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A comparative study on human loco-motor activity recognition using wearable sensors

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***Abstract*—In a worldwide scale, the population that suffers from muscular impairments, spinal cord injuries, or lower-limb amputations is estimated to be in millions, this population is in need for advanced rehabilitation devices to help them restore their lower-limb functionality. Accurate recognition of loco-motor activity is of great importance for improving rehabilitation devices that activate and take the correct action according to the current activity. However, this field of activity recognition lacks a comprehensive study on the suitability of some methods, algorithms or sensors over the others. In this paper, we carried out several experiments to reach for the best possible machine learning tools and sensor combinations or placements that can maximize off-line accuracy and minimize prediction time. Starting from a data set that combines sEMG and mechanical sensors placed bilaterally, after we specified 8 different loco-motor activities and extracted features that were used extensively in the literature, we found that EMG signals do not offer a significant improvement in accuracy unlike mechanical sensors which achieved alone an average of 97% accuracy in subject-dependent context. The optimal set of features for mechanical sensors and sEMG sensors were found to be time domain features and wavelet coefficients features respectively. The performance of KNN, LDA, QDA, LR, ANN, ETC and SVM models were compared; at which ETC was found to achieve the highest performance in terms of accuracy 92% and 97% in subject-dependent and subject-independent context respectively. LDA, LR and QDA outperformed the others in terms of time and model size measures.**

***Index Terms*—locomotion recognition,loco-motor activities, sensors combination, EMG, mechanical sensors, rehabilitation devices, classification algorithms, feature extraction.**

I. Introduction

In recent years, human activity recognition (HAR) has become an active field of research, having wide applications in customized medicine, physical rehabilitation, and even neuro-muscular abnormality diagnosis. The goal of activity recognition is to interpret and predict people's actions or intentions through observations taken from various sensing technologies, and then utilizing an expert system to assist those people or provide a sort of service [1].

Sensing technologies can vary from visual sensors to muscle electromyography (EMG) sensors depending on the application of concern. Activities can vary as well from high-level actions such as vacuuming to low-level actions such as hand close-open motions. Loco-motor activity recognition is one of the common HAR areas of research, applied mainly to rehabilitation devices (orthosis, exoskeleton and artificial lower limbs). A revolution to be made in those devices with the help of activity recognition control strategies depend mainly on the accurate recognition of the activity in order to provide the correct corresponding control action, which varies with the different activities and contexts. Minor errors in recognition can present high risks for the wearer to fall or stumble. Thus, the field is surrounded by a number of challenges and many arising questions regarding the optimal sensor selection, sensor placements, relevant features, algorithms and methods that produce the best accuracy as well as maintaining suitable prediction time, taking into account the challenge of different activities having similar characteristics. Machine learning proved to be powerful in this context. So, the contribution of this work lies in the comparisons made between the effects of some of the different methods and machine learning algorithms used in the specified stages of activity recognition represented in the literature.Also, the effect of the different sensors and sensor placements was studied .Moreover, the persistent trade-offs between accuracy and other performance measures when using these methods was investigated.

II. Related Work

Common practices in loco-motor activity recognition follow a chain of signal processing and machine learning techniques as shown in Fig. 1 below:

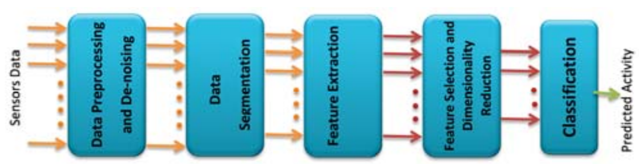

Fig. 1. Activity Recognition Chain

This chain of practices is executed during two phases: 1- when designing, building and training the model using previously acquired sensor data. And 2- when applying the trained model on new real-time data. However, this work is concerned with the first phase of loco-motor activity recognition (Fig. 1) which involves decision making and choosing the best model parameters that produce the highest levels of recognition accuracy.

