Transfer-Modal Extraction of Surface EMG Features for Upper Limb Motor Classification

Vedant Mangrulkar and Madhav Rao[a]
International Institute of Information Technology Bangalore, Bangalore, India
{vinit.mangrulkar, mr}@iiitb.ac.in

Keywords: Accelerometer, EMG, Classifier, ML, Features, Upper Limb, Synthetic Features, Random Forest.

Abstract: Surface Electromyography (sEMG) signals provide critical insights into muscular activity, aiding action classification and monitoring muscular disorders. However, their reliability is hindered by noise and unstructured data. Despite the advancements in machine learning, large datasets are essential to address these challenges and enhance decoding accuracy for further development. Hence, this work attempts to predict the sEMG features from the accelerometer signals in a view to generate synthetic data which is useful for further developments around this physiological signal. This work examines the correlation between accelerometer-generated sEMG features and those from original sEMG signals for four upper limb actions wrist flexion, wrist extension, wrist closing and wrist vibration focusing on the flexor carpi ulnaris and extensor carpi radialis muscles. Synthesized features are augmented with original features to train an ML model, achieving 91% accuracy on unseen original sEMG features. This work showcases a viable solution to generate more sEMG features corresponding to the actions under test from an altogether different modality. This work is a step towards synthesizing EMG signals and features for human limb movements which offers a strong platform to design imitation learning for rehabilitation systems in the future.

1 INTRODUCTION

The human hand is one of the most important part of our body. It plays a crucial role in our daily life helping us perform a wide range of activities starting from basic tasks to complex exercises (Schreuders et al., 2019). The wrist, a key joint in our hand movement, allows for essential movements such as flexion, extension and rotation, which are very important for various activities involving gripping, lifting and many other fine motor skills (Eschweiler et al., 2022). Unfortunately, some unexpected events or accidents leads to the partial or complete impairments in upper limb functions. Hence the patients are prescribed with specific upper limb physiotherapy based exercises towards effective rehabilitation (Jonna et al., 2024; Jonna and Rao, 2022; P et al., 2023). The recovery process although is extremely slow, but is considered effective owing to continuous improvement (Vinay et al., 2021). Over the years, the researchers have explored ways of monitoring progress and effectiveness of the therapy sessions through dedicated caretakers or paid physicians at home or clinics and centers. The visual evaluation is always marred by human bias and remains inconsistent across individuals undergoing therapy and also along the evaluators. Various methods around sensory systems to automate and nullify the human bias is explored in the past, but a more simplified and robust variant which is reliable for practising is yet to be found.

The motion classification for human limb rehabilitation presents an opportunity to develop automation in the personalized therapy program with real-time feedback and assessment systems to ensure that the routine therapy are performed accurately and effectively (Novak et al., 2012; Kwakkel et al., 2008). Automation without much support from care-takers helps the former to build their confidence and self-belief, besides giving much relief to the latter. Automated features aids in progress-tracking and continuous-monitoring, effectively improving the therapy sessions (Hiengkaew et al., 2012). Another distinct and radical approach of employing dynamically adaptive training system is introduced and further discussed in (Loureiro and Harwin, 2007) which works on self-tuning the therapy based on the outcome.

Hence an automated classification of patient

[a] https://orcid.org/0000-0003-2278-9148

Mangrulkar, V. and Rao, M.
Transfer-Modal Extraction of Surface EMG Features for Upper Limb Motor Classification.
DOI: 10.5220/0013157800003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 1*, pages 721-728
ISBN: 978-989-758-731-3; ISSN: 2184-4305

limb movements is therefore extremely crucial in the scheme of rehabilitation process (Chandrasekhar et al., 2020a).

Electromyography (EMG) signals capture the muscular activity of the human limb, and same is reported in many literature's for recognizing the upper limb actions (Vinay et al., 2022; Reddy et al., 2023). More macro-level evaluation pertains to the actions performed by the individuals under rehabilitation, and in-conjunction with EMG signal is a useful parameter to analysis. Hence EMG signal based upper and lower limb rehabilitation designs are found most suitable for evaluating the recovery process.

