An Automated Machine Learning Method to Efficiently Classify the 12-lead ECG Signal Acquisition Quality

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Abstract. *Given their low cost and non-invasive nature, ElectroCardioGram (ECG) signals have been widely used as a useful tool for diagnosing heart diseases. However, acquisition issues such as electrode interchange and oscillation noise may negatively impact expert exam interpretation and even automatic classification tasks. Here we propose an automated machine learning method to efficiently classify the 12-lead ECG signal acquisition quality. It consists of a two-stage classification process. Firstly, the ECG signals are processed and segmented aiming to classify them as noisy or acceptable signals. Then, the second classification stage yields the binary classification correct acquisition or limb electrodes interchange. Concerning the electrode positioning, the Random Forest technique presented interesting results (precision of 97%, recall of 89%, and F1-Score of 93%). Concerning noise detection, Random Forest presented a general accuracy of 85%, a recall of 57%, and a precision of 91%. All the obtained results yield to consider the proposed framework for application within a real telemedicine environment.*

1. Introduction

Electrocardiogram (ECG) signals have been widely used as a tool for diagnosing heart diseases [Li et al. 2020], predicting cardiac arrests [Kwon et al. 2020], and monitoring cardiorespiratory activity [Brüser et al. 2015], being one of the most effective ways to aid to the medical decision to prevent the progression of heart diseases [Caldas et al. 2023]. Automated ECG analysis systems require high accuracy in determining ECG signal fiducial points for precise and reliable measurements of morphological features (including amplitudes, area, wave durations, and electrical axis) of local waves such as P wave, QRS complex and T wave, and the interval features (including RR-interval, PR-interval, PR-segment, and QT-interval) [Satija et al. 2018]. A 12-lead ECG exam is a gold standard used by cardiologists and emergency medical care for detecting several cardiovascular abnormalities. Even though heart problems may not always be observed on a short 10-second recording, the 12-lead ECG is used as a standard clinical dysrhythmia analysis tool for chest pain or discomfort, electrical injuries, electrolyte imbalances, medication overdoses, ventricular failure, stroke, syncope, and unstable patients [Li and Boulanger 2020]. It consists of projections of the heart activity in both the frontal and horizontal planes and, particularly, views the surface of the left ventricle from 12 different angles, composing six limb leads (I, II, III, aVF, aVL, and AVR), and six chest leads (V1 to V6).

Most of the existing ECG analysis systems are designed to handle ECG signals with minimal noise, demonstrating promising results when applied to noise-free ECG recordings. However, these systems have significantly degraded performance when dealing with ECG records corrupted by various noise and artifacts [Satija et al. 2017], such as baseline wandering (BW), AC Interference (ACI), muscle artifacts, electrode unplugged, and others, which greatly hinder the measurement of fiducial points. In contrast, precise electrode placement within ECG signal acquisition is crucial for correct medical interpretation and is directly related to the reliability of the signal. We can find two types of electrode placement errors, namely electrode misplacement and electrode interchange. In the first one, we find deviations concerning the correct placements, for example, precordial electrodes placed in the wrong intercostal space. In the second, the members related to the correct positions are interchanged, e.g. the left arm electrode is placed on the right arm. In this context, the present work proposes an automated system for classifying the ECG signal acquisition quality, considering oscillation noise and limb electrode interchange. The experiments and validation process apply over a real telemedicine database.

The remaining structure of this paper is as follows: Section 2 presents additional approaches to this problem within the literature. Section 3 discusses the dataset of ECG signals, its characteristics, and the proposed methodology for the ECG signal quality assessment (SQA) problem. Section 4 presents the experimental results, including an analysis and comparison with related work. Finally, Section 5 provides the conclusion and suggestions for future work.

2. Related Work

ECG signal quality assessment (SQA) has been extensively explored within the literature. The review proposed by [Satija et al. 2018] presents an overview of several SQA methods that includes neural networks and traditional machine learning classifiers. It is noticed that a lightweight ECG noise analysis framework is highly demanded for real-time detection, localization, and classification of single and combined ECG noises within the context of wearable ECG monitoring devices which are often resource constrained.

