# ECG Classification Improvement Through Preprocessing and Adaptive Learning


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***Abstract*— Electrocardiography (ECG) in 12 leads is a standard method for diagnosing cardiovascular diseases. In recent years, there has been significant progress in the use of deep learning methods for ECG analysis, which has improved the accuracy of automatic pathology classification. This paper examines methods for enhancing ECG classification quality that do not require changes to the model architecture. The main focus is on approaches such as signal preprocessing, self-adaptive learning, and the inclusion of patient metadata. Experimental results show that the proposed methods contribute to improved classification accuracy, especially when analyzing long recordings and combining data from different leads. The findings have practical significance for the development of intelligent diagnostic systems for cardiovascular diseases.**



***Keywords*— ECG, deep learning, signal preprocessing, data preprocessing, self-adaptive learning**


## I. Introduction

Twelve-lead electrocardiography (ECG) is a standard method for diagnosing cardiovascular diseases, enabling the recording of the heart's bioelectrical activity. These recordings play a key role in the early detection of pathologies and the monitoring of patient conditions. Traditional ECG analysis methods, based on manual feature extraction, often face accuracy limitations as they do not always account for hidden interdependencies within the data [1].In recent years, deep learning technologies have demonstrated significant progress in the automatic processing and classification of ECG signals [2]. These approaches allow models to independently identify important patterns in signals, leading to more accurate detection of pathologies such as arrhythmias and other abnormalities[3]. However, the performance of such models heavily depends on various factors, including the quality of data preprocessing and the size of the training dataset [4].

This study focuses on investigating the impact of non-architectural modifications on ECG classification quality. The methods explored include the use of patient metadata, noise suppression techniques, and self-adaptive learning approaches. Additionally, the study evaluates the significance of parameters such as recording length, lead set, and training data volume on classification accuracy.

The presented findings and recommendations have practical significance for further improvement of automated ECG diagnostic systems and may contribute to the development of universal solutions applicable in various clinical settings.

## II. Review of Existing Solutions

Recent advancements in digital technologies and artificial intelligence have led to the active development of automated ECG-based diagnostic systems [5]. The widespread adoption of wearable devices and telemedicine technologies has contributed to the accumulation of large volumes of data, which have become the foundation for applying deep learning methods [6].

Early approaches to ECG classification focused on manual signal processing and feature extraction. For example, the use of wavelet transformation for analyzing R, QRS, and P-T waves allowed the identification of key signal characteristics [7]. However, these methods are limited in their ability to account for complex dependencies between features.

With the transition to deep neural networks, more powerful analytical tools have emerged. Recurrent neural networks (RNNs), such as LSTM and GRU, have been applied to binary arrhythmia classification tasks using single-lead data [8]. Other studies have employed multilayer perceptrons and generative models, such as GANs, to generate additional data and improve class balance [9].
The most popular solution remains the use of convolutional neural networks (CNNs). These models perform both feature extraction and classification tasks simultaneously. For instance, two-dimensional CNNs have successfully classified atrial fibrillation based on spectrograms [10], while one-dimensional CNNs with residual blocks have demonstrated superior results when working with raw signals [4].

A key challenge in ECG classification is addressing class imbalance, which often arises in medical data analysis. Data augmentation techniques, such as SMOTE or GAN-based data generation, help mitigate this imbalance but come with limitations.

This study focuses on non-architectural methods for improving classification accuracy, such as enhancing input data quality, increasing training dataset volumes, and utilizing patient metadata [5]. These approaches help unlock the potential of existing models and improve their performance without requiring complex architectural modifications.

## III.METHODOLOGY

### A. Model Architecture

For ECG signal classification, this study employed a convolutional neural network (CNN) with residual blocks (ResNet1d50), adapted for one-dimensional time series processing. A key feature of this architecture is its ability to efficiently extract essential features from the data while minimizing information loss at each processing level.

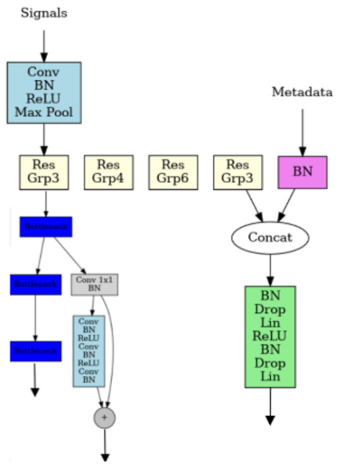


Fig. 1. Architecture of the deep learning model with core layers

The input data for the model consisted of 12-lead ECG recordings, represented as a matrix of size 10,000 × 12, where 10,000 corresponds to the number of samples for a 10-second recording at a sampling rate of 1,000 Hz. For data with a lower sampling rate, a resampling procedure was applied. Additionally, the model incorporated metadata, such as the patient's age, represented as a numerical feature.

