# Deep Learning Models for Real-World Detection of Electrode Interchange in 12-Lead ECGs: A Telecardiology Validation

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***Abstract*—Electrode interchanges during 12-lead electrocardiogram (ECG) signal acquisition is a recurring problem, capable of compromising diagnostic accuracy and generating additional costs for both the patient and the healthcare system. The automatic detection of these interchanges is essential to support clinical decision-making and improve outcomes in cardiovascular care. In this work, different combinations of deep learning architectures are investigated for the automatic detection of clinically relevant electrode interchanges, RA-LA, RA-LL, V1-V6, V2-V5 and complete precordial electrode interchanges. The models explored in this work are Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Bidirectional Long Short-Term Memory (BiLSTM) and Bidirectional Gated Recurrent Unit (BiGRU). The training and evaluation of the models were performed with a database composed of 22,886 ECGs, unbalanced and representative of a real telecardiology scenario in Brazil. In general, the model based on the CNN+RNN presented consistent performance in all classes. For the ECG without interchange and RA-LA, RA-LL, the model achieved metrics with values greater than or to 0.96, while for inversions in the precordial electrodes, the metrics were greater than 0.86. Furthermore, the CNN+RNN model exhibited the lowest number of parameters and memory usage among the evaluated architectures, highlighting its computational efficiency. The results demonstrate the feasibility and effectiveness of using deep learning techniques in the automated detection of electrode interchanges. The incorporation of the proposed models in cardiology services brings direct benefits to the entire workflow of the health system.**

***Index Terms*—Electrode interchange, 12-lead ECG, Deep learning, real-world clinical data, imbalanced dataset and telecardiology.**

## I. Introduction

Electrode interchange errors are known problems when recording the 12-lead electrocardiogram (ECG), occurring in 0.4 - 4% of all standard 12-lead ECGs [1], [2]. These errors can induce alterations in waveform morphology, potentially mimicking pathological patterns and leading to inaccurate assessments of the patient's cardiovascular condition [3].

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Among all the possible electrode interchanges, those with daily clinical practice relevance are: (1) limb electrode interchanges RA-LA and RA-LL, as others have minimal or no impact on the ECG tracing or result in signal flatline (visually detectable) [4]–[6]; and (2) precordial interchanges V1-V6, V2-V5, and complete interchange (V6, V5, ..., V1), since these electrodes capture electrical activity from distinct cardiac walls [7]–[9]. Pairwise reversals such as V1-V2, V3-V4, and V5-V6 have minimal clinical impact due to their acquisition from the same cardiac wall [8], [9].

When electrode interchange is identified by the specialist, it becomes necessary to perform a new ECG acquisition, implying additional costs for both the healthcare system and the patient [10]. This issue becomes even more critical in the context of telemedicine services, where ECG signal acquisition is performed at remote stations (small cities), while the reporting by specialist is carried out at a central station. In such cases, the presence of ECG recordings with electrode interchange necessitates the repetition of the ECG acquisition, resulting in additional direct and indirect costs for the telemedicine system and the patient [11]. For example, 1% of the 5,000 ECG recordings performed daily in the Telehealth Network of Minas Gerais (TNMG) [12] are classified as unacceptable for medical reporting due to the presence of electrode interchange in the ECG tracing.

The automatic identification of ECG electrode interchange, whether through conventional signal processing algorithms or advanced artificial intelligence models, holds significant potential for enhancing clinical decision-making accuracy and improving outcomes in cardiovascular care [3], [13]. Different methodologies for detecting electrode interchanges are available in the literature, employing information from the ECG waveform in the time and/or frequency domains, statistical analyses, and the redundancy inherent in the 12-lead ECG recording [4], [6], [14]–[17]. Although these algorithms use various indices or descriptors, they are essentially based on rule-based approaches employing empirical thresholds, decision trees, and artificial intelligence techniques.

In contrast to the variety of these types of algorithms in the literature, we speculate that they are not fully satisfactory when applied to ECG recordings performed in the TNMG. This speculation is based on the fact that these algorithms were developed on data that are not representative of a real-

world application. For example, the types and occurrences of cardiac abnormalities are insufficiently represented; noise and artifacts are, in many cases, artificially generated; and ECG recordings unacceptable for medical reporting due to electrode interchange are overrepresented (balanced datasets).