[Satija et al. 2017] proposed a traditional classifier-based SQA that uses signal quality indices (SQI) computed by flat-line detection, baseline wander extraction, and high-frequency noise detection to assess the acceptability of ECG signals. By using signals from both the MIT-BIH Arrhythmia [Moody and Mark 2001] and Physionet Challenge 2011 [Silva et al. 2011] database, they achieved a sensitivity of 95.56% and 97.85% for clean and noisy signals, respectively. [Jekova et al. 2012] developed two threshold-based methods based on frequency thresholds for QRS components, high amplitudes and steep artifacts, baseline drift, power-line interference, and muscular noises. The first method achieved a sensitivity of 98.7% and a specificity of 80.9%, while the second one achieved 81.8% and 97.8%, respectively. [Hayn et al. 2012] used four QRS measures to classify ECG signals between acceptable and unacceptable and achieved an accuracy of 93.4%, a sensitivity of 84.0%, and a specificity of 96.1%. Both studies evaluated their approaches using the PhysioNet Challenge 2011 12-lead ECG dataset.

In recent developments in neural networks, [Liu et al. 2023] utilized Resnet18 and Self-Attention to create an automatic SQA method. This deep learning technique achieved a remarkable accuracy of 92.8% and an F1-score of 95.4%. [Liu et al. 2021] designed a double-input deep convolutional neural network (DCNN) which incorporated ECG signal S-transform spectrogram and a matrix of statistical features such as lead-fall, baseline drift, and R peaks as inputs. Their deep learning approach for classification resulted in a sensitivity of 97.7%, a specificity of 77.3%, and an accuracy of 93.1%. Both studies employed the Physionet Challenge 2011 Dataset for testing their approaches and producing their outcomes. In another study, [Caldas et al. 2023] used CNN and SVM to develop various methods for binary and multi-class classification. For each type of classification, 10 experiments were conducted using 24h-ECG holter records from the University Hospital Clementino Fraga Filho (HUCFF/UFRJ) collected from patients with Chagas Heart Disease [Alberto et al. 2020]. The results indicated an accuracy of 94.24 $\pm$ 1.29% for binary classification and an accuracy of 90.00 $\pm$ 2.83% for multi-class classification.

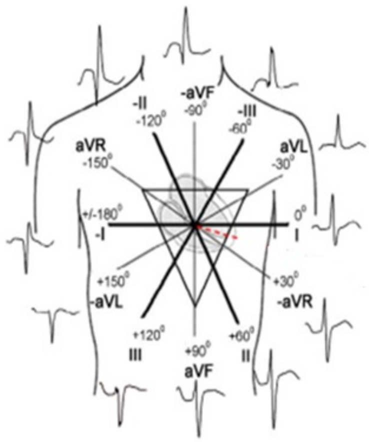
To mitigate the SQA problem, here we suggest an automated machine learning method with a new set of features like wavelet coefficients and generic signal features, morphological and interval features of the ECG characteristic waves, and SQI.

Concerning the limb electrode interchange issue, [Rjoob et al. 2020] presented a systematic review on the usage of AI methods for detecting ECG electrode displacement and interchanges. In this project, the authors analyzed deeply 14 studies that proposed different approaches to using ML (e.g. Decision Trees, Support Vector Machines, Artificial Neural Networks among others) to detect limb and/or precordial electrodes' misplacement and/or interchanges using different databases and input types (e.g. complete ECG signal, wave amplitudes, and polarities, the correlation between leads). The study concluded that classical ML techniques were able to detect limb electrode interchange with considerable sensitivity and specificity although they presented a lower performance when considering Left-arm/Left-leg interchange (LA/LL). Overall ML also showed the highest sensitivity and specificity values to detect chest electrode interchanges.

The conclusions from the previously cited study instigated us to compare classical ML techniques which apply waves' correlations in different leads to define which performs best to detect limb electrode displacement on a real Tele-ECG dataset.

Since both proposed topics are important for an ECG exam to fulfill its role as an auxiliary tool in the diagnosis of patients with cardiac problems and the literature only addresses them individually, we saw the need to obtain a method based on both topics. Therefore, our study proposes an automated method that couples both SQA and limb electrode interchange detection with the goal of determining whether an ECG signal is qualifiable for diagnostic or whether it is necessary to perform the ECG exam again.

(a) Real Noisy 12-lead ECG signal example



(b) Limb leads' representation on the frontal plane.

Figure 1. 12-lead ECG signal acquisition.