The invasive variant of acquiring EMG signals is more accurate, but does not fit this requirement of continuous evaluation. Hence surface based EMG signals also referred to as *sEMG* signals are tapped at the surface of the human body. Although these signals when probed at the surface is conducive to noise, but are processed with some success to find the signatures mapped to the limb movements (Chandrasekhar et al., 2020b). The sEMG signals are found to carry critical information of limb movements and hence are aimed toward the rehabilitation setups. However the usage of sEMG signals for the classification of the motor movements has its own share of problems. The sEMG signals are marred with huge baseline noise in addition to the distortion effects which leads to a low SNR (Campanini et al., 2020).

The occupancy of baseline noise signal makes it extremely difficult to extract discriminative features, while the

distortion alters the temporal and phase components of the signal (Merletti and Cerone, 2020). The sEMG signals are also sensitive to several other factors including human anatomy, electrode placements and muscle fatigues (Merletti and Cerone, 2020).

Other sensory systems including motion capture systems, IMU, Electromagnetic Tracking Sensor and pressure sensors fall short in reliably detecting motor imagery due to several reasons (Mason and Birch, 2003; Chizari et al., 2020). Additionally, the motion capture systems are cost ineffective when compared to sEMG or MPU(motion processing unit) sensors, and are predominantly built on camera subsystem, which invades privacy. The video grab is typically of high bandwidth and demand high computer power to process which makes it unviable for clinical trials (Vitali and Perkins, 2020).

The pressure sensors on the other hand are sensitive to their placements and alignments, which proves to be challenging for rehabilitation purposes (Lawrence et al., 2014).

Overall, the sEMG based systems are found to be an apt solution for the domestic and clinical setups where affordability is a major factor, however building the whole system requires more reliable data towards training the classifier. One way to deal with this challenge is to acquire large sEMG dataset for training, thereby making the model resilient to high degree of variability among the individuals and also along the acquisition factors. However, compiling sEMG signals requires comprehensive effort and hence for most of the custom applications, sEMG signals remain unfavourable. A synthesized set of sEMG dataset for building classifier is one of the solution towards filling the aforementioned void. An electrical model based sEMG features are reported in the past (Vinay et al., 2022), however these remains non-reliable for the real-world applications even with the addition of Gaussian modeled noise component to the synthesized features. A suitable alternative is to derive synthetic features from a different set of physical sensors which preferably is less sensitive to motion artifacts. Accelerometers are found reliable for motion classifier both for upper and lower limb, however these are not equipped to offer distal information instead offers proximal information when utilized in the human body. For instance, the muscle activity for wrist movement is captured by sEMG signal even at the distal end of the upper arm, whereas MPUs are likely to be positioned near the wrist joint to capture reliable signal. Consequently the proximal accelerometer sensory signal carries the necessary limb movement information which can be extracted to the corresponding synthetic distal sEMG signal features. These synthetic features supplement to build large dataset for realizing ML classifier model to work for real-world automated rehabilitation tasks. This paper demonstrates the principle working of the proposed transfer of modality for training model and evaluates the same using original sEMG signal features and also for the mixed (original and synthetic) dataset. The main contributions of the paper are: i) Prediction of sEMG features from the extracted real time accelerometer data, and further validating the same with ensemble model to achieve reliable results, and

ii) Extracted sEMG features show comparable performance with respect to other features extracted from original sEMG signal. The dataset and model files are made freely available at (Mod,) for further usage to the researchers and designers community.

2 PROPOSED METHOD

The proposed framework as shown in the Figure 1 comprises of three primary systems. The first system

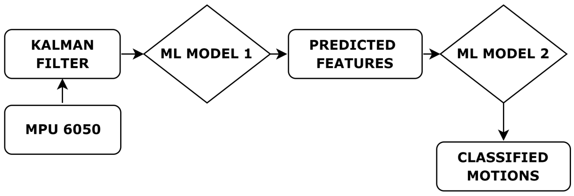

Figure 1: Proposed framework#1 comprising of Ensemble model to extract sEMG features from MPU signals and further supplying to a Classifier model. Here Model#1 is Ensemble model, and Model#2 is a Classifier model.

focuses on data acquisition from MPU sensors.

The second system involves prediction of the sEMG features from the filtered accelerometer data. The IMU data for the specific movements is taken to label the data appropriately and further train the extraction model. The last system engages in the classification of four identified upper limb movements using these synthetic features extracted from IMU data. ML MODEL 1 is the prediction model which predicts the features from the filtered data and ML MODEL 2 is the classifier model which classifies the four motions.