Here we present different combinations of deep learning architectures, using Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM), Recurrent Neural Networks (RNN) and Gated Recurrent Unit (GRU) for electrode interchange detection with clinical practice relevance, which are RA-LA, RA-LL, V1-V6, V2-V5, and complete interchange. Our models were trained and tested using unbalanced and representative data of the real clinical scenario. We selected these models specifically because each of them brings specific features, such as spatial pattern extraction (CNN) and modeling of temporal or sequential dependencies (RNN, BiLSTM or GRU) [18], which are particularly relevant for ECG recording analysis.

Among the evaluated architectures, the CNN+RNN model demonstrated consistent performance across all electrode interchange scenarios. It achieved metrics greater than 0.96 for cases without interchange and limbs interchanges, and values above 0.86 for precordial. In addition, this architecture also exhibited the lowest number of trainable parameters and memory usage, underscoring its computational efficiency and suitability for deployment in clinical environments.

The remainder of this document is organized as follows: Section II reviews related Machine Learning (ML) and Deep Learning (DL) studies to detect electrode interchanges. Section III details the Methodology, describing the dataset and its utilization in training and testing the DL models. Section IV presents the Results, including a comparative analysis of the models performance. Section V discusses the performance of the model in the test data and addresses the absence of Deep Learning (DL) in electrode detection. Finally, Section VI provides the Conclusion, emphasizing the relevance of applying neural network models for detecting electrode inversions in daily clinical practice.

## II. Related Research

ML and DL has been widely applied to ECG analysis for tasks such as prediction, detection, and intelligent decision-making, to identify complex patterns and support specialists in diagnosis and prognosis [19]. ML has already shown promise in detecting electrode interchange [1], [6], [14], [17], [20], [21]. However, DL application to the detection of electrode interchange remains limited and underexplored in the current literature, representing a gap that warrants further investigation [1].

Among the ML-based approaches, classic models such as decision trees have also been employed for this purpose [6], [22]. Notably, 6 proposed an algorithm to detect 14 types of cable interchanges, 5 in limb electrodes and 9 in precordial electrodes, using two non-public datasets: Common Standards for Electrocardiography (CSE) diagnostic [23] and Cardiology Ward of the Thoraxcenter. The interchanges were computationally generated in a balanced manner. The method is based on the reconstruction of the 12 ECG leads by linear regression and the analysis of the correlation coefficients between the original signals and their reconstructions, both in correct recordings and with interchanges. The hypothesis is that lower correlations indicate the presence of interchange. From empirical thresholds, a decision tree was constructed. The performance varied according to the type of interchange, with sensitivity between 0.17 and 1, and specificity $\geq$ 0.99 [6].

Expanding beyond decision trees, other ML techniques such as support vector machines (SVM) have also been investigated for this task [17], [21]. In particular, 17 developed a multiclass linear SVM to detect 9 types of electrode interchange: RA-LA, RA-LL, V1-V2, V1-V3, V2-V3, V3-V4, V4-V5, V4-V6 and V5-V6 [17]. For this, the authors used three datasets sources, [24], CSE [23] and Physionet PTB diagnostic ECG database [25], which included both healthy individuals and those with cardiac abnormalities, and electrode interchange were simulated on original ECGs in a balanced way. To SVM input, they used both ECG morphology information (QRS-T and P-wave amplitude, frontal axis and clockwise vector loop rotation) and redundancy information, which were derived based on the EASI™ lead system transformation. For the whole validation database, the overall sensitivity and specificity for detecting precordial cable interchange were 0.56 and 0.99, and the sensitivity and specificity for detecting limb cable interchange (excluding left arm-left leg interchange) were 0.93 and 0.99.

To the best of the authors' knowledge, the use of deep learning (DL) for electrode interchange detection has been reported in only one study [3]. In this one, two DL models were developed to detect limb and chest electrode interchanges, respectively. For limb detection, two limb electrodes and V6 were used as inputs, while for chest, six chest electrodes were used. The models were trained and validated using the Chapman database and evaluated on the PTB-XL, PTB, and LUDB databases. Electrode interchanges were simulated on the original ECG recordings in a balanced manner. The detection performance was assessed using metrics such as accuracy, precision, sensitivity, specificity, and F1 score. The experiments simulated three scenarios of limb electrode interchange and nine scenarios of chest electrode interchange. The two proposed models achieved F1 scores ranging from 0.93 to 0.99 [3].