3. Materials and Methods

3.1. Dataset

The proposed dataset is provided by a Tele-ECG system whose main objective is to provide electrocardiographic reports and emergency alerts within one hour to places without cardiologists. Currently, the report center of this Tele-ECG System serves 120 health units in 81 cities that are composed of different hospital profiles: primary, secondary, and tertiary services. The database has ECG signals with 12 simultaneous leads and 8 seconds of the record, the sampling rate is 240Hz, and a 60Hz notch and muscular filter is applied by default. All ECGs were analyzed in real life scenarios and reported by cardiologists. The present research used 511 signals, which were all collected using true patients originated from the database that contains recorded exams acquired between January and February 2022.

The telemedicine service receives more than 800 exams every day. Each exam is done remotely and evaluated by a specialist. If the exam has an insufficient quality for diagnosis, it is returned to the local health unit. This process generates many inconveniences as increased cost, loss of efficiency and, more importantly, delay to diagnose and treat the patient. The main sources of noise are greatly reduced by the filters already present in the electrocardiograph equipment itself leaving to the specialist's eye more challenging cases which could masquerade the diagnosis. Regarding the quality of the signal, the labels used in the medical routine are the following: noise, inverted electrode and normal exam.

The present dataset has 162 signals classified as noise. This label is chosen by the medical team when it is impossible to accurately analyze all the waves, complexes and segments, for example rhythm, or P-wave superimposed on the previous T-wave. An example can be seen in Figure 1a. Concerning limb electrode interchange, this dataset also has 158 signals classified as electrode interchange when there are changes in morphology and axis of frontal plane leads which are present for various combinations of arm and leg inversions. Figure 1b presents the expected QRS morphology for leads recorded in the frontal plane. Finally, this dataset has 191 signals classified as normal.

The use of a real telemedicine database with typical medical annotations is very important since it allows the models proposed in this paper to be trained with typical clinical labelling and a real possibility of implementation on a telemedicine setting. Besides, it helps to tailor the model to the application necessity since it is imperative to reduce as much as possible the chance to incorrectly reject exams which could potently cause patient harm due to the diagnostic delay.

Because of the sensitive nature of the data used to conduct this study, it is not openly available. It is available under reasonable requests sent to the manuscript's corresponding author at Instituto Dante Pazzanese de Cardiologia.

3.2. Method

The proposed methodology involves a comprehensive approach for detecting improper 12-lead ECG acquisition which includes oscillatory noise and limb electrodes interchange. The oscillatory noise detection process consists of three steps: feature extraction, feature normalization, and classification. In the feature extraction step, multiple features were considered to investigate the performance of the classification models regarding the applied input features. This step evaluated the relevance of the chosen features and their ability to provide discriminating information for classification. The extracted features consist in three types: wavelet coefficients and generic signal features, wave morphological and interval features, and ECG signal quality indices [Zhao and Zhang 2018, Li et al. 2014]. A detailed description of these features is provided below:

- Generic Signal Features and Wavelet coefficients:
  - Mean, Maximum, Minimum, Variance, Skewness, Percentiles, Percentile Differences within each signal lead;
  - Wavelet coefficients considering eight decomposition levels and *daubechies* family for wavelet transform [Vonesch et al. 2007] within each signal lead;
- Morphological and Interval Features:
  - P wave, QRS complex and T wave: duration, amplitude, area, electrical axis;
  - Heart Rate, RR-interval, PR-interval, QT-interval, QTc-interval, PR-segment, ST-deviation;
- ECG Signal Quality Indices
  - kSQI, pSQI, basSQI, qSQI.

Some of the extracted features are computed considering only one standard reference value or set of values for all twelve leads. For example, the P-wave duration is computed considering a median of starting points and a median of finish points for a given P-wave for all the available leads. After computing the median duration for each existing P-wave, we store each duration and compute the mean value. We apply analogous reasoning for computing the PR interval, PR segment, QRS duration, and QT interval. Concerning the R-R interval, we compute (as a clinical recommendation) the mean interval between QRS fiducial points using Lead-II. For the computing of the wave amplitudes and ST-deviation, we consider as an individual feature the mean value obtained for each individual lead. The generic signal processing features, such as percentiles and wavelet coefficients, are computed for each individual lead. The percentiles are calculated in the set $\{1, 2, 5, 10, 25, 50, 75, 90, 95, 98, 99\}$ and the percentile differences are calculated in a way that $PD_i = P_{100-i} - P_i$ in the set $\{1, 2, 5, 10, 25\}$, where PD_i is the percentile difference of order i, and P_i is the $i - th$ percentile.