2.1 Dataset

Surface EMG signals are captured using the Muscle BioAmp Patchy sensor, which offers an input impedance of 10^{12} Ω and includes a bandpass filter with a cutoff frequency of 72-720 Hz (Upside Down Labs, 2024). Motion data of the wrist is measured using an Inertial Measurement Unit (IMU), specifically the MPU 6050, which provides the accelerometer and gyroscope data across all three axes (InvenSense, 2013). The MPU 6050 sensor and the sEMG sensors are interfaced to the Arduino Nano board via I2C communication and analog pins, respectively. The accelerometer data offers the vector and movement information along the 3 axis and are preferred over gyroscopes which are more useful for rotational actions. Hence in this work, only accelerometer data is employed to augment the sEMG features.

Figure 2(a and b) shows the setup to acquire the sEMG signal from the targetted muscle group, and IMU for the same upper limb actions. The IMU setup was designed to

be wearable, and user-friendly, while sEMG electrodes are positioned appropriately to ensure effective data sampling during wrist movements. Two Bioamp sEMG sensors were employed to collect the signals from the targeted muscles at the same time, while the IMU data is also captured for the four identified upper limb movements. Necessary informed ethical consent was taken from 8 healthy subjects with a declaration

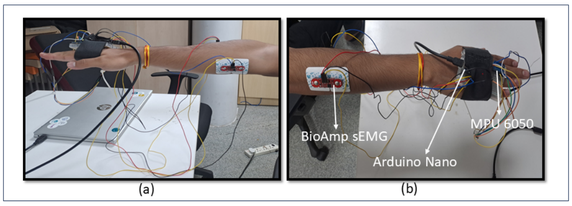

Figure 2: Snapshot illustrating the setup to acquire signals from IMU and sEMG for the defined upper limb movements. IMU sensors enclosed in a black band is wrapped around the palm of the hand, whereas the sEMG signals are acquired from the electrodes positioned at the forearm. (a) shows the position of electrodes on the flexor carpi ulnaris muscles, and (b) shows the position of electrodes on the extensor carpi radialis muscles.

approving that the subjects had no prior weakness or injury, nor any prior surgery performed in the past on any part of the upper or lower limb.

These participants were evenly distributed between 4 females and 4 males to present generic results. Participants' characteristics included an average age of 19.5 ± 0.87 years and an average weight of 62.32 ± 16.71 kg. All participants provided written informed consent before participating in the experiments. The data was collected in accordance with the Helsinki Declaration of 1975, as revised in 2000 (Ashcroft et al., 2008). The subjects were instructed to perform four distinct wrist motions: wrist flexion, wrist extension, wrist closing(extension and contraction of fingers), and wrist vibration(shaking of hand). The dataset collected for training the model comprised a total of 108,656 samples. Figure 3 shows one such instance of the real-time sEMG signal along with the corresponding accelerometer and gyroscope data in all 3 axes for all the four aforementioned wrist actions. To ensure data randomness, subjects performed wrist motions in a randomized sequence. This method mitigates potential biases and enhances the robustness of the dataset for better analysis (Ismail Fawaz et al., 2018). Electrodes were positioned on the flexor carpi ulnaris and extensor carpi radialis muscles, on the skin. Real-time signal data was captured and stored in readable files prior to feature extraction from sEMG signals and further labelling the signal for the corresponding actions.

2.2 EMG Feature Extraction from IMU Data

The signals were uniformly collected at a sampling rate of 500 Hz, as proven efficient in the literature (Chen et al., 2017). Accelerometer data underwent Kalman filtering (Process Noise Covariance(Q) : 0.01*eye(3), Measurement Noise Covariance(R) : 0.1*eye(3), Initial Estimation Error Covariance(P) :

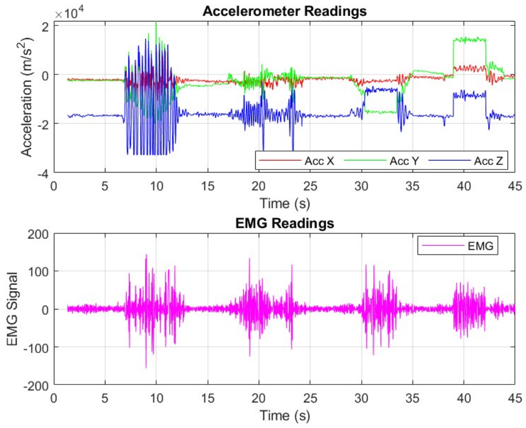

Figure 3: Pre-processed sEMG signal with the corresponding Accelerometer signals for the four upper limb wrist actions - flexion, extension, closing of wrist, and vibrations.