Despite the significant advances in DL applied to various ECG-related tasks, its use for detecting electrode interchange remains notably scarce. Given the growing adoption of DL in healthcare and the critical impact of electrode interchanges on diagnostic accuracy and additional direct and indirect costs generated by these interchanges, further exploration of DL techniques in this domain is not only timely but also essential. In recent years, several DL architectures have been proposed to improve the accuracy of various learning tasks, including CNN, RNN, GRU, BiLSTM, as well as hybrid models that combine these architectures [26]. Therefore, we apply these

architectures and combinations of them for electrode inversion detection.

## III. Methodology

The present study was structured into five main stages: data preprocessing, the design and configuration of four different models (CNN, CNN+RNN, CNN+BiLSTM, and CNN+BiGRU), the training phase, and the subsequent testing of these models. This entire workflow is illustrated in Figure 1.

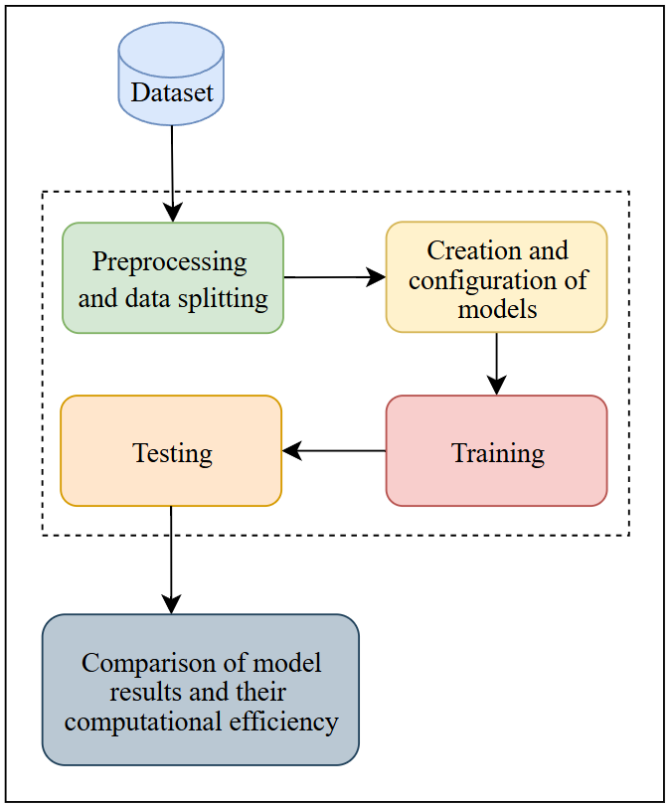


Fig. 1: Overview of the methodological workflow proposed in this study.

### A. Dataset

The database, used with approval from the Research Ethics Committee of the Federal University of Minas Gerais - UFMG (protocol 68496317.7.0000.5149), contains 22,886 ECG recordings collected by TNMG, with 54% of pathological recordings and 46% healthy. The dataset was divided into two subsets: ECGTrainingSet for training, containing 70% of the recordings (16,020), and ECGTestSet for testing, with the remaining 30% (6,865). All ECG recordings consist of 12-lead ECGs lasting between 7.5 and 10 seconds, recorded with a minimum sampling frequency of 300 Hz and a resolution of at least 12 bits. Only ECG recordings classified by TNMG specialists as insufficient technical quality or possible electrode interchange (without any specification of which electrode interchange) were excluded from these datasets. Subsequently, the interchanges used in this study (RA-LA, RA-LL, V1-V6, V2-V5 and Complete precordial interchange) were computationally applied to randomly selected ECG recordings. Table I presents the distribution of the training and testing sets across the various interchange categories.

TABLE I: Distribution of the training and test datasets, including the number of electrode interchange cases in each subset

| **Category** | **ECGTrainingSet** | **ECGTestSet** |
|---|---|---|
| Total Records | 16,020 | 6,866 |
| No interchange (%) | 9,615 (60) | 6,541 (95) |
| RA-LA (%) | 1,281 (8) | 69 (1) |
| RA-LL (%) | 1,281 (8) | 69 (1) |
| V1-V6 (%) | 1,281 (8) | 69 (1) |
| V2-V5 (%) | 1,281 (8) | 69 (1) |
| COMP (%) | 1,281 (8) | 69 (1) |

The representativeness of the training and test datasets can be observed based on Table I. The ECGTrainingSet consists of 16,020 ECG recordings, 50% of pathological ECG recording and 8% of unacceptable. The ECGTestSet contains 6,866 records, with 50% pathological ECG recordings and only 1% for each type of lead interchange, reflecting clinical reality. We intentionally included a higher proportion of these cases in the training set to enhance representativeness and, consequently, improve the models' learning performance.

