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*Article*

# Light Weight Residual Convolutional Neural Network for Atrial Fibrillation Detection in Single-lead ECG Recordings

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**Abstract.** Electrocardiogram (ECG) analysis constitutes the most important approach able to classify heart infarction anomalies. These anomalies can be identified from the changes in various features of the ECG signal. In this paper, we are proposing a new features-based classification method of short-time single-lead ECG signals. The goal of this method is to classify these ECG signal into one of the following classes: normal, atrial fibrillation, other abnormalities, and too noisy as defined by the dataset. This is a challenging problem because of the severe imbalance between the classes, where the normal class makes up the majority of the samples in the dataset. The second challenge in this dataset is the fact that the sample ECG signals have a variable length (it varies between 3 to 60 seconds). The proposed method considers three main processes. The first process consists of detecting inverted ECG record by analyzing the signal range and mean in a sliding-window. The second process involves the extraction of many features effective in characterizing ECG signals and detecting abnormalities. These features include morphological, Heart Rate Variability, statistical, time/frequency amplitudes, and special Atrial Fibrillation (AF) features. The third process represents the main contribution by designing a lightweight residual Convolutional Neural Network (CNN) model for the classification of short-time single-lead ECG signals. This model is composed of five layers with two residual connections where advanced CNN concepts such as Batch Normalization, DropOut, and Leaky-ReLU are used. Compared to state-of-the-art solutions, the proposed method achieved the best performance with F1-score of 95.11% using inversion correction.

**Keywords:** Short-time single-lead ECG, AF detection, deep residual CNN, inverted signal.

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## 1. Introduction

The electrocardiogram (ECG) is an interesting cardiovascular examination that can provide an assortment of valuable health information. It constitutes a fundamental aspect to diagnose cardiac patients. Cardiovascular disease is a main open concern and socioeconomic issue in the world. There are several cardiac health monitoring systems like echocardiography, magnetic resonance imaging (MRI) and computerized tomography scan. However, they have (1) high cost and (2) do not support long-term continuous monitoring of a patient without disrupting their daily activities.

Because of its inexpensive price, long-term recording capacity, and ease of use without disturbing the patient, wearable ECG recorders (W-ECG) are becoming nowadays more and more popular. Moreover, surface ECGs are fast and simple to acquire based on relatively simple electrophysiological concepts. The ECG recorders are existing in a more compact form that enables the user to wear for ECG recording without affecting or crippling their routine activities.

The conventional 12-lead ECG system invented to record ECG, identified five detection main points in the cardiac cycle: P, Q, R, S, and T. These five points are repeated to form a quasi-periodic ECG signal [1]. ECG data produced by electronic recorders have a large volume which requires automated methods for analyzing them. The electronic recorder affects the type and configuration of the ECG data, so it could be composed of a single-lead or multi-lead signal. Consequently, the analysis method is also single-lead or multi-lead ECG processing algorithms. The wave forms (morphologies), spectra, and repeatability of the cardiac cycle represent the major factors that allow studying the single-lead ECG waveform. However, extra factors such as simultaneous features, taken from other leads in multi-lead ECG processing algorithms, may ensure more immunity against interference signals.

The irregular heart rhythm is known as arrhythmia. Cardiac arrhythmias might be classified into:

- Origin: ventricular arrhythmia, atrial arrhythmia (Atrial Fibrillation), or junctional arrhythmia.
- Mechanism: re-entry, triggered, automaticity.
- Rate: bradycardia (< 60 bpm) or tachycardia (> 100 bpm) both for adults.
- Duration: sustained (≥ 30 s) or non-sustained (≤ 30 s).
- AV Conduction: delayed, blocked, normal.

According to the American College of Cardiology (ACC), the European Society of Cardiology (ESC), and the American Heart Association (AHA), the Atrial Fibrillation (AF) is a "tachyarrhythmia characterized by predominantly uncoordinated atrial activation with consequent deterioration of atrial mechanical function" [2]. AF is the pervasive and continuous cardiac arrhythmia. It materializes in 1-2% of the populace and is connected to mortality through linkages in relation to heart failure, strokes, coronary artery disease, etc. [3], [4].

In excess of twelve million residents in western jurisdictions have been assessed to be afflicted by AF. In the next thirty to fifty years, the number of afflicted by AF is expected to rise to almost forty million individuals [5]. As with many health conditions age is a major factor in those afflicted by this condition: for those between 40-50 years of age it is 0.5%; for those at the age of 80 it is between 5%-15% [6].