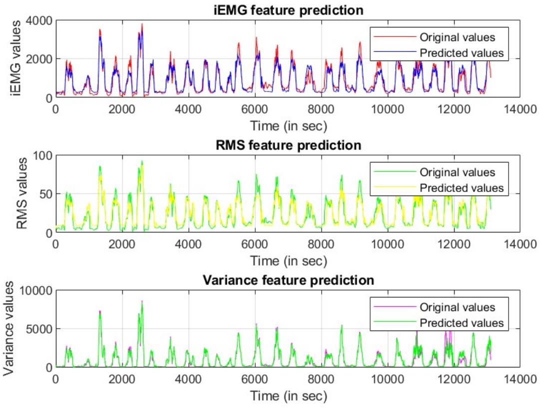

Figure 4: Original features versus trained ML Predicted features for all four selected upper limb actions.

eye(3), State Transition and Covariance : eye(3)) to significantly enhance accuracy by reducing noise and improving the reliability of the IMU data (Farag, 2020). Surface electromyography (sEMG) signals were processed with the help of a Butterworth 4^{th} order band-pass filter for enhanced efficiency (Shi, 2012). Following data acquisition, feature extraction was conducted for a window size of 50 samples (100 ms) with a step size of 1 sample (2 ms) to retain higher order of dataset. Time-domain features including Integrated EMG (iEMG), Root Mean Square (RMS), and Variance were extracted and analyzed for each motion. These features serve as the most discriminative inputs for further motion classification tasks (Phinyomark et al., 2012).

$$\begin{cases} iEMG = \int_0^T |EMG(t)|dt \\ RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(EMG_i)^2} \\ Variance = \frac{1}{N}\sum_{i=1}^{N}(EMG_i - \mu)^2 \end{cases} \quad (1)$$

2.3 Model Feature Prediction

Filtered accelerometer data and extracted sEMG features serve as input and output, respectively, for predicting sEMG features. Each feature (iEMG, RMS, Variance) is predicted independently. To predict iEMG and RMS features, we employed an ensemble model combining a Convolutional Neural Network (CNN) and a Random Forest (RF) to enhance predictive performance. CNN was employed for its ability to capture spatial hierarchies in the data through convolutional layers (LeCun et al., 2015). Random Forest was used for its robustness and ability to handle nonlinear relationships (Khalilia et al., 2011). For predicting Variance, an ensemble model combining Random Forest (estimators=500, depth=30, MinSamplesSplit=3, MinSamplesLeaf=2, RandomState=42) and LightGBM(estimators=500, LearningRate=0.05, depth=30, leaves=40, MinchildSamples=20, RandomState=42) was utilized for improved accuracy. LightGBM is particularly effective for time series feature prediction due to its fast training speed, low memory usage, and ability to manage large datasets and complex feature interactions efficiently (Ke et al., 2017). The outputs from these models were combined to achieve a more robust and accurate predictions. The CNN architecture consisted of multiple convolutional layers followed by pooling layers, batch-normalization, and dropout layers to prevent over-fitting, and dense layers for the final output (Krizhevsky et al., 2012; Ioffe and Szegedy, 2015). The RF model was tuned with hyperparameters such as the number of trees, maximum depth, and minimum samples split to achieve optimal performance. For feature engineering, rolling statistics : mean and standard deviation are calculated with a window size of 10 to enhance the input feature set.

The predictions from both models were then ensembled using a weighted average approach. The weights were determined based on the individual performance of each model on a validation set. This ensemble approach leveraged the strengths of both models, leading to improved overall performance compared to using each model individually (Zhou, 2012). The prediction model was trained for 70% of the dataset, 10% for validation, and remaining 20% for testing. The ensemble model achieved R^2 value (coefficient of determination) of 0.789 and 0.775 for the prediction of iEMG and RMS features with respect to the original extracted features respectively. The ensemble model for the prediction of Variance showed R^2 value of 0.715. Figure 4 showcases the plot of all the three predicted features in contrast with the original features. The R^2 value is a crucial metric in regression analysis as it quantifies the proportion of the variance in the dependent variable that is predictable from the independent variables. R^2 is a key indicator of model performance and reliability in predictive analytics (Frost, 2019).