### B. CNN Model

CNN is composed of three convolutional layers, each followed by Batch Normalization, Pooling, and Dropout, which are responsible for accelerating training, stabilizing learning, reducing dimensionality, and preventing overfitting [27], [28], as we can see in Figure 2. The convolutional layers detect local patterns in the ECG signals, such as wave characteristics (P, QRS, T), to identify changes caused by electrode interchange [29], [30]. The first convolutional layer contains 64 filters with a kernel size of 3 and a ReLU activation function, while the subsequent layers have 128 and 256 filters, respectively. After the convolutions, the data are flattened by the Flatten layer and passed through a Dense layer with 128 neurons and a ReLU activation function, which combines the extracted features into compact representations. The final layer uses the SoftMax activation function for multiclass classification, distinguishing between different types of ECG recordings, see all this details in Figure 2.

### C. Architectural Variations: CNN Combined with RNN, BiLSTM, and BiGRU

The different combinations of deep learning architecture (CNN+RNN, CNN+BiLSTM and CNN+BiGRU) share a common architecture that combines convolutional feature extraction, a recurrent layer for temporal modeling, an attention mechanism, and fully connected layers for classification. Each model starts with two convolutional layers that extract local

patterns from ECG signals using 64 and 128 filters with kernel sizes of 7 and 5, respectively. These layers are followed by Batch Normalization, MaxPooling, and SpatialDropout to enhance generalization and reduce overfitting. After the convolutional blocks, the recurrent models differ in the type of recurrent layer used, which plays a crucial role in capturing the temporal dependencies of the ECG sequences:

- CNN + SimpleRNN + Attention: Uses a unidirectional SimpleRNN layer to model temporal patterns, followed by an attention mechanism to emphasize relevant time steps in the sequence [31], [32].
- CNN + BiLSTM + Attention: Similar to CNN+RNN, but employs a Bidirectional LSTM layer (BiLSTM) instead, which is particularly effective at capturing long-range dependencies in time-series data [33].
- CNN + BiGRU + Attention: Replaces the CNN+RNN with a Bidirectional GRU layer (BiGRU), allowing the model to learn dependencies in both forward and backward directions of the ECG sequence [34].

In all models, the output from the attention mechanism is flattened and passed through a dense layer with 128 neurons, followed by LeakyReLU activation, Batch Normalization, and Dropout. Finally, a Softmax layer performs multiclass classification, distinguishing between various types of ECG signals. The architectural overview of all three models is illustrated in Figure 3.

## IV. Results

This section presents the evaluation results of the proposed models CNN, CNN+RNN, CNN+BiLSTM and CNN+BiGRU in the ECGTestSet. Using the convention that positive (P) is an unacceptable ECG recording (ECG with interchange) and negative (N) is an acceptable one (without interchange).

First, we computed the number for true/false positive/negatives (TP, FP, TN, FN) and then the performance of each architecture was assessed using sensitivity (Se), specificity (Sp), positive predictive value (PPV), and F2-score. More specifically, we opted for the F2-score, as it is a more appropriate metric for evaluating the performance of algorithms on imbalanced datasets, unlike other metrics such as accuracy, which can be misleading in such scenarios [11]. In addition to predictive performance, computational efficiency was evaluated in terms of the number of trainable parameters, memory usage, and floating-point operations per second (FLOPs).

An analysis of Tables II and III shows that, while the CNN+BiLSTM model offers great performance, its higher computational cost requires considering more efficient alternatives. The CNN+BiGRU model emerges as a compelling trade-off, achieving comparable performance with significantly lower GFLOPS. In contrast, the CNN + RNN model offers great performance and excels in efficiency, having the lowest parameter count and memory footprint. These findings highlight that model selection requires balancing the desired performance with the available computational resources.