The Wavelet coefficients are obtained through signal decomposition using Daubechies-4 (db4) decomposition filters and the ECG signal quality indices refer to Kurtosis (kSQI), power spectrum distribution of QRS wave (pSQI), baseline relative power (basSQI) and matching degree of R peak detection (qSQI) [Zhao and Zhang 2018]. The process for ECG signal segmentation comprises the steps of R-peak detection, QRS delineation and P/T-wave detection and delineation. The R-peak detection is implemented considering the combining of Continuous Wavelet transform, Hilbert transform and derivative filter [Madeiro et al. 2012]. Then, the QRS delineation process and P/T-waves detection and delineation are performed considering Area-Curve length (ACL) technique [Ghaffari et al. 2009]. Finally, the ECG signal quality indices are computed with the assistance of Python's *NeuroKit2* library.

Next, to ensure consistency in magnitude across all features, normalization was performed before the classification stage. This process entailed rescaling all features between 0 and 1 to mitigate any discrepancies in magnitude and facilitate accurate comparison of the features. Finally, in the classification stage, the normalized attributes were used to train and test the models. For this step, Multi-Layer Perceptron (MLP) and ensemble techniques, such as Bagging on Decision Trees (BDT), Random Forest (RF), and XGBoost (XGB) were used with the support of Python's *scikit-learn* and *XGBoost* libraries. Initially, several machine learning classifiers were tested, but, of these, only the models mentioned were able to effectively extract essential information from the data and have good performances. In addition, it is worth mentioning that, as this is an initial study and with a limited amount of data, the objective was to find a reference line using classical methods, to suit as a basis for further studies that will potentially involve deep learning. About the training method, the dataset was split into 75% for training and 25% for testing in a stratified way. Inside the training set, the 10-fold cross-validation was used together with a grid search approach to hyperparameter tuning. Figure 2 illustrates the entire process used to perform the noise classification in ECG signals.

From the samples classified as non-noisy in the previous step, the subsequent step is to classify the incorrect/correct electrode placement. In order to do that, the data was preprocessed and two different ML algorithms, i. e, Random Forest (RF) and Support Vector Machine (SVM) were used for limb electrodes interchange detection. The choice of these models was based on [Rjoob et al. 2020] which presented the best models for detecting this events. For the algorithm presented in this paper, the preprocessing was done by separating the ECG waves for every lead and calculating the cross correlation between leads for each individual wave. In order to do so, the ECG was first segmented using the same algorithm previously discussed. Then, all the P waves from each lead were extracted on a single signal. This signal was then interpolated to guarantee the same amount of points in every lead. The same method was used for the QRS complex and the T wave.

Once the signal for each lead and wave was obtained, the cross-correlations were calculated and used as the input features for the ML algorithms. The chosen feature was cross-correlation since it is a comparison metric between two leads and changes its value according to signal polarity. The value of cross-correlation ($corr_{a,v}$) of two signals a and v is given by the sum of the product for every sample a_n and b_n.

One computes the correlation for every wave (3) and for every combination of the limb leads (21) resulting in a total of 63 calculated parameters for each patient, which were used as input parameters for the classifiers.

Before applying machine learning techniques, the dataset was split into training and testing sets (75% for training and 25% for testing). Regarding the classification with SVM, to obtain optimal results, four different kernels were used to evaluate and compare their performances in the same dataset. Figure 3 illustrates the electrode interchange detection workflow. Once the feature extraction was done, two ML techniques were used, RF and support vector machine.

4. Experimental Results

Initially, the feature extraction and normalization process were performed as illustrated in Fig.2. After this, the resultant best parameters from the grid search approach were incorporated into the models. To reduce the variability of the results, the classification was performed 100 times, and we take mean values of the computed performance metrics. It should be noted that the score used for the models' hyperparameter tuning was formulated to minimize the number of non-noisy (class 0) samples classified as noisy (class 1) while maximizing the detection of noisy samples. In essence, the specificity (Sp) and positive predictive value (PPV) were prioritized before focusing on the sensitivity (Se) , while the negative predictive value (NPV) was not taken into account in the scorer. The score was calculated utilizing a 70% weight for the harmonic mean of the specificity and the PPV and a 30% weight for the sensitivity. The general results of the models are presented in Table 1, while the scoring metrics for each class individually are summarized in Table 2.