2.4 Motion Classifier Model

Post the prediction of the sEMG features, the data was labelled for the classification of the wrist movements. The classifier model used 70% of the dataset for training, 10% for validation, and remaining 20% of the dataset for testing. A grid search was conducted to optimize hyperparameters, using a 5-fold cross-validation for all models. The 70-10-20 split for training, validating and testing dataset is proved to be efficient due to its balance between training, and evaluation (Arlot and Celisse, 2009). Between the various models trained, RF offered the best results for the classification of the wrist movements with parameters(estimators = 200, depth = 20, samplesSplit = 5, MinSamplesLeaf = 2, RandomState = 42, Criterion = 'gini', bootstrap = True, features = 'sqrt') RF is widely recognized as an effective classifier for movement recognition tasks due to its robustness and ability to handle complex, non-linear relationships in data. It combines multiple decision trees to improve predictive accuracy and reduce the risk of overfitting, making it particularly suitable for classifying movements from sensor data (Pal, 2005). Amongst the other classification models attempted were SVM model with RBF and poly kernel, and Gradient Boosting model (Van Messem, 2020; Stoean and Stoean, 2013; Friedman, 2006).

3 RESULTS AND DISCUSSIONS

The proposed pipeline framework (#1) extracts sEMG features from accelerometer data which is further supplied to classifier model. The proposed pipeline framework which transfers the modality of sensors data is benchmarked with two staright-forward methods. One where the original sEMG features are extracted from the original sEMG signals and further classified for upper limb movements also referred to as Benchmark framework#1. The other one which employs accelerometer data to classify the motions, which is referred to as Benchmark framework#2. These two benchmarking frameworks are illustrated in Figures 5 (a, b). The proposed framework (#2) is comprised of extracted synthetic sEMG features from the accelerometer data and further merging with the original sEMG features. The augmented dataset consists of synthetic features and original features which is then employed to train the classifier model. The overall process flow is illustrated in Figure 6. All the benchmark frameworks are compared with the proposed ones. While the first proposed framework extracts the sEMG features from a different modality of sensors, the second proposed framework utilizes the same but augments the dataset with original features to build the classifier model. Table 1 shows the accuracy of the classifier models including the proposed one and the benchmark model for the four wrist movements. The proposed synthetic features evolved framework shows better precision than the original features extracted proposed framework (#1) which is expected considering the features are extracted from accelerometer data in the proposed work which are proximally placed whereas the EMG electrodes are distally placed. Additionally the proposed framework (#2) trained with augmented synthetic and original sEMG features shows comparable accuracy with respect to the original ones. As expected the accelerometer devised classifier shows high precision over others which is attributed to the proximal placement of sensors, that captures the dynamic motions accurately.

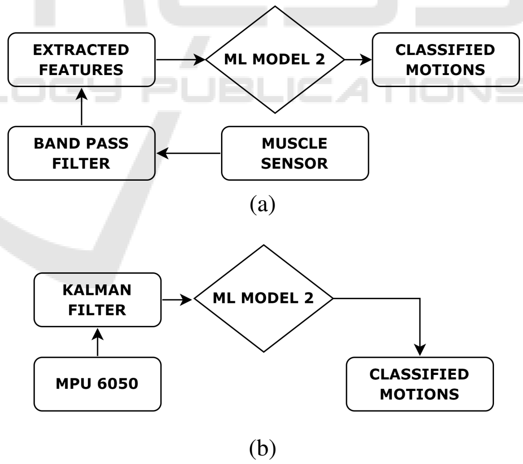

Figure 5: (a) Benchmark framework#1 where the original features from sEMG signals are extracted and further supplied to classifier model, and (b) Benchmark framework#2 where the accelerometer are used to classify the motion instead of extracting sEMG features from Accelerometer data.

The proposed frameworks along with two other benchmark frameworks are evaluated for Precision, Recall, and F1-score. Table 1 lists the accuracy metrics for the proposed model (#1), two benchmark frameworks and proposed merged classifier

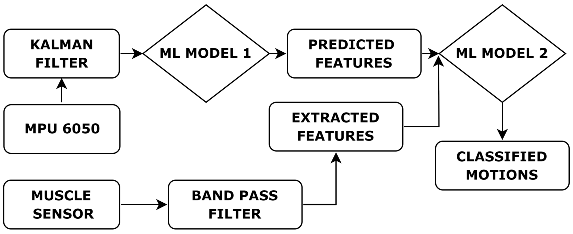

Figure 6: Proposed framework (#2) where the synthetic and original sEMG features are supplied to train classifier models.