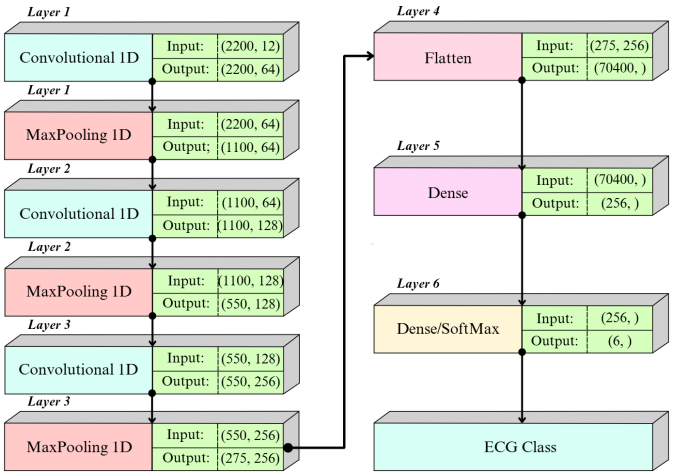


Fig. 2: Architecture of CNN model

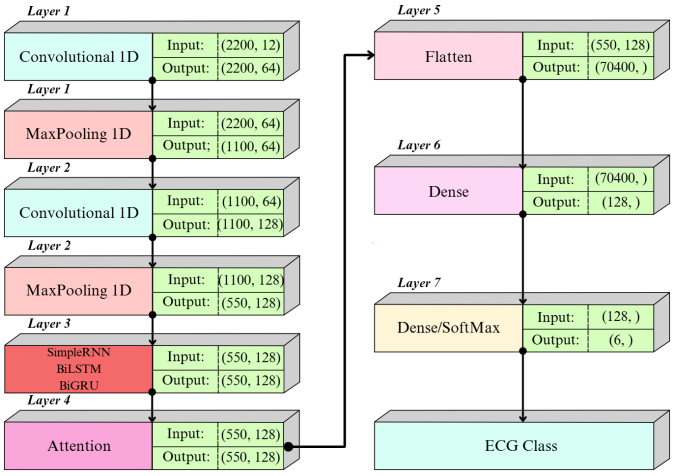


Fig. 3: Overview of Model Architectures: CNN with RNN, BiLSTM, and BiGRU.

## V. Discussion

In this study, we proposed models to detect electrode interchanges in 12-lead ECG recordings in a real-world scenario. The main findings were: 1) according to the metrics considered, all proposed models performed satisfactorily in the ECGTestSet, which is representative of the clinical reality in terms of types and occurrence of pathological and unacceptable recordings; 2) the application of DL to this problem is limited, with only one study identified to date that explores DL for electrode interchange detection. This context highlights the motivation behind the development of the method presented in this study; and 3) the performance of the proposed models in the ECGTestSet dataset suggests that its use in a real telecardiology application could substantially reduce costs.

### A. DL models performance in ECGTestSet

A strong indication of the robustness and reliability of the proposed models is their great performance, according to the metrics presented in this study, on the ECGTestSet. To the best of the authors' knowledge, this is the only

TABLE II: Model performance by ECG type: Se, Sp, PPV and F2-score

| Metric / ECG Type | CNN | CNN+RNN | CNN+BiLSTM | CNN+BiGRU |
|---|---|---|---|---|
| **No interchange - Se** | 0.98 | **0.99** | **0.99** | **0.99** |
| **No interchange - Sp** | **1.00** | **1.00** | **1.00** | **1.00** |
| **No interchange - PPV** | **1.00** | **1.00** | **1.00** | **1.00** |
| **No interchange - F2** | 0.98 | **0.99** | **0.99** | **0.99** |
| **RA-LA - Se** | 0.91 | **0.97** | **0.97** | 0.94 |
| **RA-LA - Sp** | **0.99** | **0.99** | **0.99** | **0.99** |
| **RA-LA - PPV** | 0.96 | **0.97** | **0.97** | **0.97** |
| **RA-LA - F2** | 0.93 | **0.97** | **0.97** | 0.95 |
| **RA-LL - Se** | 0.97 | **1.00** | **1.00** | **1.00** |
| **RA-LL - Sp** | **1.00** | **1.00** | **1.00** | **1.00** |
| **RA-LL - PPV** | **1.00** | **1.00** | **1.00** | **1.00** |
| **RA-LL - F2** | 0.98 | **1.00** | **1.00** | **1.00** |
| **V1–V6 - Se** | 0.93 | **0.99** | 0.96 | 0.94 |
| **V1–V6 - Sp** | 0.97 | **0.99** | **0.99** | **0.99** |
| **V1–V6 - PPV** | 0.95 | **0.97** | **0.97** | **0.97** |
| **V1–V6 - F2** | 0.93 | **0.98** | 0.96 | 0.95 |
| **V2–V5 - Se** | 0.84 | 0.87 | 0.90 | **0.93** |
| **V2–V5 - Sp** | 0.97 | **0.99** | **0.99** | **0.99** |
| **V2–V5 - PPV** | 0.94 | 0.95 | 0.96 | **0.97** |
| **V2–V5 - F2** | 0.88 | 0.90 | 0.92 | **0.94** |
| **COMP - Se** | 0.91 | 0.91 | **0.96** | **0.96** |
| **COMP - Sp** | **0.99** | **0.99** | **0.99** | **0.99** |
| **COMP - PPV** | **0.96** | **0.96** | **0.96** | **0.96** |
| **COMP - F2** | 0.94 | 0.94 | **0.96** | **0.96** |

