Classification of Fine-ADL Using sEMG Signals Under Different Measurement Conditions

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Keywords: sEMG, Fine-ADL, Feature Extraction, Neural Networks, CNN Bi-LSTM, Class-Wise Analysis.

Abstract: Most studies on surface electromyography (sEMG) related to finger activities have concentrated on grips, grasps and general arm movements without any emphasis on the correlation of body postures and hand positions on the finger-centric activities. The main objective of the new dataset is to investigate activities of daily living (ADL) needing focus on finer motor control in diverse measurement conditions. In this paper, we present a novel dataset of finger-centric activities of daily living comprising 5-channel sEMG signals collected under different body postures and hand positions. The dataset encompasses sEMG signals acquired from 10 subjects, performing 10 distinct fine-ADLs in various body postures and hand positions. Further, a machine learning framework for classification of the fine-ADL is developed as follows. Each signal is segmented into 250ms windows and Time Domain (TD), Frequency Domain (FD), Wavelet Domain (WD) and Eigenvalues features are extracted. Four classifier frameworks using the features are implemented for the analyses. The results reveal that a hybrid CNN Bi-LSTM achieves an average test accuracy of 76.85%, followed by a 5-layered fully connected neural network (FCNN) with 72.42%, in aggregate scenario. An average subject-wise test accuracy of 88% is achieved by the FCNN across all body postures and hand positions combined. Most importantly, the CNN Bi-LSTM, enhances subject-wise classification by an average test accuracy of 27.47% than the FCNN under varying body postures. Dependencies of the test accuracy on measurement conditions are analyzed. *Stand* body posture is found to be the easiest to classify in Aggregate scenario, whereas *Folded Knees* was the most difficult to classify. An increase in test accuracy with an increase in training data is observed body postures combinations analysis.

1 INTRODUCTION

1.1 Background

Activities of Daily Living (ADL) refer to the basic tasks and activities that individuals perform on a daily basis. ADL are particularly important for individuals with disabilities or chronic illnesses who may require assistance or accommodations to perform them. Furthermore, insights gained from studying ADL can inform the design of assistive technologies to help individuals with disabilities perform daily tasks independently.

The applications of ADL assessment are wide-ranging and include geriatric care, rehabilitation, disability evaluation (Chen et al., 2022), and assistive technology design. In geriatric care (Sandberg et al., 2012), the ADL assessment can help identify functional decline and enable healthcare providers to implement interventions to maintain independence and quality of life (Faria et al., 2020). In rehabilitation care, it is important for establishing baselines, tracking progress (Dai et al., 2021), and developing effective treatment plans (He et al., 2021). In the design of assistive technology, it can help ensure that devices are tailored to the specific needs and abilities of a user (Park et al., 2020).

We propose Fine-ADL as a class of activities of daily living that require fine motor ability as described in (Fauth et al., 2017) for precise control of the fingers and wrists. Examples include ADL such as writing, typing, and using standard mechanical tools such as a kitchen knife. Assessment of Fine-ADL is important in evaluation of the ADL score (Katz, 1983) and various related applications. ADL are analyzed using motion sensors, visual information and sEMG signals

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Naidu, S., Turlapaty, A. and Sagar, V.
Classification of Fine-ADL Using sEMG Signals Under Different Measurement Conditions.
DOI: 10.5220/0012346000003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 1*, pages 591-598
ISBN: 978-989-758-688-0; ISSN: 2184-4305

(Toledo-Pérez et al., 2019).

Surface electromyography (sEMG) is a non-invasive measurement technique to record a muscle's electrical activity providing valuable information into its contractions. Hence, this method finds application in the examination of these finer activities. Pattern recognition of sEMG signals is a promising approach for wearable robotic control. To realize their widespread real-world adaptation, it is important to develop control technologies that can perform Fine-ADL for the users (Castellini et al., 2009). Toward realization of this goal a fundamental requirement is a pattern recognition framework that can reliably classify intended actions of a user based on multi-channel sEMG signals.