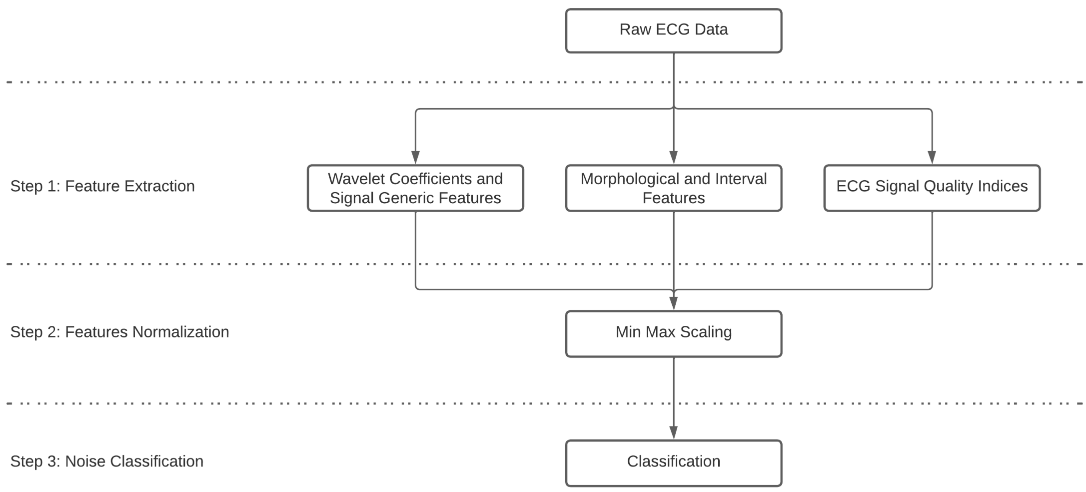


Figure 2. Oscillatory Noise Detection Workflow

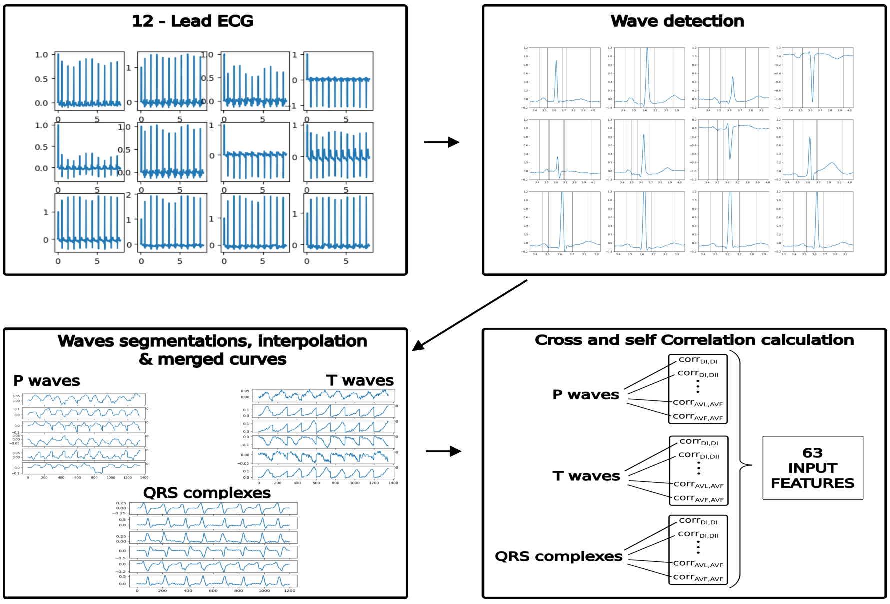


Figure 3. Limb electrodes interchange detection workflow

Table 1. Comparison of the general results from all the models used in noise detection.

Model	Precision	Recall	Accuracy	F1-Score
Bagging on Decision Trees	0.92	0.52	0.83	0.66
Random Forest	0.91	0.57	0.85	0.70
XGBoost	0.73	0.73	0.83	0.73
Multi-Layer Perceptron	0.67	0.83	0.74	0.81

Table 2. Comparison of the results for each class from all the models used in noise detection.

