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Comparison of Machine Learning Techniques for Activities of Daily Living Classification with Electromyographic Data*

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Abstract— **Advances in data science and wearable robotic devices present an opportunity to improve rehabilitation outcomes. Some of these devices incorporate electromyography (EMG) electrodes that sense physiological patient activity, making it possible to develop rehabilitation systems able to assess the patient's progress when performing activities of daily living (ADLs). However, additional research is needed to improve the ability to interpret EMG signals. To address this issue, an off-line classification approach for the 26 upper-limb ADLs included in the KIN-MUS UJI dataset is presented in this paper. The ADLs were performed by 22 subjects, while seven EMG signals were recorded from their forearms. From variable-length EMG time windows, 18 features were computed, and 13 features more were extracted from frequency domain windows. The classification performance of five different machine learning techniques, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Gated Recurrent Unit (GRU) network, XGBoost, and Random Forests, were compared. CNN performed best amongst individual models, with an accuracy above 80%, compared to SVM with 77%, GRU with 73.9%, and the tree-based models below 64%. Ensemble learning with four CNN models achieved an even higher accuracy of 86%. These results suggest that the CNN ensemble model is capable of classifying EMG signals for most ADLs, which could be used in off-line quantitative assessment of robotic rehabilitation outcomes.**

I. Introduction

Patients with musculoskeletal disorders or injuries often suffer from mobility limitations that affect their quality of life. Regardless of whether they recover their full mobility through physical rehabilitation, or end up with a permanent disability, it is physically and mentally debilitating to deal with a musculoskeletal disorder [1]. Upper limb disabilities are particularly detrimental to patients' quality of life because the hands are used for almost every basic activity [2]. Incorporating a smart mechatronic device—for example, a wearable exoskeleton—to assist patients in rehabilitation therapies help them to improve the performance of activities of daily living (ADLs), thereby improving their quality of life [3]. Although the field of rehabilitation robotics is well-established, there is potential to improve the use of these devices by employing data analytics techniques [3]–[5].

Intention recognition, real-time intelligent control, and off-line quantitative assessment analysis are the three main application areas of machine learning algorithms in robot-assisted upper limb rehabilitation [5]. In off-line assessment, analysis is done after the completion of the rehab exercises. This means that there are fewer limitations on computing time and computing capacity, allowing for the use of large machine learning architectures. Off-line analyses could be used by clinicians and patients to monitor and improve the rehabilitation process. For instance, a tool that takes advantage of an accurate rehab exercise classification could help patients to keep track of the exercises that they need to complete and help clinicians to assess and adjust the progress of rehabilitation therapies. This is useful because one of the most challenging aspects of therapy is ensuring that the patient completes their exercises, which impacts the patient's ADL outcome [4]. Moreover, a robot-mediated therapy could use that tool to increase the effectiveness of rehabilitation interventions.

This paper explores an off-line approach for classifying upper-limb ADL exercises using recordings of surface electromyography (sEMG) signals from the forearm. To achieve this goal, the KIN-MUS UJI dataset developed by Jarque-Bou et al. was used, which contains EMG data recordings of 22 subjects performing 26 ADLs [6]. These raw EMG signals were processed to extract features, and then train several classification models. Solving this time series classification (TSC) problem was attempted using both commonly used machine learning algorithms such as Support Vector Machines (SVM) and Random Forests, as well as deep learning approaches such as Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU) network. Finally, three ensemble approaches were compared to further improve results.

The comparison of machine learning techniques as well as their results in the classification of a wide set of ADLs, as presented in this paper, is done to aid development of techniques for off-line analysis of robotic rehabilitation exercises.

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II. Background

A. Activities of Daily Living

ADLs are fundamental skills required to care for oneself. The inability to perform ADLs may result in dependence on others or mechanical devices, and decreased quality of life [7]. This makes them particularly important in a clinical setting to determine the level of care and physical therapy needed for a patient. Upper-limb ADL representative exercises have been developed to assess patient abilities. These provide an effective way to study the hand functions required for ADLs. One of these is the SHFT (Sollerman Hand Function Test) protocol which was used to develop the KIN-MUS UJI dataset applied in our work [8].