Special attention was given to signal preprocessing. To remove artifacts such as baseline wander, the locally weighted scatterplot smoothing (LOWESS) method was applied. This approach helped reduce noise interference and improve the quality of signal analysis.

### B. Dataset

The study was conducted on a dataset containing 74,931 ECG recordings, collected through a telemedicine system across various regions. The data was anonymized and annotated by more than 200 experts.

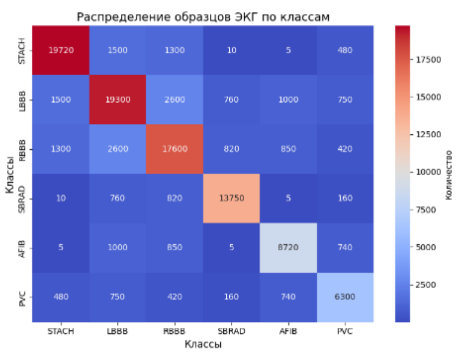


Fig. 2. Class-wise distribution of ECG samples

The age of patients ranged from 18 to 96 years, and the recording duration varied from 4 to 69 seconds. To standardize the analysis, longer recordings were segmented into 10-second intervals.

The classification covered six key pathologies:

- Premature Ventricular Contractions (PVC)
- Sinus Bradycardia (SBRAD)
- Sinus Tachycardia (STACH)
- Left Bundle Branch Block (LBBB)
- Right Bundle Branch Block (RBBB)
- Atrial Fibrillation (AFIB)

### C. Improvement Methods

To enhance classification quality, the following approaches were applied:

- Data Preprocessing: Noise removal using the LOWESS method.
- Metadata Utilization: Inclusion of patient age as an additional feature.
- Self-Adaptive Learning: A method that adjusts to data characteristics and reduces the impact of misannotated samples.

The model was trained using the PyTorch framework, which provided flexibility in adapting the model for one-dimensional time series analysis.

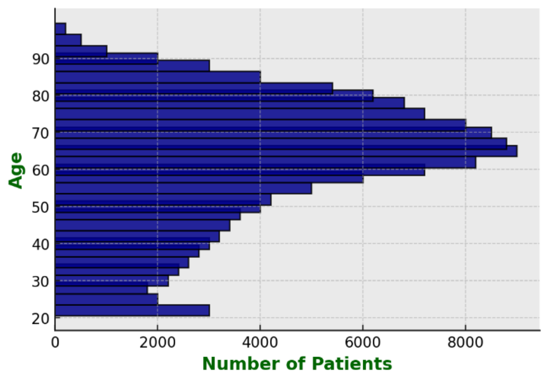


Fig. 3. Age distribution of patients in the ECG dataset

## IV.EXPERIMENTS

As part of this study, a series of comprehensive experiments were conducted to assess the impact of various factors on ECG classification quality. The primary focus was on signal preprocessing, training dataset size, input signal length, and lead set selection.

Classification performance was evaluated using the following metrics:

- ROC-AUC (Receiver Operating Characteristic - Area Under Curve)
- Average Precision (AP)
- F1-score

To ensure the reliability of the results, 5-fold cross-validation was applied.

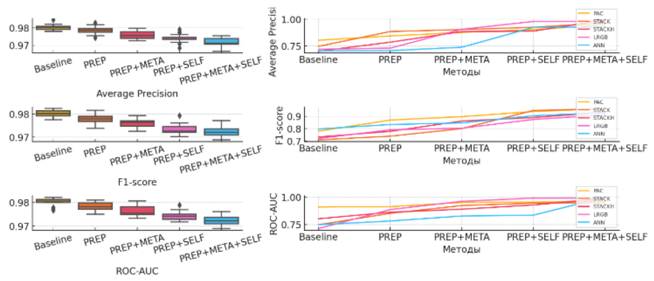


Fig. 4. Impact of different methodologies on ECG classification metrics

### A. *Impact of Data Preprocessing*

To evaluate the effect of preprocessing, five model configurations were tested:

1. Baseline model (ResNet1d50) with raw signals.
2. Model with preprocessed signals (LOWESS method applied).
3. Model with preprocessed signals and metadata (patient age included).
4. Model with preprocessed signals and self-adaptive learning technique.
5. Model utilizing all the mentioned approaches.

