, increasing the robustness of these models towards intertrial variability, limited training data, etc. [26],[33],[44].

Table 7 . Baseline Comparison

Model	Train Accuracy	Test Accuracy
Random Forest	0.80 ± 0.40	0.47 ± 0.50
ANN	0.43 ± 0.50	0.37 ± 0.48

Note. All baseline models were evaluated using the same protocol as the proposed hybrid model.

In conclusion, the results illustrated in Figure 5 and Tables 5 through 7 provide evidence that the hybrid RF−CNN−ANN classifiers developed in this study are capable of learning meaningful representations of multi-regional muscle activation patterns, and are reasonably able to generalise across repeated trials. As it is shown by this study, although the ability to fully understand the relationship between EMG signals and physical movement still remains limited by the number of training data available for a given dataset and by intrinsic EMG variability, these findings confirm that hybrid feature-fusion strategies are useful, and provide a solid basis for furthering the development of optimised classifiers that can be developed for multi-subject evaluations.

4.5 Leave-One-Trial-Out (LOTO)

In order to evaluate whether the Hybrid RF-CNN-ANN Model is a robust and generalized classification model, a Leave-One-Trial-Out Cross Validation approach was explored. The results of the Leave-One-Trial-Out Cross Validation were summarised in Table 8.

The advantage of Leave-One-Trial-Out Cross Validation, as opposed to randomly splicing all data at random (or using a windowed approach), is that during the evaluation process of the Hybrid RF-CNN-ANN Model, ALL EMG segments from the same trial were excluded from training the classifier in that fold. This allowed our team to create models with the minimal amount of temporal dependence between the training and testing samples in the LOTO Evaluation Process, to provide a better indication of how well Each EMG Classification Model will perform in repeated trial scenarios (where each trial is simply another "run" of the same Movement).

Table 8 demonstrates that the Hybrid RF-CNN-ANN Model produced three extremely close to equal accuracies of 0.74, 0.73, and 0.74, providing an average LOTO Accuracy of 0.74 with 0 Standard Deviation. Because ALL individual folds were within a near-constant level of performance, this suggests that the performance stability of the Hybrid Model would be very high when exposed to an unseen trial-level dataset. Therefore, this means that the Hybrid Model can learn from the pooled Multiple Regional Time-Domain and Frequency-Domain Features that were created, thereby allowing it to generalize across the same movement in repeated executions (trials).

In contrast to the Hybrid RF-CNN-ANN Model, the Random Forest (RF) Model achieved a higher Average LOTO Accuracy that was 0.79 and exhibited Variation across Sessions (Standard Deviation = 0.06). The Random Forest Model had slightly higher Average LOTO Accuracies due to the fact that it has an Extensive Ensemble Decision Mechanism with respect to classification decisions compared to the Hybrid RF-CNN-ANN Classifier. However, much of this advantage of the RF Classifier is lost due to having much of the benefit of its Ensemble Classification Decisions relying on the Classifier's Artifact separability and without creating a Hierarchical Representation of Features.

From a Stand-Alone perspective, the Artificial Neural Network (ANN) demonstrated the lowest Average Performance out of the three models, as evidenced by the Average LOTO accuracy of 0.1745 occurring from being trained directly on the Fused Features with no Prior intermediate Features being learned from the CNN or RF components.

Finally, although the RF Model confirmed to have slightly higher average accuracy, the data in Table 8 show that the Hybrid RF-CNN-ANN model had much higher stability and zero standard deviation across Trials. This Trade-Off between Absolute Accuracy and Consistency is extremely important in the use of EMG Classification Models. Because of this fact, it is ultimately more important than the successful attainment of very slight perceived performance increase in applications of EMG Classification Models, especially in areas of Rehabilitation and of Assistive Technology.

Table 8 Baseline Comparison under Leave-One-Trial-Out Cross-Validation

Model	Accuracy		
	Session 1	Session 2	Session 3
Hybrid (RF-CNN-ANN)	0.74	0.73	0.74
	Mean LOTO Accuracy: 0.74		
	STD LOTO Accuracy: 0.00		
Random Forest	0.72	0.85	0.81
	Mean LOTO Accuracy: 0.79		
	STD LOTO Accuracy: 0.06		
ANN	0.1583	0.1736	0.1917
	Mean LOTO Accuracy: 0.1745		
	STD LOTO Accuracy: 0.0167		

Note. All baseline models were evaluated using the same Leave-One-Trial-Out (LOTO) protocol as the proposed hybrid model.