B. Machine Learning Techniques

To compare both classical algorithms and deep learning techniques, SVM, Random Forests, XGBoost, GRU, CNN, and an ensemble approach were selected to be applied to the TSC problem, as described below:

- SVM, as a classifier, searches for one or more hyperplanes that separate classes and maximize the distance between the support vectors that define the boundaries between classes [9], [10]. This algorithm uses kernel functions to map nonlinear data to a feature space where the classes are linearly separable [10]. In this paper, the Radial Basis Function (RBF), polynomial, linear, and sigmoid kernels were considered.
- Random Forest is a decision-tree-based algorithm. It is helpful for obtaining predictions using the bagging method. Those predictions are made using the mean of the decision trees outputs. The hyperparameters used are the number of estimators, max depth, random state, and bootstrap [11].
- XGBoost is also a decision-tree-based ensemble algorithm that uses a gradient boosting framework and parallel processing. The hyperparameters are the number of decision trees in the model, the maximum size of each decision tree, the learning rate, the minimum sum of weights of all observations required in a child tree, the fraction of observations to be randomly sampled for each tree, and the subsamples ratio of columns when constructing each tree [12].
- CNN is a deep learning technique in which the network architecture is typically constructed by stacking convolutional blocks. Each convolutional block consists of a convolution layer that produces a feature map then a pooling layer that down samples the feature map. To implement classification, the output from the stacked convolutional blocks is flattened into one dimension, and a softmax layer is applied to make predictions [13].
- GRU network is a deep learning technique based on Recurrent Neural Networks (RNN). The GRU has an update gate and a reset gate that dictate whether the hidden state of each unit should be changed or forgotten. These gates prevent the vanishing gradient problem, allowing the network to identify longer patterns in the signal than an RNN [13]. A GRU network is structured with one or more GRU layers, followed by a dense layer and a softmax layer.
- An ensemble learning approach provides a means of combining several models to improve performance. Various techniques for combining model exist [14], including the hard voting method, where the class that has been selected by most models is selected; the soft voting method, where the class with the maximum summation of models expected probabilities is selected; and the stacking technique that adds a layer to learn on the predictions of the best models to produce the final predictions [15], as shown in Fig. 1.

III. Related Work

Many approaches have been proposed to classify hand gestures through different machine learning algorithms. These gestures are basic movements such as close and open hands, rest, diverse types of grips, as well as wrist flexion, extension, abduction, adduction, pronation, and supination [16]–[19]. Those approaches are helpful for controlling electromechanical devices to help people with neurological disabilities [17]. However, patients need to perform more complex movements in their daily living such as eating, drinking, pouring, or dressing. Therefore, an ADL classifier could help with the patient's rehabilitation through an assessment of the patient's progress. In recent years, research on the classification of ADLs have increased [20].

Commonly, EMG signals are used to classify ADLs because those biological signals have a direct relationship with the movement, velocity, and forces applied by the patient while performing an activity. For example, in 2015, Azaripasand et al. [21] published a classification of five upper-limb ADL movements. They used 14 features extracted from the EMG signals to compare five algorithms: SVM, Decision Tree, k−nearest neighbors (KNN), Linear Discriminant Analysis, and Bayes. With a hierarchical classification, they obtained a final accuracy between 52% and 100%, depending on the algorithm tested. In 2016, the same algorithms, except for the Bayes one, were compared with a CNN architecture to classify around 50 classes of hand movements [22]. From EMG signals, the authors calculated the following features: marginal Discrete Wavelet Transform, histogram, waveform length, and the Root Mean Square (RMS). The CNN accuracy obtained was similar to the results from the average reference methods, but CNN performance was not as good as the Random Forests result.

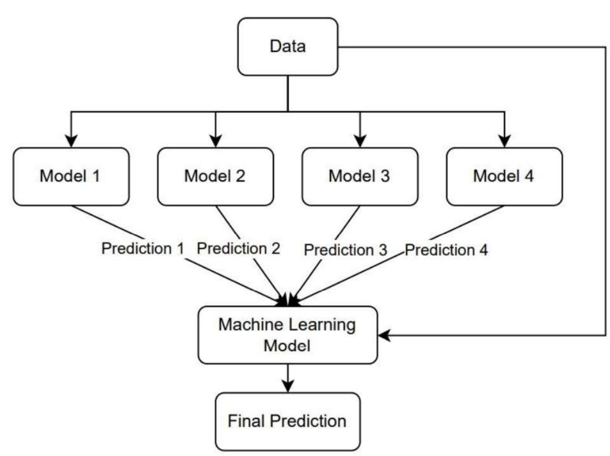

Fig. 1. The architecture of stacking based on four models.

Their average classification accuracy was between 60% and 75% in the datasets with nondisabled subjects.