One major challenge is the limited performance of the pattern recognition algorithms under variable measurement conditions different from the controlled laboratory experiments. One reason for this limitation is tasks performed in controlled circumstances with limited trials and specific instructions may not reflect the variability and complexity of Fine-ADL in the everyday life. (Rosenburg and Seidel, 1989) observed a significant correlation between sEMG signals and body postures. However, the underlying mechanisms driving this relationship have remained elusive. The observed variability has been attributed to bio-mechanical factors such as lever arm of muscles, force distribution across muscles, gravity and others. Consequently, it is important to incorporate diverse measurement conditions when conducting sEMG studies.

There are a few efforts available in literature studying the impact of measurement conditions, specifically body and hand positions on classification of ADL and other limb movements based on different measurement modalities. In (Song and Kim, 2018), a classification algorithm using a single inertial sensor to categorize three fundamental gait activities was proposed. The experiments in this study included measurements both within a gait lab and in an outdoor walking course, allowing analysis under varying conditions. Another study (Williams et al., 2022) explored control strategies for myoelectric prostheses that incorporate position awareness. By considering the positional information of the prosthetic hand, a natural and intuitive control can be achieved. In (Yang et al., 2015) and the references therein, the impact of upper limb positions and dynamic movements on classification of finger motions, which usually contribute to Fine-ADL, is demonstrated. However in the existing literature there is no study or sEMG dataset with focus on Fine-ADL under different measurement conditions. Furthermore, our objective is to collect sEMG signals during Fine-ADL from a group of Indian subjects and analyze the impact of measurement conditions on ADL classification.

Table 1: List of Activities and activity duration.

Activity Name (Class)	Action
Swiping on a Phone (C1)	5s
Zoom In on a Phone (C2)	5s
Zoom Out on a Phone (C3)	5s
Pressing Button using Thumb (C4)	5s
Flipping a Switch (C5)	5s
Cutting a fruit (knife) (C6)	7s
Eating With Spoon(C7)	7s
Flipping a Bottle cap (C8)	5s
Writing on paper with pen (C9)	7s
Using Scissors (C10)	7s

Table 2: Body Postures and Hand Positions.

Body Postures	Hand Positions
Folded Knees (b1)	
Folded Legs (b2)	P1
Sit (b3)	
Sit to Stand (b4)	P2
Stand (b5)	

1.2 Contributions

- A novel sEMG dataset is developed that corresponds to Fine-ADL under different body postures and hand positions.
- The impact of different body postures and arm positions on the classification of Fine-ADL and class-wise analysis are studied through various experiments.
- Various classical Machine Learning (ML) frameworks and hybrid CNN Bi-LSTM are implemented for the classification of Fine-ADL.

2 METHODOLOGY

2.1 Fine-ADL sEMG Dataset

In this work, a new sEMG dataset corresponding to Fine-ADL is presented. The data is collected from 10 subjects who have no abnormalities or impairments in their upper limbs. The group of subjects have diverse demographics, consisting of 7 males and 3 females, with 2 left-handed and 8 right-handed individuals. In terms of age distribution, there are 8 subjects in the $17-20$ age group, 1 subject above 30, and 1 subject above 40. The research study was approved by the