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To our knowledge, there is no published comparative study that studies different methods in different stages of the recognition chain. Several studies identified locomotion using both mechanical and surface EMG (sEMG) sensors unilaterally, these studies reached a steady-state accuracy that ranges from 87%-99% using only 1 algorithm for predicting the activities which were either SVM, decision trees, LDA, PSO-SVM or LDA [2]–[7]. Another study compared between DBN and LDA models according to steady-state and transition errors and studied the effect of sEMG sensors on the speed of recognition and accuracy [8]. Still, there is a lack of work that studies and compares more algorithms against various performance measures. Moreover, there is little published work on the features that best suit locomotion recognition from bilateral wearable sensor signals. In a research paper done in the area of activity monitoring and fall detection, 15 types of EMG features were extracted and evaluated according to different measures that include classification accuracy and complexity level [9]. Also, in another study, optimal sets of wavelet-based EMG features were found for the application of EMG decomposition and classification [10]. Nevertheless, these studies only concerns unilateral EMG signals and does not include mechanical sensors nor investigate the relevance to the application of loco-motor activity recognition.

III. Methodology

A. The Data set

We utilized in this research the ENABL3S data set that is available online [11], which was collected from 10 subjects (7 males and 3 females without any known gait impairment) at the University of Northwestern. This data-set contains signals from sEMG electrodes and other mechanical sensors placed bilaterally on the lower limbs and have the following characteristics:

Surface EMG electrodes were placed on the following muscles: Tibialis Anterior (TA), Medial Gastrocnemius (MG), Soleus (SOL), Vastus Lateralis (VL), Rectus Femoris (RF), Biceps Femoris (BF), and Semitendinosus (ST), which were sampled at 1 kHz then amplified by x1,000 and hardware band-pass-filtered between 20 and 450 Hz. Thus, resulting in 14 EMG signals from both legs. IMUs (Tri-axial gyroscope and accelerometer Ax, Ay, Az, Gx, Gy and Gz) were placed on the thigh and shank on both legs, then sampled at 500 Hz. Resulting in 24 signals of IMU data. Goniometers (GONs) were placed in each knee and ankle and sampled at 500 Hz, resulting in 4 signals of angle data that represents knee and ankle position on the sagittal plane.

Every candidate performed 25 repetitions of 2 different sequences of 7 loco-motor activities (sitting (ST), standing (SA), level walking (LW), ascending/descending a ramp (RA/RD), and ascending/descending a four-step staircase (SA/SD). However, when this sequence was visualized using the goniometer data (knee position during different activities) it appeared to us that the standing activity was not suitably performed for our study purposes (it was performed very briefly at the beginning, and included what appears to be a turning movement that the candidates did to be able to sit down at the end), and that could impose confusion leading to misclassification. Thus standing was relabelled to be a transition rather than a steady-state activity either from sitting to walking or from walking to sitting, and therefore the total activities were 6 rather than 7 in addition to the 2 transitions. Refer to Fig. 2.

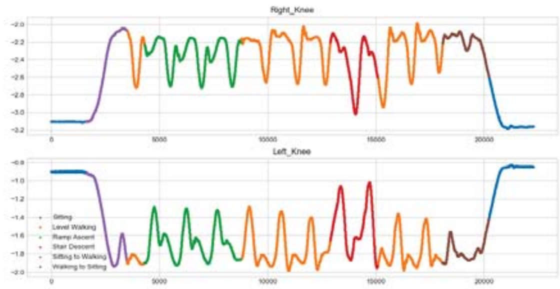

Fig. 2. Left and Right Knee Positions in One Sequence of Activities after Label Modification

EMG data then was pre-processed (de-noised) using band-stop, high and low pass Butterworth filter, while mechanical (IMUs and goniometer) sensor data was de-noised using low-pass Butterworth filter [11].

B. Evaluation Metrics

Since using accuracy as a metric is not suitable to evaluate models in the case of imbalanced classes, F1-score was used instead which takes the measures: true positives (TP), false positives (TN), true negatives (FP) and false negatives (FN) into consideration. Normalized confusion matrix, model size in Kbytes and model prediction time in microseconds per segment were used in the evaluation process.

C. Feature Extraction

Processed data is then segmented using overlapping sliding windows of 800ms size and 80% overlap. In order to reach an approximation for the optimal set of features for the application, most of the possible features that were used in the literature were extracted for the 2 types of sensors (sEMG and mechanical sensors) for each segment, and its corresponding label was assigned to be the dominant label in the window (the activity that represents at least 80% of the window samples was considered the dominant activity), windows with no dominant activity were discarded. In this way along with the overlap between windows, we can guarantee that neither information loss nor mislabeling can occur. The following listings show the types of features extracted in our work and the types of sensors they were extracted from:

1) Time Domain Features:
   - Extracted from sEMG sensors: mean absolute value (MAV), variance (VAR), root mean square (RMS), zero crossings (ZC), waveform length (WL), simple square integral (SSI), integrated EMG (IEMG) and 6th-order auto-regressive (AR) model coefficients [6], [12]–[16].