Also, Sharif et al. [23] used EMG signals to classify eight dynamic ADL tasks. They extracted spectrograms and Mean Absolute Values (MAV) from those signals. SVM and CNN algorithms were compared using accuracy as the main metric. They obtained accuracies between 65 and 92% for dynamic tasks. Another approach [24] combined EMG and inertial motion data to predict four categories of functional activities. These categories were created by grouping 17 ADLs. A KNN machine learning algorithm was used to predict the categories, obtaining an accuracy of 89.2%.

Only one published paper has applied machine learning algorithms to the KIN-MUS UJI dataset [25]. Salatiello and Giese utilized an LSTM network and forearm EMG activity to predict hand kinematics. Although our work uses the same dataset, it does not have the same classification goal. Thereby, this paper is the first reported work on ADL classification using the raw EMG data from this dataset.

IV. Methods

A. Dataset

The KIN-MUS UJI dataset contains recordings of seven EMG channels and 18 joint-angles data from 22 subjects performing 26 actions that are representative of ADLs. Table I shows descriptions of the ADLs. Some recordings were performed with the subjects standing and others while they sat down on a chair [6].

TABLE I. ADLs in the KIN-MUS UJI dataset [6].

ADL	Action description
1	Collecting a coin and putting it into a change purse
2	Opening and closing a zipper
3	Removing a coin from a change purse and leaving it on the table
4	Catching and moving two different sized wooden cubes
5	Lifting and moving an iron from one marked point to another
6	Taking a screwdriver and using it to turn a screw clockwise 360°
7	Taking a nut and turning it until completely inserted inside the bolt
8	Taking a key, placing it in a lock and turning it counterclockwise 180°
9	Turning a door handle 30°
10	Tying a shoelace
11	Unscrewing two lids and leaving them on the table
12	Passing two buttons through their respective buttonhole using both hands
13	Taking a bandage and putting it on their left arm up to the elbow
14	Taking a knife with the right hand and a fork with the left hand and splitting a piece of clay (sitting)
15	Taking a spoon with the right hand and using it 5 times to eat soup (sitting)
16	Picking up a pen from the table, writing their name and putting the pen back on the table (sitting)
17	Folding a piece of paper with both hands, placing it into an envelope and leaving it on the table (sitting)
18	Taking a clip and putting it on the flap of the envelope (sitting)
19	Writing with the keypad (sitting)
20	Picking up the phone, placing it to their ear and hanging up the phone (sitting)
21	Pouring 1L of water from a carton into a jug (sitting)
22	Pouring water from the jug into the cup up to a marked point (sitting)
23	Pouring the water from the cup back into the jug (sitting)
24	Putting toothpaste on the toothbrush
25	Using a spray over the table 5 times
26	Cleaning the table with a cloth for 5 seconds

Each subject performed each ADL once while their EMG were recorded using a Biometrics Ltd. device with surface electrodes placed at specific locations on the forearm. These EMG signals were acquired at a sampling rate of 1000 Hz, amplified by 1000, and then band-pass filtered between 20 Hz and 460 Hz [6]. The KIN-MUS UJI dataset was chosen due to its consistent protocol for placing the EMG electrodes on forearm areas verified to represent ADL performance [6]. Furthermore, the representative set of ADLs in this dataset are based on the reliable SHFT [8]. This test has been used and validated in the assessment of hand functions in patients with diverse musculoskeletal disorders or injuries [26]–[28]. These characteristics make the dataset ideal for developing tools for assessing rehabilitation processes as proposed in our paper.

B. Preprocessing and Feature Engineering

Many of the ADLs in the dataset are similar, varying by minor differences in the type of grip and the length of each motion. For example, turning a screwdriver and turning a door handle are similar actions. Thus, to ensure that there was sufficient information in each example to classify the ADLs, each trial in its entirety was used as one input example to the machine learning model. In contrast, previous studies split each trial into windows and used each window as a single input example, which enabled their techniques to be used in real-time. Since our work is intended for analysis after rehabilitation exercises, longer input sequences could be used with larger models. However, this approach introduced challenges because each signal was a different length (ranging from 4.66 s to 33.62 s), but most machine learning models require fixed input lengths. To solve this problem, the methodology shown in Fig. 2 was applied. For each of the time domain (TD) EMG signals in each trial, a Fast Fourier Transform (FFT) was computed. Thus, seven frequency domain (FD) representations were obtained from each trial. Then, each TD and FD representation were divided into 100 segments and features were calculated for each segment. The features for every signal (seven EMG channels and seven FFTs) and every segment were concatenated into a feature matrix. The feature matrix for each trial was considered as one input example for the machine learning models.