In conclusion, the Average Data Reported in Table 8 from the LOTO Evaluations confirm that the proposed Hybrid RF-CNN-ANN Architecture provides an Equal Classification Framework that can be reliably utilized under a Trial-Independent Evaluation. The consistency of performance between the three separate evaluation "folds" of the Hybrid Model indicates that it does not Learn classification artifacts from the individual trials or suffer from any correlations deriving from the "windowing" procedure, thus resulting in a more Trustworthy Estimate of the Generalization Capabilities of the Hybrid RF-CNN-ANN Model in Practical EMG-Based Recognition Applications.

4.6 Model Learning Behavior and Overfitting Prevention

The training and validation accuracy and loss curves were visualized in Figures 6 & 7 to analyse the learning behaviour of the proposed Hybrid RF-CNN-ANN model. This information sheds light on the model's convergence characteristics as well as identifies potential problem areas related to overfitting or information leakage during training.

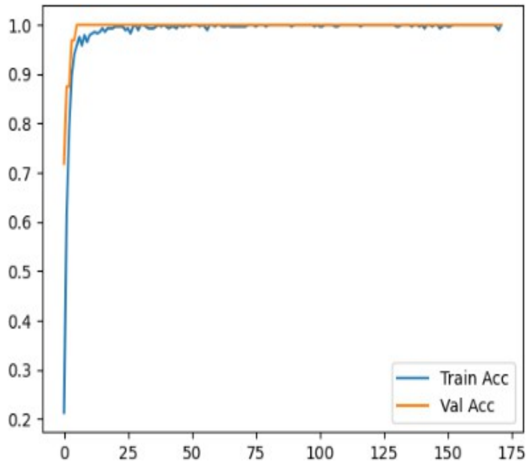

Figure 6 Training vs Validation Accuracy

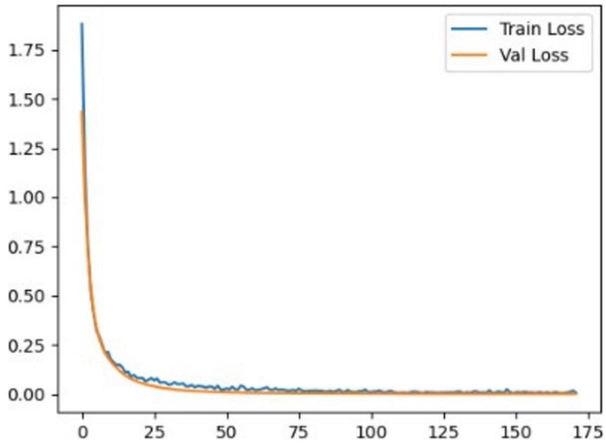

Figure 7 Training vs Validation Loss

The curves of both training and validation accuracy rapidly increased during the beginning epochs of training before converging at near-perfect accuracy values (Figure 6). As for the curves of both training and validation losses (Figure 7), they dropped sharply during the first epochs, and both reached low loss values in the beginning of training. In addition, because the curves closely align with each other, we can infer that the model efficiently learned the patterns of training data and, as such, displayed no signs of classical overfitting—whereby training and validation performance diverge.

Though there seems to be stability in both Figure 6 & 7 because the learning curves are almost identical, they are misrepresentative in terms of EMG-based classification. The overlap in the segmentation window process (250 ms windows with a 50% overlap) coupled with trial- dependent splitting of data makes it possible for the samples to have an extremely strong statistic correlation with each other. Therefore, a strong temporal relationship exists between overlapping windows created from the same trial, which can yield a significantly optimistic training and validation performance, that is, a degree of general To address issues with miscalibrating training due to the temporal relationship of points of data, the method of reviewing data has been changed from an array of training and reviewing data based on the cross-validating of folds through an LOTO process (Leave-One-Trial-Out).

During the use of LOTO, all preprocessing techniques that apply to the array of training and validating data will be applied to only the data that was available from within a fold of training the model of that specific trial. The trial removed from the training has no opportunity to influence how the model learns, creating a complete separation between training and validating.