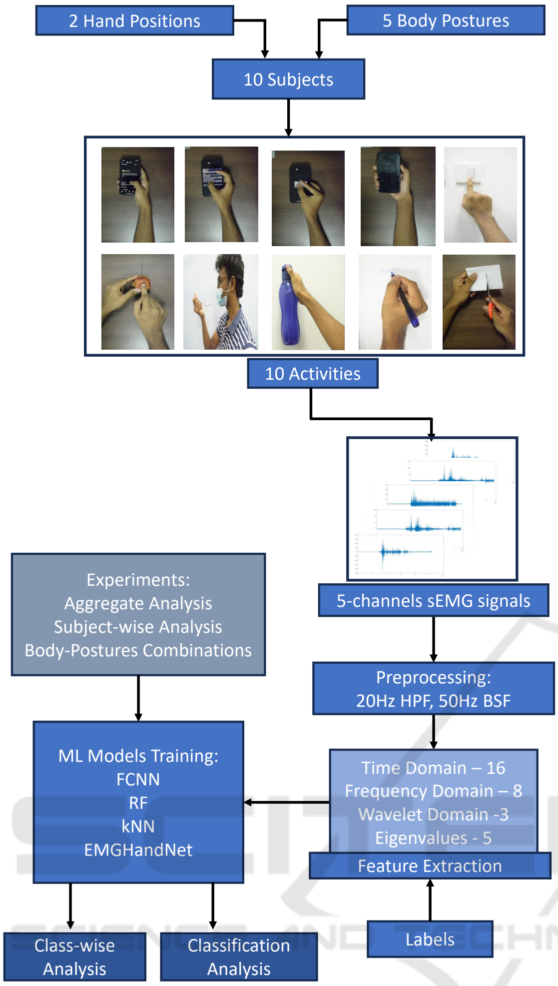

Figure 1: Block Diagram.

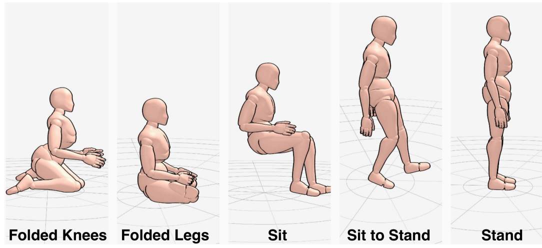

Figure 2: Body Postures.

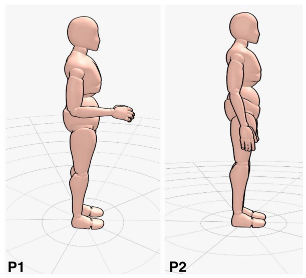

Figure 3: Hand Positions.

ethics committee at the Indian Institute of Information Technology, Sri City (No. IIITS/EC/2022/01) and is in accordance with the principles of the Declaration of Helsinki. The data acquisition process is non-invasive and prior to a measurement session, each subject gave a written informed consent and was introduced to the experimental protocol.

In this study, each subject performed a series of 10 activities of different durations as listed in Table 1. Further, to ensure accurate measurements, these activities in the selected body postures and hand positions were demonstrated to the subjects. The EMG signal from the hand is recorded using a wireless 5-channel Noraxon Ultium sEMG sensor configuration. The electrical contact is made with dual Ag/AgCl self-adhesive electrodes at the densest region of the selected forearm muscle sites (Criswell, 2010) given in Table 3. Prior to electrode placement, the hands are cleaned using an alcohol-based wet wipe. Each subject is asked to perform each of the fine-activities of daily living in three phases: rest, action, and release. Subjects start with the rest phase, where they relax the muscles and refrain from any physical activity. During the action phase, the activity is executed and the release phase denotes a smooth transition from the action state to the rest state.

During a measurement session, the subject performs 10 Fine-ADL in 5 different body postures as shown in Fig. 2 and 2 different hand positions as shown in Fig. 3. Thus, the total number of measurement conditions is 10. The signal specifications are as follows: 1) sampling rate: 4000 samples/sec, 2) duration of a trial: 11s or 13s, and 3) the break between two consecutive body postures: 5 minutes. Each activity in a given posture is repeated 5 times. Hence the total number of trials is 10 subjects $\times$ 5 postures $\times$ 2 positions $\times$ 10 activities $\times$ 5 trials = 5000.

2.2 Methodology

The methodology for classification of the sEMG signals corresponding to Fine-ADLs consists of the following stages: 1) data preparation, 2) segmentation, 3) feature extraction, 4) ML model training, and 5) testing and analysis as shown in Fig. 1.