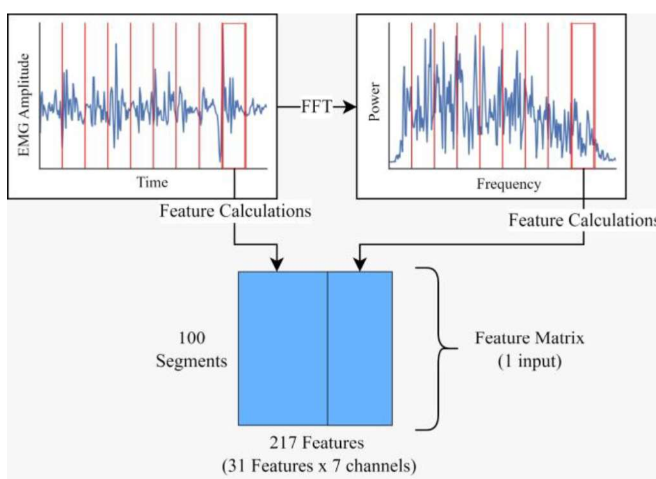

Fig. 2. Segmentation performed to TD and FD signals to obtain a features matrix. With preprocessing, each trial produces a matrix of 217 features (31 features x 7 channels) by 100.

Based on the classification studies of EMG signals [29]–[31], the computed features from each TD segment were the Mean, variance of EMG, MAV, Integrated EMG (IEMG), Simple Square Integral (SSI), RMS, Waveform Length (WL), Zero Crossing (ZC), and the Willison Amplitude (WAMP). Other statistical features were computed from a rectified version of each TD segment. These added measurements were the maximum value, minimum value, standard deviation (STD), median, 1st Quartile, 3rd Quartile, and the coefficients of a second-order Auto-Regressive (AR) model. Although the TD segments were of different lengths, calculating these features retained most of the sequence information while equalizing the dimension of each input example by diving each signal into equal number of segments.

On the other hand, the computed FD features were the Mean Power (MNP) [30], Total Power (TTP) [30], SSI, RMS, variance, WL, and WAMP. The statistical features added from the FD segments were the maximum power value, minimum power value, STD, median, 1st Quartile, and 3rd Quartile.

C. Hyperparameter Optimization

The TD and FD features were used to train and test the performance of an SVM, a Random Forest, a CNN, an XGBoost, a GRU, and three ensemble architectures (hard, soft, stacking), on the ADLs classification. The ensemble approaches were built with four models obtained from the best training performance techniques to evaluate which approach would improve the alone-model performance.

The dataset was randomly split into training (80%) and testing (20%) sets such that the testing set had four or five trials from each ADL. At this way, an activity from a single person was assigned to only one of the two sets, but not in both. The hyperparameters were tuned using manual and grid searches. During tuning, all models were trained and validated through a 5-fold cross-validation. In this technique, the training set is divided into five same-size sections/folds, then four of them are used to train one model and the remaining one is used to validate the model. The process is repeated five times, each time with a different fold as the validation set. Each fold was normalized using Min–Max Normalization to a range between zero and one.

D. Comparison Metrics

To compare the techniques, the classification performance was computed using the following metrics:

1) Classification Accuracy is the result of dividing the number of correctly classified samples by the total number of samples. Values closer to 1 indicate better performance [9].

2) F1-score considers is the harmonic mean of precision and recall. It can assume values between 0 and 1 with higher values indicate better performance [9].

3) Confusion Matrix collects the number of correctly and incorrectly classified samples in a square matrix, with actual labels in the rows and predicted labels in the columns. Correct predictions increase the values of diagonal matrix elements, while misidentified classes increase the off-diagonal values. This metric allows a direct comparison between the class predictions [9].

V. Results

A. Validation Results

After applying the hyperparameter search on the training set, the best models from each technique were selected to compare their performance in the testing data. The hyperparameters of the best models are given in Table II and the cross-validation results are shown in Table III.

The CNN performed best with 83.6% validation accuracy, 4.6% better than the second-best model (GRU). Fig. 3 shows the CNN architecture implemented, which has four convolutional layers with a ReLU as the activation function, three average pooling layers, two fully connected layers, and a softmax layer. It was noticed that changing certain hyperparameters of the CNN altered the classification performance. The number of filters, the filter size, and the optimizer, all affected the results for each model. Therefore, the four best CNN models were selected for use in three ensemble learning approaches, hard-voting, soft-voting, and stacking. Table IV shows the best four CNN hyperparameters.