- Extracted from mechanical sensors: variance (VAR), root mean square (RMS), zero crossings (ZC), mean value, minimum value (MIN), maximum value (MAX), standard deviation (STD), initial value (INIT), final value (FIN) and 6th-order auto-regressive (AR) model coefficients [1], [6], [15], [17], [18].

2) Frequency Domain Features:
   - Extracted from sEMG and mechanical sensors: frequency median (FMD), frequency mean (FMN), modified frequency median (MFMD) and modified frequency mean (MFMN) [14].

3) Time-Frequency Domain Features:
   - Extracted from sEMG sensors: All of the above sEMG time domain features were extracted from wavelet-transformed signal coefficients : CD1 to CD4 and D4. [9], [10], [19]

D. Feature Selection

Our approach was to extract as many features as the literature suggests to guarantee the presence of the optimal set. Extracting this many features has its negative impact on the performance, that is; the ”Curse of Dimensionality” problem. Therefore, an appropriate selection scheme was adopted. One of the methods for eliminating redundant features is the embedding method based on extra trees classifier selection. This method was chosen here because it performed faster than wrapper methods and more accurate than filter methods.

E. Machine Learning Algorithms: Parameter Tuning

1) K Nearest Neighbors (KNN):

Euclidean distance metric was used, and neighbours votes were weighted based on the distance from the examined sample. Randomized cross-validation was used to choose the optimal K value. It was done by randomly choosing a value for K from the range [1-8] 5 times, then cross-validating each value on the data using 3 folds, the average F1-score across all folds was used for evaluation.

2) Logistic Regression (LR):

Randomized cross-validation was used to determine the value for the regularization term, values in the logarithmic scale range [-2-10] were randomly chosen 5 times, then cross-validated using 3 folds and evaluated using the average F1-score. Limited-memory Broyden Fletcher Goldfarb Shanno (L-BFGS) solver was used to solve the optimization problem.

3) Linear Discriminant Analysis Classifier (LDA):

Singular value decomposition (SVD) was used to calculate the covariance matrix, no other parameters were tuned.

4) Quadratic Discriminant Analysis Classifier (QDA):

Singular value decomposition (SVD) was used to calculate the covariance matrices, and a regularization parameter was chosen using 5-times randomized cross validation from the logarithmic scale range [-4,0], then 3-fold cross-validated and evaluated using F1-score.

5) Support Vector Machines (SVMs):

A radial basis function (RBF) kernel was used, and the regularization parameter was chosen using 5-time randomized cross validation in the logarithmic range [-5 , 4], then 3-fold cross-validated and evaluated using F1-score.

6) Extremely-Randomized Trees Classifier (ETC):

The number of trees used in the classifier was tuned using 5-times 3-folds randomized cross validation in the range [200 , 1200], and the minimum samples per leaf were fixed to 1 sample. The function used to measure the quality of a split was chosen to be Gini.

7) Artificial Neural Networks (ANNs):

A neural network with a single 10-neuron hidden layer was designed, the activation functions were chosen to be sigmoid and softmax in the hidden and output layer, respectively. The optimization problem was solved using ’Adam’ optimizer, and early stopping was utilized to prevent the network from over-fitting. Furthermore, a 15% validation set was used to evaluate the training procedure; the categorical-cross-entropy loss was used to evaluate the network during training.

F. Experiments

1) Optimal feature/sensor set selection for all subjects and sensors:

We performed subject-independent feature selection strategy in which the optimal feature set was obtained (according to the F1-score acquired by ETC selection), taking a combination of 8 subjects chosen randomly 10 times. The union of the selected features in all 10 repetitions are considered to be the most effective feature and sensor types for subject-independent classification.

2) classification and Evaluation Experiments:

we conducted the conclusive experiments on all the data acquired using selected features from the previous step. All features were normalized to have a Gaussian distribution with 0 mean and unit variance. In addition, the class imbalance was further maintained by class equalization into a uniform distribution.

a) Subject-dependent Training :

We trained each model and tested it on the same candidate’s data with 75% training set - 15% testing set split. This was repeated 10 times (once for each candidate), and the results were averaged for a final estimation.

b) Subject-independent Training :

We trained each model on 8 candidates then tested the model on the other 2 candidates, repeated this process 10 times then averaged the results.