2.2.1 Data Preparation

In this phase, all the 5-channeled sEMG signals are processed by two digital filters. Initially, the sEMG signals are high-pass filtered with a lower cut off frequency of 20Hz to remove any motion artifacts. The output of this filter is processed by a 50Hz notch filter to remove any electric line noise. From the filter

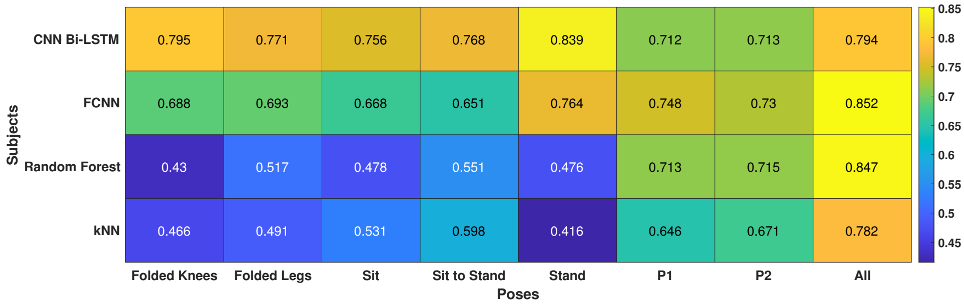

Figure 4: Test accuracies from classification under various Conditions using different Classifiers in the aggregate scheme.

output, the rest phase and the samples from the final one second of the release phase are discarded to retain the action and 2 seconds of the release phase. These processed sEMG signals are annotated with the relevant class labels corresponding to the Fine-ADL categories.

2.2.2 Feature Extraction

To improve classification performance, the preprocessed sEMG signals are segmented into windows of 250ms duration. For each of these sEMG segments, 16 time domain features (Sapsanis et al., 2013),(Karnam et al., 2021), 8 frequency domain features, 3 wavelet domain features and eigenvalues are computed. The features from each of these segments and the 5 channels of a signal are concatenated to build the full feature vector. The specific combination of features is used after analysing various feature combinations.

2.2.3 Classification Framework

The next stage consists of model training and testing four classifiers: Fully Connected Neural Networks (FCNN), Random Forests (RF), k-Nearest Neighbors (k-NN), and the CNN Bi-LSTM (Karnam et al., 2022) with minor modifications. Note that in the case of the deep learning model the feature extraction is implicit within the ML framework. The modifications to the CNN Bi-LSTM include changing the dropout rate to 0.3, the CNN window size to 4×7, and the batch size to 8. The FCNN consists of five dense layers with respective number of neurons: 256, 128, 64, 16, and 10. The ReLU activation function is utilized in the first four layers and the softmax function used in the output layer.

3 IMPLEMENTATION

In this paper, three distinct experiments, 1) the aggregate scheme, 2) the subject-wise scheme and, 3) impact analysis of body postures combinations are conducted. These experiments investigate the impact of the body postures and the hand positions on classification performance.

Table 3: Sensor placement on hand muscles.

Channel No.	Muscle Name
1	Abductor digiti minimi
2	Extensor pollicis brevis
3	First dorsal interosseous
4	Abductor pollicis brevis
5	Brachioradialis

3.1 Aggregate Scheme

This experiment involves the utilization of the aforementioned four classifiers to classify the feature data from all of the 10 subjects. The objective of this scheme is to investigate the general impact of different measurement conditions on the classification of Fine-ADL and also to analyse if the classifiers can learn and classify across different individuals. The classifiers are evaluated for the following three conditions.

Body Postures. In this case, the trials of the 10 subjects from any set of four body postures are employed for training purposes while the trials in the left out body posture are utilized for testing. This process is repeated till trials from the five body postures are tested separately(Fougner et al., 2011). This methodology is referred to as Leave-One-Posture-Out analysis.

Hand Positions. In this case, the trials of all subjects from one hand position are utilized for training while the trials from the other hand position are used for testing. This process is repeated for both hand positions(Fougner et al., 2011).

All Positions. In this case, 80% of all trials from each combination of a body posture and a hand position, aggregated across all subjects are utilized for training. The remaining 20% of the trials are tested.