TABLE II. Hyperparameters of the Best Models

Technique	Hyperparameters
SVM	Kernel: RBF C (regularization parameter) = 1117.3 Gamma = 0.0002
Random Forest	Number of estimators: 350 Maximum depth: 35
XGBoost	Number of estimators: 340 Maximum depth: 4 Learning rate: 0.03 Minimum child weight: 1 Subsample: 0.797 Column sample by tree: 0.463
CNN	Filters in the first layer (doubles each layer): 16 Kernel size: 3 Learning rate: 0.001 Optimizer: Adam Dropout: 0 Number of neurons in dense layer: 1024 Activation function: ReLU (Rectified Linear Unit) Pooling technique: Average
GRU	Number of layers: 4 Number of neurons in each layer: 100

TABLE III. Model 5-fold Cross Validation Results

Technique	Validation Accuracy
SVM	65.4%
Random Forest	57%
XGBoost	47.7%
CNN	83.6%
GRU	79%

TABLE IV. Hyperparameter Differences in Four CNN Models

Model	Filters (1st Layer)	Kernel Size	Optimization
CNN1	16	3×3	Adam
CNN2	32	2×2	Adamax
CNN3	16	2×2	Adam
CNN4	32	2×2	Adam

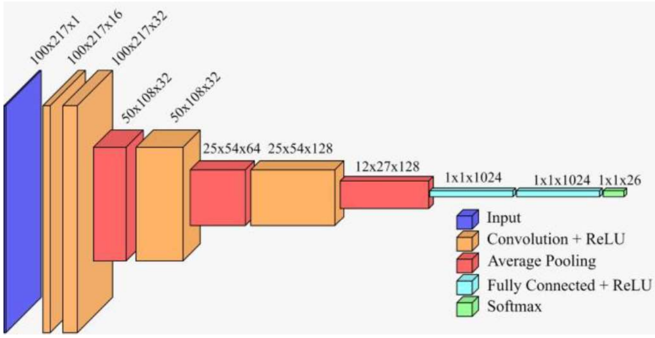

Fig. 3. CNN architecture.

B. Testing Results

All the best models obtained from the validation were tested once using testing data. The average classification accuracy and the average F1-score were used to compare their performance. Fig. 4 shows metric results in percentages. The results of both Accuracy and F1-score are similar, indicating that the correct and incorrect classified classes are equally affecting performance. The metrics also show that the worst performances are obtained with the decision tree algorithm approaches, Random Forest and XGBoost, with accuracies of 63% and an F1-score of 57%. The best performances were obtained from the CNN architectures and their ensembles, with accuracies between 80% and 86%, and F1-score between 79% and 86.1%. The hard voting CNN ensemble was the best one with an accuracy and F1-score of 86%. The GRU model had lower performance than the CNN, with a test accuracy of 73.9%.

A confusion matrix for the hard voting CNN ensemble model is presented in Fig. 5. The model perfectly classified 13 out of 26 ADLs. Of the 13 classes with incorrect predictions, 10 of them had 2 or less misclassifications. The model had the most difficulty with ADL 2, ADL 10, and ADL 12.

Except ADL 22, all activities performed in a sitting posture were classified without errors or with just one error (See Table I and Fig. 5). In contrast, almost all ADLs incorrectly classified were performed by the participants in a standing posture. These differences could be generated because the upper limb EMG signals are significantly affected by different body postures [32].

On the other hand, the algorithm has a consistent confusion between ADLs 10 and 12 (See Table I and Fig. 5). This misclassification appears because these two activities are made with both hands, with similar smooth movements, and low muscle activations. Another noticed error is that the model sometimes identifies ADL 2 as ADL 8, this could be happening because both activities include a lateral pinch grip [6]. ADL 8 incorporates a hand rotation that helps the model to identify this activity better than ADL 2.

The model performance results are comparable with other studies of ADL detection using EMG feature engineering [21]–[24]. However, this is the first one dealing with classifying a wide variety of ADLs performed with diverse upper-limb movements.