IV. Results

A. Optimal features selected from all subjects and sensors

Regarding the time-domain features; the tree-based selection algorithm selected the Mean, STD, INIT, FIN, Max and Min as the optimum set for both IMUs and Goniometer sensors. However, when using sEMG sensors ,it selected only two time-domain features which were WL and IEMG. For the frequency-domain features, FMD and MFMD were found to be the optimum features for all mechanical sensors. However, there is no frequency domain feature selected for sEMG sensor.Moreover, The only time-frequency domain features selected from the 4 level wavelet decomposition coefficients of the signal were IWT, RMS and MAV features. Optimum sensor positions for IMUs were found to be on both right and left shank and thigh, with high superiority to acceleration in the X direction and angular velocity in X, Z directions over the other directions. Also, the left and right knee and ankle appeared to be the best in representing the angular position (Goniometer sensor). Whereas the selected sEMG electrodes were positioned on the muscles: MG, VL, RF and SOL.

B. classification and Evaluation

Using the selected features for the mechanical sensors, the F1-scores were found to be as shown in Fig. 3.

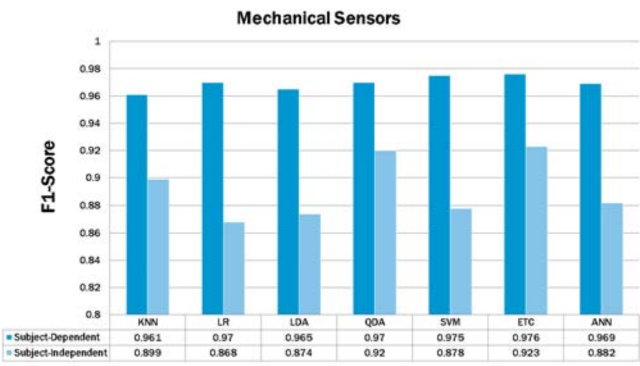

Fig. 3. F1-Scores for All Algorithms in Subject-Dependent and Subject-Independent Schemes Using Mechanical Sensors.

Using the selected features for sEMG sensors, the F1-scores were found to be as follows in Fig. 4.

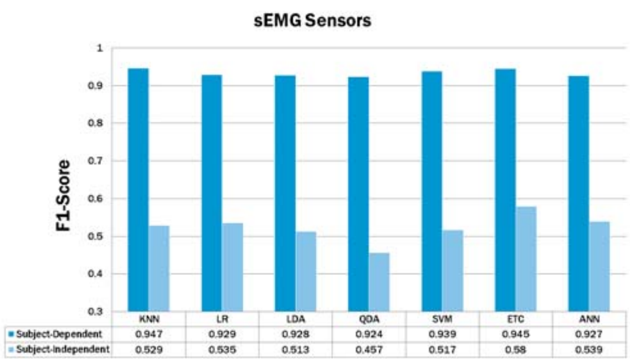

Fig. 4. F1-Scores for All Algorithms in Subject-Dependent and Subject-Independent Schemes Using sEMG Sensors.

Fig.5 shows the results of using the selected features from both sEMG and mechanical sensors.

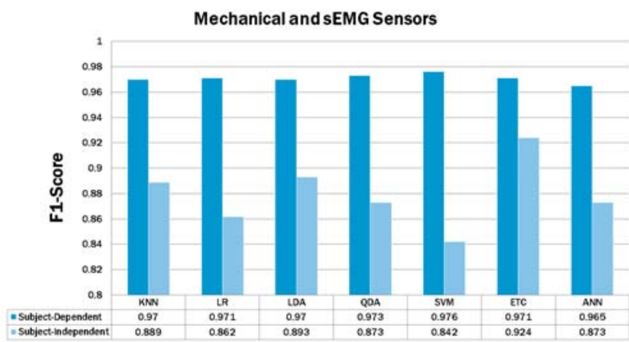

Fig. 5. F1-Scores for All Algorithms in Subject-Dependent and Subject-Independent Schemes Using both sEMG and mechanical Sensors.

Prediction time for all algorithms in Subject-Dependent and Subject-Independent Schemes using both sEMG and mechanical sensors is shown in Fig. 6.