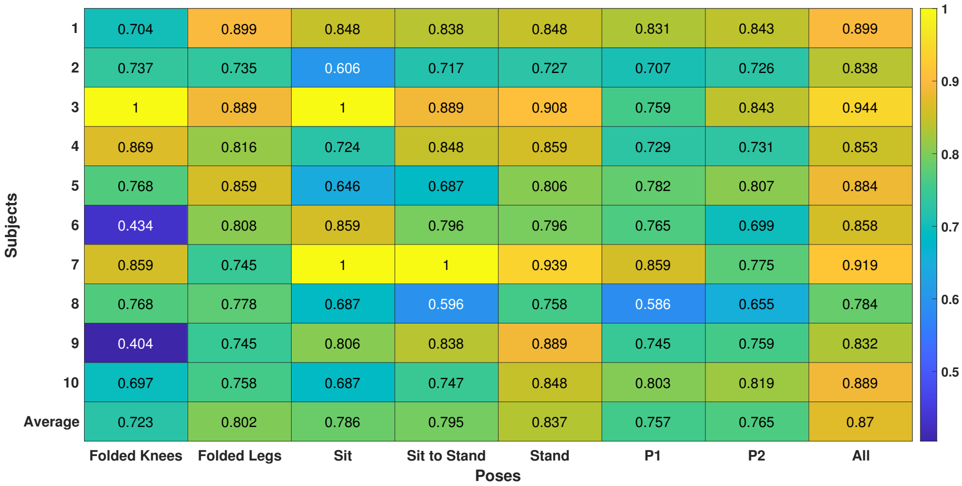

Figure 5: Test accuracies from Subject-wise average performance under various conditions using the hybrid CNN Bi-LSTM.

3.2 Subject-Wise Analysis

In the subject-wise experiment, a model's learning capability at the subject level is evaluated. In this experiment, only the results from the hybrid CNN Bi-LSTM are reported. For the signals from each of the ten subjects, the training, testing, and performance analysis is carried out under the three sets of conditions mentioned previously. Hence, in the subject-wise scheme, in a given classification analysis, the amount of data analyzed is only one tenth of the first experiment. Finally, the results averaged across the subjects are also reported.

3.3 Body Postures Combinations Analysis

In the body posture combinations analysis, the impact of diverse body postures on Fine-ADL is investigated. The study encompasses data from each of the 10 subjects. The methodology involves training the model using different sets of body postures and testing on the remaining body postures (Fougner et al., 2011). The number of specific combinations when i conditions are used in training is 5_{C_i}. The total is $\sum_{i=1}^{4} 5_{C_i}$ resulting in the examination of 30 distinct scenarios. The averaged results from FCNN across the 4 categories and the class-wise F_1 scores are reported.

4 RESULTS AND ANALYSIS

4.1 Aggregate Analysis

Fig. 4 illustrates the results of the aggregate scheme. Across various body postures and hand positions, on average, the hybrid CNN Bi-LSTM performs the best, achieving an average test accuracy of 76.89%, followed by the FCNN with 72.42%. In the classification analysis versus the body postures, Fig. 4 shows that the *Stand* position is the least challenging posture for the model to understand with a test accuracy of 83.93% by hybrid CNN Bi-LSTM, while *Sit* posture is the most difficult with 75.62%. An 8% difference in accuracy is observed between the *Stand* and *Sit* postures indicating an impact of body postures on Fine-ADL classification. However, in the hand position analysis, the FCNN is the top-performing classifier with an average test accuracy of 73.9%. Moreover, reduction of the training data to 50% has little impact on the accuracy for most classifiers. The hand positions seem to be less influential in case of aggregate analysis as they produce similar accuracies. In the third condition where all positions are considered, the FCNN outperforms others with an accuracy of 85.2%, followed by the RF with 84.7% and the hybrid CNN Bi-LSTM with 79.4%.