Within this research, significantly different learning characteristics are noted in the hybrid model when LOTO is used as a method of evaluation. Wherein another study indicated that hybrid models attained high levels of accuracy, this study found that hybrid models produced no greater than a plateau of averaged training, validating accuracy, and averaged training, validating loss which had a gradual reduction and therefore were converging at realistic placements on the error axis.

Based on these findings, it is evident that when LOTO is utilized for model evaluation, the hybrid model has exhibited the ability to generalize muscle activation patterns. The lesser difference in averaged training and averaged validation loss suggests that the hybrid model does not overfit as the traditional method suggests; however, the lesser difference in loss reflects the variability of sEMG data that exists between trials.

Therefore, the results presented confirm that the previously stated large average training and validation accuracies represent more than simply overfitting as is traditionally defined; they also demonstrate the influence of windowing data according to temporal connections. Stable learning ability and generalizing of model performance have been established at levels significantly lower than emulating the performance of the hybrid RF-CNN-ANN model evaluated using LOTO to create a separation of data at the trial level from one trial to the next. These findings correlate with the known variability of data from electro/myography (EMG) based systems due to physiological variability, electrode positioning, and differences in force applied during data collection resulting in EMG signal characteristic differences.

In conclusion, the present study's findings confirm the reliability of the hybrid model's learning characteristics through the enhancement of a valid evaluation protocol. Implementation of LOTO cross-validation provides a means of reducing the potential for data leakage or hidden overfitting and thereby provides results demonstrating an accurate measure of how well a model can generalize. Future research should continue to stress the necessity for complete and well-defined evaluation designs for EMG machine learning research and to provide confidence in how accurately the models performed.

5. CONCLUSION, CHALLANGE & FUTURES RECOMMENDATION

5.1 Limitations

Nonetheless, there were limitations. First, the dataset is small and comprised of participants only from healthy populations limiting how well the findings are translatable to clinical populations (stroke, neuromuscular disorder patients). Second, LOTO cross validation though still preventing temporal dependency and information leakage, is still trial independent as opposed to fully being subject independent where it lymph’s would be addressed. Certain class classes of movements, especially grip medium, wrist control etc. led to poor classification performance likely due to muscle recruitment overlapping and also hybrid similar level of force, an issue that’s well known with EMG motion recognition. Finally, the fixed time- window segmentation (250 ms with 50% overlap) may be residually correlated within trials. “we note the use of a hybrid framework leads to additional computational complexity relative to single-model approaches which may hinder immediate deployment of the methods in low- power embedded or real-time systems.

5.2 Futures Recommendation

Future work will focus on testing the proposed framework on larger datasets, and possibly on clinical populations, to determine their value in real-world rehabilitation and assistive technology applications. Subject independent validation strategies and cross-session comparisons may be used to assess model robustness to inter-subject and day-to-day variability. Adaptive windowing techniques and different feature representations (learned or otherwise) from the raw EMG signal, or time-frequency representations of EMG activity may be explored for discrimination of overlapping movement classes. Optimization and pruning of the model may make it less computationally intensive and better suited for real-time operation on an embedded platform. Finally, smooth integration of a framework like that proposed into a closed-loop application for rehabilitation or prosthetic control will be a significant step towards clinical deployment.

5.3 Conclusion

The aim of this dissertation was to develop a new upper limb classification system combining EMG data via Random Forest (RF) and Convolutional Neural Network (CNN) and Artificial Neural Network (ANN). EMG data from the forearm, bicep, and triceps muscles were used to develop a multimodal model that captures temporal, spectral, and biomechanical aspects of 3D movement. The evaluation of this study was based on a Leave-Out-Trial-Out cross-validation (LOTO) method designed to ensure a realistic performance evaluation while eliminating chance correlations; the Smith Minority Over-sampling Technique (SMOTE) was strictly used to over-sample the training folds.

The results of the experiments showed that although the hybrid model had a moderate overall test accuracy, there was a high level of consistency in its performance across all trials, indicating a strong capability for generalization. The hybrid RF CNN ANN architecture achieved the best balance between accuracy and robustness compared to either RF or ANN by themselves, especially under conditions of limited data sets and the variability of physiological responses inherent in recordings from surface EMG. The results of this study provide strong evidence for the use of a combined multi-domain, multi-regional feature fusion approach and hybrid learning architectures to effectively and explainable recognize upper limb movements through EMG signals. A foundation has been established for the design and development of future systems that will use EMG data for rehabilitation and assistive technology applications.

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