The results showed that signal preprocessing and self-adaptive learning significantly improved classification performance. However, the inclusion of metadata had minimal impact on the classification of the studied pathologies.

### B. *Impact of Training Dataset Size*

To analyze the dependence of classification quality on the training dataset size, the data was split into training, validation, and test sets. The training was conducted on subsets of different sizes, ranging from 10% to 100% of the available data.

The analysis demonstrated that increasing the dataset size improves classification performance, but with a nonlinear dependency. For some pathologies, such as sinus tachycardia and atrial fibrillation, the improvement in classification quality plateaued after reaching 45% of the training data, suggesting that further increases in dataset size provide diminishing returns and that model optimization time could be reduced without significantly sacrificing accuracy.

### C. *Impact of Input Signal Length*

To examine the effect of input signal length on classification quality, experiments were conducted with signal durations ranging from 2 to 10 seconds, while the test data remained fixed at 10 seconds.

The results indicated that for most pathologies, the optimal signal length ranged from 4 to 6 seconds. However, for the classification of premature ventricular contractions (PVCs), a longer signal duration was required, as more extensive temporal information was beneficial for accurately detecting these abnormalities.

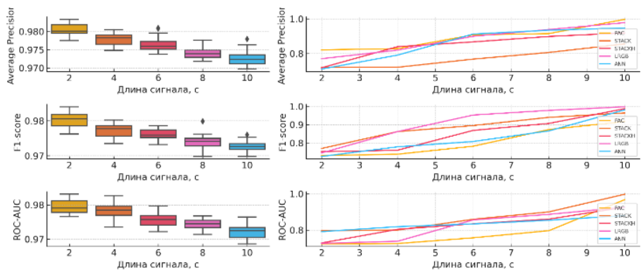


Fig. 5. Impact of input signal length on quality metrics

### D. *Impact of Lead Set Selection*

The study also analyzed the impact of different lead combinations on classification performance. The following lead sets were evaluated:

- Two leads (I, II).
- Three leads (I, II, V1).
- Six precordial leads (V1–V6).
- Seven leads (I, II, III, aVL, aVR, aVF, V1).
- Eight leads (I, II, V1–V6).

The best results were achieved when using three-lead or eight-lead combinations, highlighting their importance for accurate diagnosis. In contrast, using only limb leads or only precordial leads resulted in lower classification performance.

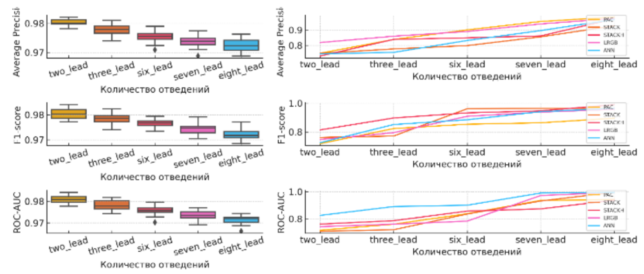


Fig. 6. Impact of lead set selection on classification performance

## V. Conclusion

This study explored methods for improving ECG classification accuracy that do not require changes to the model architecture. The findings demonstrated that signal preprocessing, self-adaptive learning, and the inclusion of additional patient data can significantly enhance classification performance.

Key Findings of the Study:

- Signal preprocessing using the LOWESS method effectively removes noise and improves classification accuracy [6].
- Self-adaptive learning reduces the impact of misannotated data, which is particularly important for medical applications.
- Incorporating metadata (patient age) provides only a minimal improvement for most pathologies, suggesting its selective use.
- Increasing the size of the training dataset positively impacts classification performance, but for some pathologies, a saturation effect is observed when using more than 45% of the available data.
- The length of the input signal significantly affects classification quality. A duration of 4–6 seconds is sufficient for most pathologies, except for premature

ventricular contractions (PVCs), which require longer recordings for optimal detection.

- The best results were achieved when using a combination of precordial and limb leads. A three-lead combination (I, II, V1) provides high classification quality while minimizing computational costs.

The proposed approaches can be applied across a wide range of ECG analysis tasks and integrated into various automated diagnostic systems. Future research may focus on more advanced metadata integration techniques, data augmentation strategies, and the development of models with enhanced adaptability to signal characteristics.

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