TABLE III: Comparison of the computational efficiency of models

| DL Model | Parameters | Memory (MB) | GFLOPS |
|---|---|---|---|
| CNN+RNN | **4.566.662** | **17.42** | 1.0417 |
| CNN+BiGRU | 9.134.406 | 34.85 | **0.2896** |
| CNN+BiLSTM | 9.158.726 | 34.94 | 0.5792 |
| CNN | 18.172.102 | 69.32 | 0.8388 |

dataset representative of the real clinical scenario that has been used, to date, for the validation of algorithms aimed at detecting electrode interchanges in 12-lead ECG recordings. Additionally, the models proposed in this work were developed to detect the interchanges of the RA-LA, RA-LL, V1-V6, V2-V5 and COMP electrodes, which are truly relevant in daily clinical practice, i.e., which effectively make a medical diagnosis impossible or difficult.

The fact that the test database used in this study is the only one representative of the real scenario and is unbalanced and that the clinically relevant electrode interchanges are those presented here, raises two relevant questions: 1) Although it is widely reported in the literature that electrode interchanges in daily clinical practice are a problem of extreme class imbalance (i.e., $P \ll N$) [6], [14], [35]–[37], the algorithms reported in the literature were developed and validated on datasets with overrepresentation of the P class (electrode interchange). This leads these algorithms to present satisfactory performance only in these types of data and, consequently, unsatisfactory performance when tested in datasets representative of the clinical context [38], [39]. 2) The recurrent development of algorithms in the literature for the detection of all limb electrode interchanges and precordial sequential interchange in pairs may have led developers to underestimate the fact that the clinically impactful electrode interchanges are: RA-LA, RA-LL, V1-V6, V2-V5 and complete inversion (V6, V5, ...., V1) [4], [5], [7], [8].

### *B. The limited use of DL for electrode interchange detection*

A literature review conducted in 2020 highlighted the absence of deep learning (DL) approaches for detecting electrode interchanges in 12-lead ECG recordings. The authors emphasized that, among the 14 studies reviewed, none employed DL, relying exclusively on traditional ML techniques. They further pointed out the need to develop DL-based algorithms capable of achieving high sensitivity and specificity in this task [1]. Since then, the application of DL to this problem has remained extremely limited, with only one study identified to date that explores DL for electrode interchange detection [3]. This clear gap in the literature reinforces the relevance and necessity of the present work, which proposes a deep learning-based approach to address this critical issue in ECG signal quality assurance.

The all aforementioned issues were the main motivation to: a) build a dataset (ECGTestSet) that is truly representative of clinical reality in terms of types and occurrences of pathological and unacceptable ECG recordings, and large enough to avoid problems related to small-scale datasets with limited ECG recording characteristics; b) Propose models that minimize the impacts of electrode interchanges in daily clinical practice, focusing on those that have greater clinical relevance; c) propose the development of DL models to address the yet underexplored problem of electrode interchange detection in ECGs. Despite the high relevance of this task in daily clinical practice and the proven success of DL-based approaches in various other ECG-related applications, current scientific literature lacks in-depth investigations within this specific domain.

## VI. Conclusion

Effective and robust DL models were proposed and validated based on data from a telecardiology system for detecting electrode interchanges, classifying the 12-lead ECG recording as acceptable or unacceptable for medical reporting in daily clinical practice.

The incorporation of the proposed models into any cardiology service may represent a valuable addition to cardiology services, since it brings benefits to the entire workflow of a health system, such as those listed below: 1) Paramedics who perform ECG signal acquisition: indication of electrodes that are possibly positioned incorrectly; 2) Specialist physicians: avoid rework in the preparation of reports that do not generate a diagnosis; 3) Patients: reduce the response time for the correct diagnosis and for appropriate treatment. Additionally, they reduce costs related to possible risks related to a late diagnosis; and 4) Public or private health service providers: reduce direct and indirect costs related to the delay in the cardiac diagnosis process.

## VII. Acknowledgement

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