4.2 Subject-Wise Analysis

Fig. 5 illustrates the subject-wise test accuracy of the hybrid CNN Bi-LSTM across the different postures and positions. CNN Bi-LSTM outperforms the FCNN in the body posture analysis, achieving an average test accuracy of 78.93% compared to FCNN's 51.46%. In terms of variations across subjects, the data from subjects 3 and 7 have the highest test accuracies averaged across the different conditions at 89.8% and 88.2% respectively. The lowest average performance is observed for data from subject 8 at 68.9%. In the body postures analysis, *Folded Knees* prove to be the most challenging posture for the clas-

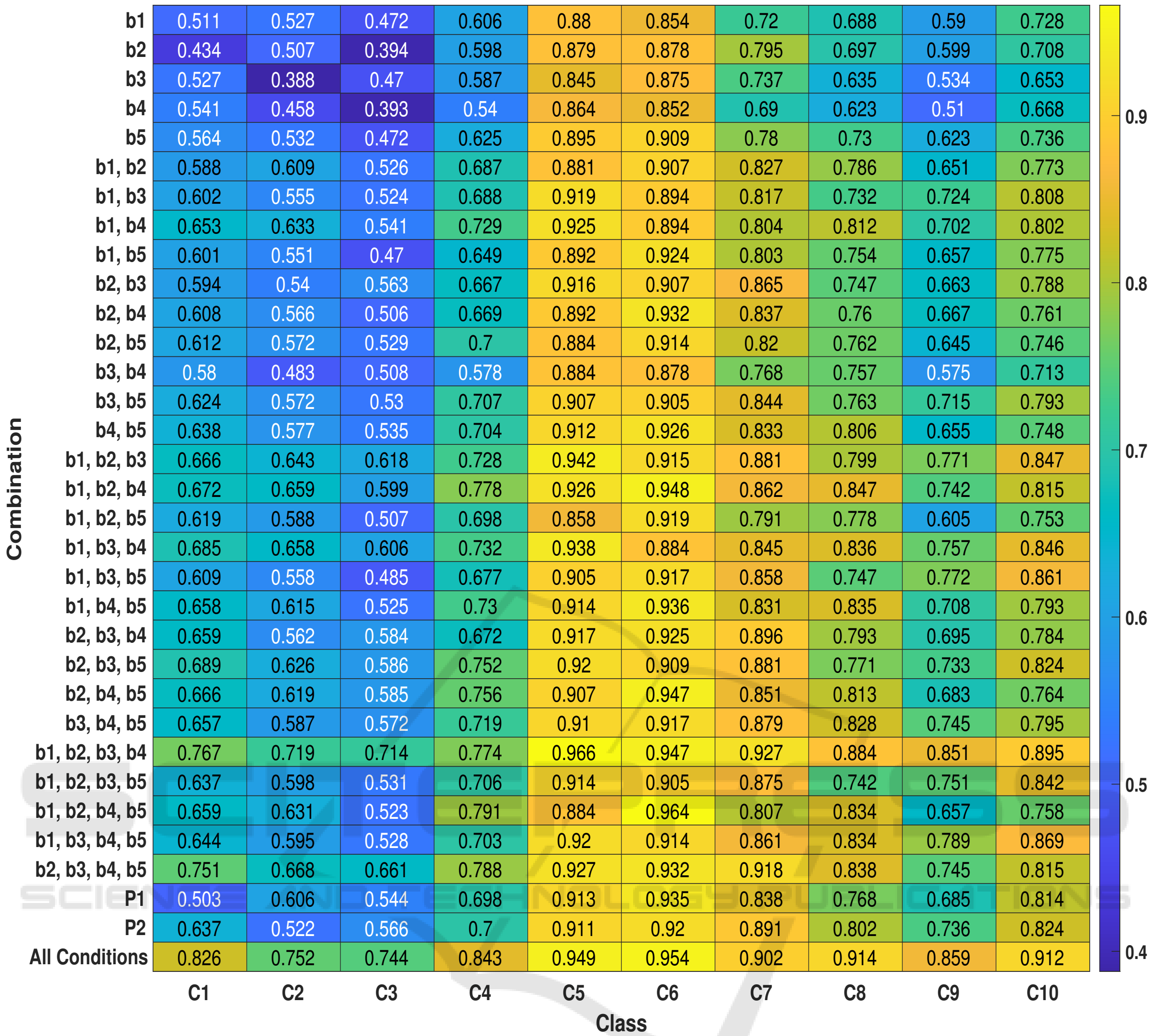

Figure 6: Class-wise F1 score averaged across the test conditions as function of combinations of training conditions.

sifier, with an average test accuracy of 72.39%. In contrast, *Stand* posture yields the highest accuracy of 83.78%, exhibiting an 11.39% difference. The results show that the body postures have a significant influence among the subject level results. On average, there is a 23% gap in accuracy between the highest and lowest performing postures. This distinction is particularly pronounced in subjects 9 and 6, with a substantial 42.42% and 48.48% disparity between *Folded Knees* and *Stand*, respectively. Interestingly, while *Stand* posture boasts the highest average accuracy, *Folded Knees* and *Folded Legs* emerge as the top performers in three subjects each, while *Stand* prevails in only two subjects. These results suggest that the impact of body postures is notably intricate on a subject-specific basis.

In the hand positions analysis, as shown in Fig. 5, the hybrid CNN Bi-LSTM seems to have an average accuracy (across subjects) close to 76% for both the hand positions. The standard deviation across subjects is 7.55% and 6.3% respectively. Subjects 3, 8, 7, and 6 exhibit considerable discrepancies in hand position accuracy, highlighting distinct subject-specific trends. Generally, the performance closely aligns with the aggregate analysis. Finally, in all positions case, the hybrid CNN Bi-LSTM achieves an average test accuracy of 86.99%, with a minimum of 78.39% and a maximum of 94.44%.

4.3 Body Postures Combinations Analysis

Figs. 6 and 7 illustrate class-wise F1 scores when different combinations of body postures are used for

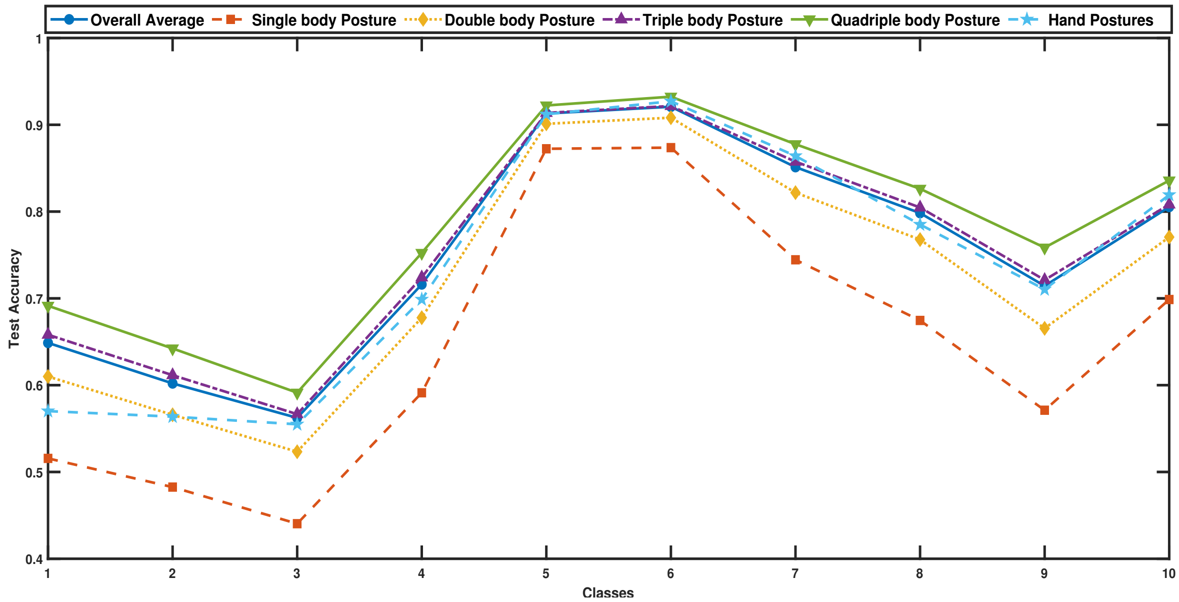

Figure 7: Class-wise test F1 score averaged across a group of training conditions when a number of conditions are used for training.