Table 1: Accuracy metrics for the proposed frameworks along with other benchmark frameworks.

Models	Motions	Precision (%)	Recall (%)	F1 SCORE (%)
Proposed framework#1	0	78	72	75
	1	88	88	88
	2	85	77	81
	3	81	73	77
Benchmark framework#1	0	76	78	77
	1	73	66	69
	2	70	57	62
	3	79	77	78
Benchmark framework#2	0	99	94	96
	1	94	94	94
	2	91	92	92
	3	90	85	88
Proposed framework#2	0	77	77	77
	1	80	70	74
	2	78	74	70
	3	77	71	74

model. The proposed framework (#1) which classifies the four wrist movements using three predicted sEMG features derived from accelerometer readings, achieves an average precision of 83%, with average F1 score of 80.25% This proposed framework leverages the mapping of two different modality of sensors - accelerometer and sEMG, by predicting sEMG features from accelerometer readings before classifying the wrist movements. The trained prediction model tries to map the sEMG features for an accelerometer signal that is generated on wrist action. This prediction is not real, but it forsees that sEMG features from the accelerometer signal which is generated from movement dynamics and not from muscle activity. The mapping of muscle activity to movement is performed by the prediction model.

The prediction model is trained to accurately map the accelerometer signal with sEMG features for all the four wrist movements.

In comparison, the benchmark framework#1 shown in Figure 5 (a), classifies wrist movements through the three sEMG features directly extracted from the original sEMG signals, achieving an average precision of 74.5% as listed in the Table 1.

While this framework benefits from the direct measurement of muscle activity through sEMG signals, the electrodes positioned at distal end is prone to lose critical information and hence the drop in accuracy. Multiple electrodes at the distal end is bound to improve the accuracy by consolidating vector features.

Direct sEMG readings offer high temporal resolution and are effective for muscle activity detection, but are limited by noise and variability in electrode placement.

The benchmark framework#2 as portrayed in Figure 5 (b), which classifies wrist movements directly from accelerometer readings, achieves the highest average precision of 94% among all the frameworks. This framework's great precision underscores the effectiveness of accelerometer data in capturing the dynamics of wrist movements. Accelerometers provide detailed motion data, including acceleration and angular velocity, which are directly related to the physical movements being classified. The high precision indicates that accelerometer readings are highly reliable for distinguishing between different wrist movements. However, this framework lack insights into the underlying muscle activity, which is crucial in certain applications such as rehabilitation or bio-mechanical analysis. Besides, the accelerometers positioning is always restricted to specific regions thereby limiting the design space for rehabilitation and related tasks.

The proposed merged framework#2 as illustrated in the Figure 6, combines the dataset of predicted EMG features along with the dataset of original sEMG features, thus creating a richer dataset. It is then employed as input to classify the upper limb motions. The proposed merged dataset devised framework achieves an average precision of 77.5% which is comparable with the original sEMG feature trained framework (74.5%). This strengthens the proposal of augmenting the dataset through predicted sEMG features from the other modality of sensors whenever the original sEMG signal and data acquisition is not possible. It is also noted that pure synthetic features present classifier (proposed variant) accuracy of around 83%, which is vastly deviated from the original framework (#1). Hence the augmented dataset is much closer to the real sEMG signal generated and devised framework.

Additionally, the merged dataset devised model (proposed #2) was evaluated on original unseen sEMG features and synthetically generated but unseen sEMG features individually.

Accuracy of 91% is achieved when the proposed framework 1 (which is trained completely on the original unseen dataset) is used and is given the augmented training dataset of the proposed framework 2 for testing. Accuracy of 95% is achieved when the proposed framework 2 (which is trained on the augmented dataset) is used and is given the original unseen dataset to test. This strongly supports the use of accelerometers derived sEMG features for augmenting the dataset and further employing the trained model on unseen dataset successfully. The mapping of accelerometer data to sEMG features although does not fully capture the electro-muscular activity but it augments the dataset well to train the model and extract discriminative features for original and unseen sEMG features. The augmentation of sEMG dataset through other modality of sensors opens up several avenues to train the model for human limb. The four wrist actions are purely to showcase the effect of synthetic features and the dataset.