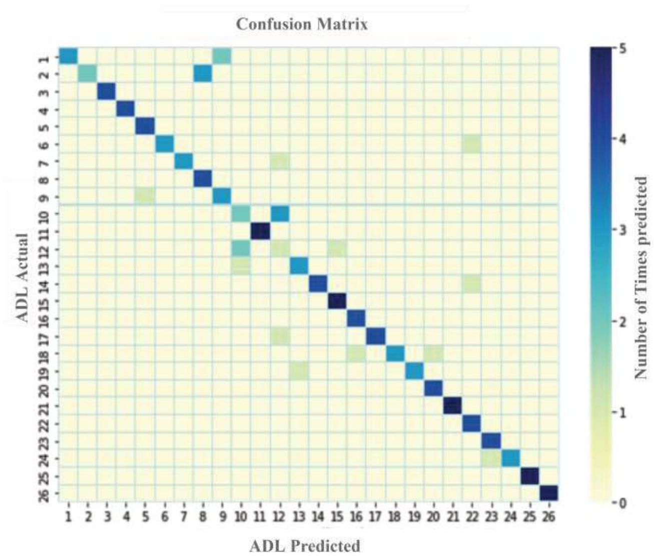

Fig. 5. Confusion matrix obtained from the best model in the testing set.

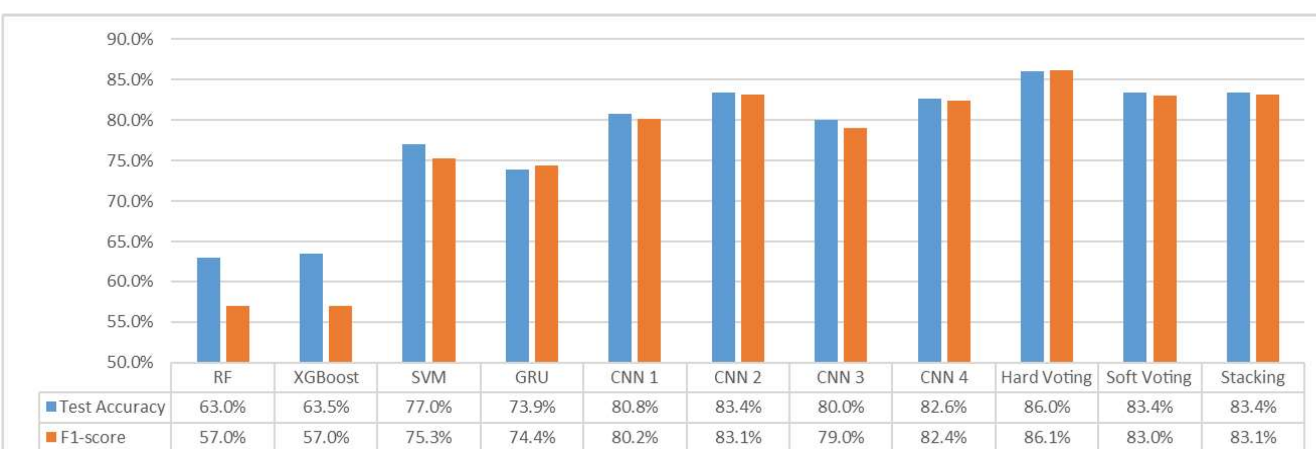

Fig. 4. Testing results comparison between the best models.

VI. CONCLUSIONS

This work compared several machine learning algorithms on the classification of 26 ADLs using EMG recordings from the forearm. This was the first work performing an ADL classification task on the dataset developed by Jarque-Bou et al. [6]. To prepare the data, each trial was divided into 100 segments and 31 time- and feature-based features were calculated from each signal. Hyperparameter optimization, was performed with 5-fold cross validation on the training data. Then, the final models were applied to the testing data and evaluated using the accuracy and the F1-score as comparison metrics.

CNNs performed better than random forest, XGBoost, GRU, and SVM approaches in the classification of the 26 ADLs. CNN achieved a testing accuracy of 83.4%. When paired with hard voting using four CNNs, an accuracy of 86% and a F1-score of 86.1% were achieved. These results are meaningful when they are compared with the range of results achieved on similar datasets because of the difference in the amount and complexity of the ADLs classified.

The hard voting ensemble CNN model correctly classified most ADLs, mainly those performed in a sitting posture. These results indicate that the approach presented in this research could be used in rehabilitation systems to off-line assess the progress of the patient's ability to perform ADLs. Moreover, the classifier could be incorporated into a robot-assisted upper limb rehabilitation system that captures EMG signals from the patient's forearm.

Additional work is needed to make our approach useful in practice, such as developing a model for identifying the start and stop of each activity and obtaining a larger dataset to improve generalization, including data from people with upper-limb disabilities. Furthermore, improving the efficiency of the model may be necessary, which could be done by identifying the most important features and reducing the number of feature calculations. Moreover, combining GRU and CNN is suggested as an extension to this work to improve accuracy.

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