training. Fig. 6, shows the test F1 scores for each of the classes (columns) when a specific combination of conditions is used for training (rows). Fig. 7 shows the test F1 scores further averaged across the 5_{c_i} conditions for each i, indicating the average performance when any of i conditions are used for training. From these Figs., the F1 scores increase as the number of body postures used for training increases. On average, using one posture yields an F1 score of 64.64%, while employing two, three, and four postures results in F1 scores of 72.11%, 75.87%, and 78.3% respectively. The combination $\{b1, b2, b3, b4\}$ exhibits the highest F1 score, reaching 84.5%. It's worth noting that b5 proves to be the easiest posture to learn, even without explicit training from the same condition. Interestingly, as the number of postures used for training increases, the increase in F1 score diminishes. The class-wise analysis reinforces the observation that C3 has the lowest F1 score, while C5 and C6 consistently demonstrate the highest scores across all combinations of body postures.

Moreover, the average for hand postures falls between that of a single combination and all other combinations. This suggests that while hand postures do contribute to accuracy, they are not as influential as combined body postures. Furthermore, it's notable that activities C2 (Zoom In) and C3 (Zoom Out), being very similar in nature, might be causing substantial confusion for the model. Surprisingly, a dip in F1 score is observed for C9 (Writing), which could be attributed to potential similarities with other activities, leading to mis-classification.

4.4 Discussion

The hybrid CNN Bi-LSTM model consistently outperforms other models in both Subject-wise scenario and Body Posture analyses within the Aggregate scenario. Moreover, the FCNN demonstrates superior classification ability specifically for Body Posture Combinations analysis. Consistent trends are observed in both aggregate and subject-wise analyses. *Stand* posture is always the easiest to classify on average. Additionally, as the amount of training data increased, there was a noticeable improvement in test accuracy, particularly evident in the hand position analysis where 50% of the data was utilized, compared to body postures which utilized 80% of the data. This incremental trend was also apparent in the analysis of body posture combinations. The consistent shape of Fig. 7 indicates that the ranking of class performance remains stable across various combinations. The subject-wise analysis further emphasized the impact of measurement conditions and the subject-specific nature of Fine-ADL. Overall, these findings underscore the impact of measurement conditions on Fine-ADL.

5 CONCLUSION AND FUTURE WORK

This paper presents a new sEMG dataset consisting of 10 Fine-ADL activities conducted under various measurement conditions. The dataset includes data captured in different body postures and hand positions. The analysis of the dataset is carried out from two perspectives: Aggregate and Subject-wise, considering three cases: body postures, hand positions, and all positions in both experiments along with class-wise analysis on impact of body postures. Among the classifiers examined, the hybrid CNN Bi-LSTM demonstrates the best performance, successfully recognizing Fine-ADL even in diverse measurement conditions. The most challenging body posture for the classifier is *Folded Knees*, while the least challenging is the *Stand* posture. Interestingly, both the hand positions considered yield similar accuracies. Nevertheless, the current outcomes highlight the potential of the proposed framework for real-time Fine-ADL and also demonstrate the impact of various measurement conditions on Fine-ADL. In terms of future work, there is potential for further enhancing the model through fine-tuning to achieve improved results. Additionally, the impact of the amount of training data, pertaining to a specific measurement condition, on testing accuracy needs to be investigated. Furthermore, feature selection analysis also requires further improvements and the generalization ability of the model to new subjects needs to be explored.

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