Model	NPV	Sp	PPV	Se	Accuracy
Bagging on Decision Trees	0.81	0.98	0.92	0.52	0.83
Random Forest	0.83	0.97	0.91	0.57	0.85
XGBoost	0.87	0.87	0.73	0.73	0.83
Multi-Layer Perceptron	0.81	0.85	0.67	0.83	0.81

Tables 1 and 2 show a trade-off between minimizing the number of non-noisy samples classified as noisy and maximizing the number of detected noisy samples. The BDT and RF models can detect more than half of the noisy samples (52% and 57%, respectively) while incorrectly classifying as noisy only a small number of normal samples, as indicated by the specificity (98% and 97%, respectively) and PPV (92% and 91%, respectively). In contrast, the XGBoost and MLP models have a higher sensitivity, detecting more of the noisy samples (73% and 83%, respectively) but at the cost of discarding some non-noisy samples.

Concerning assessing the methods for limb electrode interchange detection, to verify these methods' performances, the test was done considering the worst-case scenario (the noise-detector classifying all exams as non-noisy) so we used the complete dataset to evaluate the techniques' performance. The detection of limb electrode interchange was done by pre-processing the ECG signals and then applying 2 ML techniques (RF and SVM with different kernels: linear, polynomial, radial basis function [RBF], and sigmoid). Just as was done for the noise detection, to evaluate the quality of the models, we prioritized mainly the capability of the model of correctly classifying most of the exams that had the electrodes rightly placed (class 0) while maximizing the number of correctly identifying exams presented this interchange (class 1). In essence, the specificity and PPV were prioritized, and the other scores, such as accuracy and F1-Score, were used as tiebreaks. The general results of the models are presented in Table 3, and the scoring metrics for each class individually were summarized in Table 4.

Table 3. Comparison of the general results from all the models used in limb electrode interchange detection

Model	Precision	Recall	Accuracy	F1-Score
SVM Linear	0.97	0.89	0.87	0.87
SVM Polynomial	0.90	0.20	0.59	0.52
SVM RBF	0.85	0.80	0.83	0.83
SVM sigmoid	0.85	0.66	0.77	0.77
Random Forest	0.97	0.89	0.93	0.93

Table 4. Comparison of the results for each class from all the models used in electrode interchange detection

Model	NPV	Sp	PPV	Se	Accuracy
SVM Linear	0.85	0.98	0.97	0.89	0.87
SVM Polynomial	0.55	0.98	0.90	0.20	0.59
SVM RBF	0.80	0.86	0.85	0.80	0.83
SVM sigmoid	0.72	0.88	0.85	0.66	0.77
Random Forest	0.89	0.98	0.97	0.89	0.93

According to our criteria, the SVM with a linear kernel and the Random Forest models presented the best values for the prioritized scores (specificity 0.98 and PPV 0.97). However, the Random Forest Model turned out to also have the highest scores for accuracy and F1-Score (0.93 for both of them), so it is the best model among them. The SVM with a Polynomial kernel could also be highlighted as a promising model for the task of correctly classifying exams' electrode placement because it presented 0.98 of specificity, which is the same as the RF and Linear SVM models. However, it has a lower value of PPV and the lowest values of NPV, sensitivity, accuracy, and F1-Score (0.55, 0.20, 0.59, and 0.52 respectively).

5. Conclusion

The present work presents an approach for classifying ECG signal acquisition quality considering three possible classes: normal acquisition, oscillation noise, and electrode interchange. The classification process is structured in two stages: (i) a first binary process considering oscillatory noisy and acceptable signals, performed on all the data; (ii) a second binary process considering interchanged and non-interchanged electrodes, performed on the data classified as acceptable. The set of extracted parameters and the set of applied machine learning models provide a framework that presents satisfactory results concerning the automatic classification of ECG signal acquisition quality. The results are evaluated considering the maximization of obtaining the correct classification of clean signals and the exams that had the electrodes correctly placed (true negatives) and the correct classification of noisy signals and the exams with electrode interchange (true positives). As innovative points, we can highlight the use of a real tele-ECG dataset for experimental tests and performance evaluation, the combination of the two algorithms (signal quality assessment and limb electrode interchange detection) in a single pipeline, and the hyperparameters' tuning considering the prioritization for specificity and positive predictive value. As limitations, we can highlight the strong dependency of the algorithms from accurate ECG fiducial point detection and delineation, the low availability of signals classified as unacceptable for our experimental tests, the non-inclusion of samples of pathological signals in the dataset of acceptable signals, the use of a signal already filtered by a low-pass filter as input data and the low sampling rate of 240 Hz for the processed signals. Considering the current status of the algorithms, our future work is to evaluate the impact of the automatic classifications (working onboard at the collect edge) over a real Tele-ECG system.

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