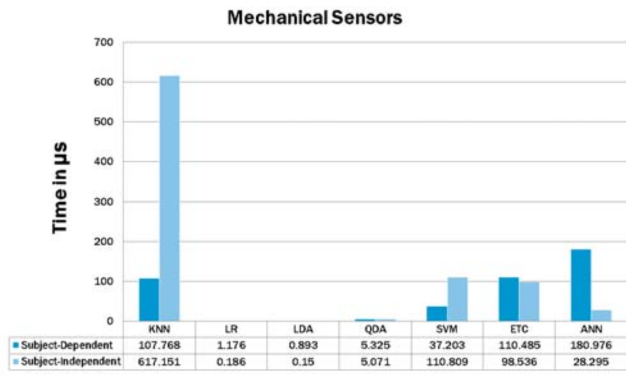

Fig. 6. Prediction Time for All Algorithms in Subject-Dependent and Subject-Independent Schemes Using both sEMG and mechanical Sensors.

Fig. 7 illustrates the model size for all algorithms in Subject-Dependent and Subject-Independent Schemes using both sEMG and mechanical sensors.

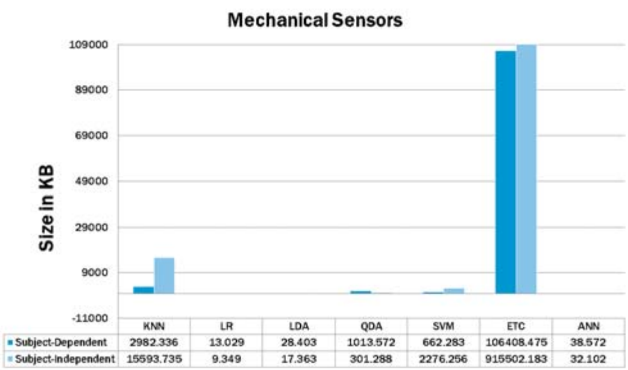

Fig. 7. Model size for All Algorithms in Subject-Dependent and Subject-Independent Schemes Using both sEMG and mechanical Sensors.

The normalized confusion matrices for QDA and ETC classifiers using both sEMG and mechanical sensors in subject dependent (Fig. 8) and independent (Fig. 9) cases respectively are shown below.

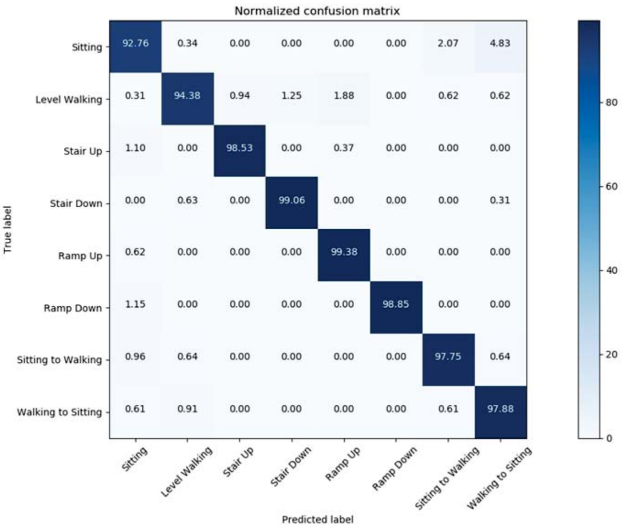

Fig. 8. QDA Confusion Matrix for Subject-Dependent Activity Recognition Using Mechanical and sEMG Sensors

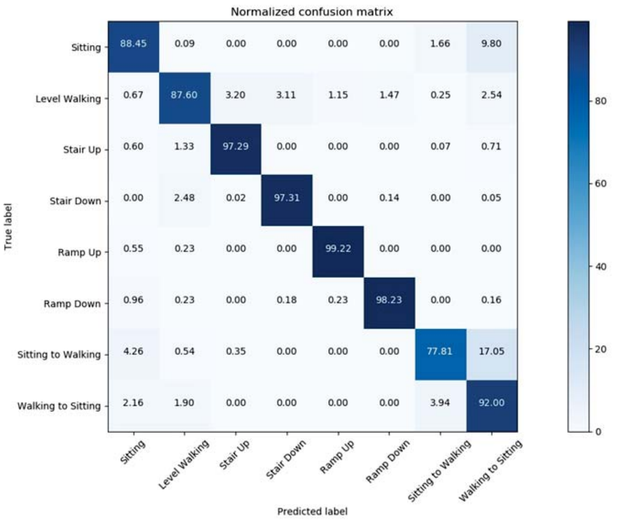

Fig. 9. ETC Confusion Matrix for Subject-Independent Activity Recognition Using Mechanical and sEMG Sensors

V. Discussion

A. Feature Selection Based on Subject-Independent Activity Recognition

Referring to section A in the results, it was obvious that time-domain feature subset (mean, minimum, maximum, standard deviation, initial and final value) were dominant in our results, while only two of the frequency-domain features were selected (frequency median and modified frequency median), showing the significance of the time-domain over the frequency-domain features. On the other hand, EMG characteristics were found to be best represented by extracting time-domain features from the wavelet-transformed signal rather than the signal itself.