4 CONCLUSION

The proposed sEMG features extracted from a different modality of sensor is introduced in this work towards classifying four of the upper limb motions. These motion classifiers are useful to design and develop an adaptive rehabilitation system with predictive control strategy. The proposed synthetically generated sEMG features from the ML model show high degree of correlation with the original sEMG generated features for four of the wrist actions. The data collected was based on the four motions which were restricted to the flexor carpi ulnaris and extensor carpi radialis muscles. An ensemble model was proposed and verified for attaining maximum accuracy for extraction of sEMG features. Post the prediction of the features, RF classifier was employed for classifying the four identified motions. The machine learning models were optimised with appropriate hyperparameters and features ensuring best possible results. The predicted sEMG features augmented with orginal features demonstrates comparable motion classifier accuracy. Additionally for unseen original sEMG features, the proposed augmented dataset trained model showcased a superior accuracy of 91%. This is a step for developing large dataset of human limb motion, which will possibly give a much needed impetus for designing a generic human limb rehabilitation system that is applicable to the most of the needy ones. The generic rehabilitation system will further reduce the cost to the users. The dataset and model files are made freely available at (Mod,) for further use to the researchers and scientific community.

REFERENCES

Dataset and model files are available at: https://drive.google.com/drive/folders/1fEIuRkBEIlyJBbj79CEXPjqh9B16Ibon?usp=sharing.

Arlot, S. and Celisse, A. (2009). A survey of cross validation procedures for model selection. *Statistics Surveys*, 4.

Ashcroft, R. E. et al. (2008). The declaration of helsinki. *The Oxford textbook of clinical research ethics*, pages 141–148.

Campanini, I., Disselhorst-Klug, C., Rymer, W. Z., and Merletti, R. (2020). Surface emg in clinical assessment and neurorehabilitation: Barriers limiting its use. *Frontiers in Neurology*, 11.

Chandrasekhar, V., Vazhayil, V., and Rao, M. (2020a). Design of a portable anthropomimetic upper limb rehabilitation device for patients suffering from neuromuscular disability. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 4708–4712.

Chandrasekhar, V., Vazhayil, V., and Rao, M. (2020b). Design of a real time portable low-cost multi-channel surface electromyography system to aid neuromuscular disorder and post stroke rehabilitation patients. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 4138–4142.

Chen, H., Zhang, Y., Zhang, Z., Fang, Y., Liu, H., and Yao, C. (2017). Exploring the relation between emg sampling frequency and hand motion recognition accuracy. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 1139–1144.

Chizari, A., Knop, T., Sirmacek, B., van der Heijden, F., and Steenbergen, W. (2020). Exploration of movement artefacts in handheld laser speckle contrast perfusion imaging. *Biomedical optics express*, 11(5):2352–2365.

Eschweiler, J., Li, J., Quack, V., Rath, B., Baroncini, A., Hildebrand, F., and Migliorini, F. (2022). Anatomy, biomechanics, and loads of the wrist joint. *Life*, 12(2).

Farag, W. (2020). Kalman-filter-based sensor fusion applied to road-objects detection and tracking for autonomous vehicles. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 235:095965182097552.

Friedman, J. H. (2006). Recent advances in predictive (machine) learning. *Journal of classification*, 23(2):175–197.

Frost, J. (2019). How to interpret r-squared in regression analysis. statistics by jim, making statistics intuitive. *Statistics by Jim Making Statistics Intuitive*.

Hiengkaew, V., Jitaree, K., and Chaiyawat, P. (2012). Minimal detectable changes of the berg balance scale, fuglmeyer assessment scale, timed “up & go” test, gait speeds, and 2-minute walk test in individuals with chronic stroke with different degrees of ankle plantarflexor tone. *Archives of Physical Medicine and Rehabilitation*, 93(7):1201–1208.

InvenSense, I. (2013). Mpu-6000 and mpu-6050 product specification revision 3.4. *United States*.

Ioffe, S. and Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning*, pages 448–456. pmlr.

Ismail Fawaz, H., Forestier, G., Weber, J., Idoumghar, L., and Muller, P.-A. (2018). Data augmentation using synthetic data for time series classification with deep residual networks.

Jonna, P., Madurwar, A., BK, A., and Rao, M. (2024). Design of 6-dof holonomic drive-based upper and lower-limb stroke rehabilitation system. In *2024 10th International Conference on Automation, Robotics and Applications (ICARA)*, pages 233–239.

Jonna, P. and Rao, M. (2022). Design of a 6-dof cost-effective differential-drive based robotic system for upper-limb stroke rehabilitation. In *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 1423–1427.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., and Liu, T.-Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30.

Khalilia, M., Chakraborty, S., and Popescu, M. (2011). Predicting disease risk from highly imbalanced data using random forest. *BMC medical informatics and decision making*, 11:51.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Pereira, F., Burges, C., Bottou, L., and Weinberger, K., editors, *Advances in Neural Information Processing Systems*, volume 25. Curran Associates, Inc.

Kwakkel, G., Kollen, B. J., and Krebs, H. I. (2008). Effects of robot-assisted therapy on upper limb recovery after stroke: A systematic review. *Neurorehabilitation and Neural Repair*, 22(2):111–121. PMID: 17876068.

Lawrence, E. L., Fassola, I., Werner, I., Leclercq, C., and Valero-Cuevas, F. J. (2014). Quantification of dexterity as the dynamical regulation of instabilities: Comparisons across gender, age, and disease. *Frontiers in Neurology*, 5.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553):436–444.

Loureiro, R. C. and Harwin, W. S. (2007). Reach & grasp therapy: Design and control of a 9-dof robotic neuro-rehabilitation system. In *2007 IEEE 10th International Conference on Rehabilitation Robotics*, pages 757–763.

Mason, S. and Birch, G. (2003). A general framework for brain-computer interface design. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11(1):70–85.

Merletti, R. and Cerone, G. L. (2020). Tutorial. surface emg detection, conditioning and pre-processing: Best practices. *Journal of Electromyography and Kinesiology*, 54:102440.

Novak, D., Mihelj, M., and Munih, M. (2012). A survey of methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing. *Interacting with Computers*, 24(3):154–172.

P, J., GVK, S., Rao, M., Bapat, J., and Das, D. (2023). Xorehab: Iot enabled wheelchair based lower limb rehabilitation system. In *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 1–5.

Pal, M. (2005). Random forest classifier for remote sensing classification. *International journal of remote sensing*, 26(1):217–222.

Phinyomark, A., Nuidod, A., Phukpattaranont, P., and Limsakul, C. (2012). Feature extraction and reduction of wavelet transform coefficients for emg pattern classification. *Elektronika ir Elektrotechnika*, 122(6):27–32.

Reddy, M., Jonna, P., Perala, S., Rao, M., and Vazhiyal, V. (2023). Automated microsurgical tool categorization using a surface-based emg system. In *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 1–5.

Schreuders, T., Brandsma, J., and Stam, H. (2019). *Functional Anatomy and Biomechanics of the Hand*, pages 3–21.

Shi, Y. (2012). The application of the butterworth low-pass digital filter on experimental data processing. In *2011 International Conference in Electrics, Communication and Automatic Control Proceedings*, pages 225–230. Springer.

Stoean, R. and Stoean, C. (2013). Modeling medical decision making by support vector machines, explaining by rules of evolutionary algorithms with feature selection. *Expert Systems with Applications*, pages 2677–2686.

Upside Down Labs (2024). Muscle-bioamp-patchy. https://github.com/upsidedownlabs/Muscle-BioAmpPatchy/tree/main/hardware. [Online; accessed 11-June-2024].

Van Messem, A. (2020). Chapter 10 - support vector machines: A robust prediction method with applications in bioinformatics. In Srinivasa Rao, A. S. and Rao, C., editors, *Principles and Methods for Data Science*, Handbook of Statistics, pages 391–466.

Vinay, K., Nagaraj, K., Arvinda, H. R., Vikas, V., and Rao, M. (2021). Design of a device for lower limb prophylaxis and exercise. *IEEE Journal of Translational Engineering in Health and Medicine*, 9:1–7.

Vinay, K., Vazhayil, V., and Rao, M. (2022). An event driven approximate bio-electrical model generating surface electromyography rms features. In *2022 35th International Conference on VLSI Design and 2022 21st International Conference on Embedded Systems (VLSID)*, pages 204–209.

Vitali, R. V. and Perkins, N. C. (2020). Determining anatomical frames via inertial motion capture: A survey of methods. *Journal of Biomechanics*, 106:109832.

Zhou, Z.-H. (2012). *Ensemble methods: foundations and algorithms*. CRC press.