B. Subject-Dependent and Subject-Independent Activity classification Performance

All algorithms were found to achieve similar F1-scores in the subject-dependent context in all three cases: mechanical sensors, sEMG sensors and both, with a maximum standard deviation of 0.009 in the case of sEMG sensors. On the other hand, subject-independent activity recognition presented more variations in the F1-scores between the algorithms in all three cases with a maximum standard deviation of 0.037 in the case of sEMG sensors again. However, ETC is the winner in all the subject-independent cases suggesting that its generalization capabilities are best suited to the characteristics of the data features.

Regarding the trained models' size, ETC was the heaviest model in all cases weighting approximately 0.1 MB, this is due to a large number of fully grown unpruned trees. The choice not to limit the depth of the trees is to achieve the highest possible recognition accuracy since limiting the depth resulted in a decreased accuracy of recognition; the complexity of the data features required a complex tree formulation. The second heaviest trained model is KNN since it memorizes the training data to predict new ones, the more data used in the training the more weight it gains. LR is the lightest algorithm of all in all cases, followed by LDA with a maximum trained model size of 20.5 KB and 50.8 KB, respectively when trained for subject-dependent recognition using both mechanical and sEMG sensors.

LR and QDA also competed on the shortest time required to predict a new segment with an approximate mean time of $1.2\,\mu\mathrm{sec}$ in the subject-dependent cases and $0.2\,\mu\mathrm{sec}$ in the subject-independent cases. KNN, ETC and ANN competed on the other side for the longest prediction time in different ranges.

The confusion matrices illustrate that some activities were most likely to be confused across all algorithms in all cases; this is probably due to the very similar characteristics of the activities. For instance, 'Level Walking' is often confused with 'Stair UP', 'Stair Down', and sometimes with 'Ramp Up' and 'Ramp Down'. Another reason for the confusion is the imperfect ground truth annotation that does not perfectly match the length of the activity being performed, for example; the transitions 'Sitting to Walking' and 'Walking to Sitting' often got confused with 'Sitting' and 'Walking' since they happened between these two activities, and the assignment of the ground truth annotation did not always resemble the perfect distinction between the activity and the transition. The transitions also got confused with each other due to their similarities.

Overall, mechanical sensors achieved much better recognition results compared to sEMG sensors especially in the subject-independent recognition where EMG learners confused most of the activities, mechanical sensors achieved an average (across all algorithms) F1-score of $96.94\mp0.526\%$ and $89.2\mp 2.23\%$ in subject-dependent and subject-independent recognition, respectively.

VI. Conclusion

The aim of this research was to perform a study on the effects of some of the various methods used in the different stages of recognition of loc-omotor activities, focusing mainly on the effects on off-line accuracy and time. Firstly, the optimal placement of the sEMG electrodes was found to be the bilateral placement on Vastus lateralis (VL), rectus femoris (RF), soleus (SOL) and medial gastrocnemius (MG) muscles, while mechanical sensors (IMU and GON) yield better performance if placed bilaterally on both shank and thigh, knee and ankle. Secondly, for the feature extraction stage, we extracted as many features as the literature suggested and used tree-based selection to find the optimal set for each sensor type; time-domain features for mechanical sensors and wavelet features (time-frequency domain features) for sEMG sensors were found to perfrorm the best in terms of accuracy measures. Finally, seven different classification algorithms (KNN, LR, SVM, ANN, ETC, LDA and QDA) were experimented with in this setup and tuned properly under subject-dependent and subject-independent learning.

Based on the F1-score, model size and prediction time performance measures; we found that there is no algorithm that performs equally well on all these three measures, there is always a trade-off. If taken accuracy as the desired measure; in the subject-independent context, ETC was the leading algorithm with 92%, and 97% in subject-dependent case. However it failed miserably in terms of model size and prediction time. LDA, LR and QDA were best suited if resource constraints in time and memory are present, although they achieved lower scores.

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