Regardless of the importance of this problem, AF detection is still a difficult problem exceptionally in the case of automatic detection. The previous work on AF detection is limited because they usually used selected clean ECG heartbeats only and focused on the classification of these heartbeats into two classes normal and AF rhythms. Also, the methods developed so far, only use ECG signals from a few patients, and when we try to generalize them to a large number of patients the performance degrades. Finally, all methods are trained to work well in one dataset, but when you switch to another dataset, the method needs to be retrained on the new data.

Furthermore, the sure detection of AF from a single-lead is challenging due to the broad taxonomy of rhythms. Especially, many rhythms other than AF may displays irregular intervals of RR similarly to AF.

In this work, we will use a consecutive group of ECG beats, known as short-time single-lead ECG signal (the length between 9 to 60 seconds), instead of a single heartbeat, for AF detection in ECG signals. The motivation behind this is that using a window of neighboring heartbeats may contain more rich information that allows the system to classify ECG signals more accurately. Also, to deal with the broad taxonomy of rhythms in ECG signals, we have considered all abnormal rhythms except AF as one class and require the system to classify the rhythms as one of the following classes only: 1) Normal sinus rhythm, 2) AF, 3) Other rhythms, or 4) Too noisy to classify.

Researchers and clinicians were given a challenge by PhysioNet/Computing in Cardiology in 2017 to develop a trustworthy method for detecting atrial fibrillation (AF) from short-duration single-lead ECG signals obtained with a widely available, reasonably priced hand-held device [7]. These portable ECG devices cannot replace the larger and more expensive hospital equipment, but they can significantly help in the early detection of AF through routine daily monitoring over an extended period of time [3]. The imbalanced class sizes in the dataset make difficult the operation of many classification methods. In addition, this dataset contains ECG records that range in length from 9 to 60 seconds, which makes it challenging to use directly as an input to many classification algorithms in raw format.

The rest of the paper is structured as follows. Section 2 provides a background in terms of ECG signal, Machine learning concepts specifically the most known CNN architectures. Section 3 surveys some related work achieved on short-time single-lead ECG signal classification. Section 4 presents the proposed classification method using deep residual CNN. In addition, it defines the performance metrics, shows the obtained results for short-time single-lead ECG classification and analyses and compares these results with the state-of-the-art methods. Section 5 outlines the most notable conclusions and major contributions of the work and provides some guidelines for future development.

## 2. Background

An ECG constitutes the electrical activity of the heart muscle as it fluctuates over time. The electrical depolarization of the muscle cells causes the heart muscle contraction. The cardiac muscle contracts because of the electrical depolarization of the muscle cells. The aggregate of this electrical action, when amplified and recorded for only a few seconds (usually 10 seconds) provides an ECG.

### 2.1. ECG Features

The ECG signal is obtained by placing 12 electrodes on the patient's skin using 12 different recording lead (directions). A cycle of normal heartbeat is shown in Fig. 1. It contains waves, intervals, complexes, and segments. ECG waves and intervals have an expected time period, a range of acceptable amplitudes (voltages) and a typical morphological pattern. Using this information, we can design and develop computer-based techniques to detect any anomaly found in the ECG signal. Table 1 presents the main features as well as their specifications of the normal ECG signal for an adult person.

### 2.2. Heart Arrhythmias

Any irregular changes in the heart rhythm called arrhythmia. Arrhythmias happen once the electrical signals of the heart that synchronize heartbeats are not running correctly. Some arrhythmias have no symptoms or not serious. On the other hand, some of them can cause a stroke or cardiac arrest. Early diagnosis of arrhythmias helps reducing the risk of severe complications.

Arrhythmias can be classified into different types according to the rate of heartbeats, the duration of the abnormal beats or the mechanism of the abnormality. Arrhythmias can also be classified by the site of origin: atrial, junctional and ventricular arrhythmia [11].

AF is an abnormal heart rhythm caused by the rapid and abnormal beating of the heart-atrial chambers. Figure 2 clarifies the difference between normal and AF ECG. Often, it begins as a short period of abnormal beating which becomes longer and possibly constant over time. The patient may feel symptoms like chest pain, weakness, breathlessness, and palpitation. Regularly, symptoms develop rapidly. However, sometimes there are no symptoms at all appearing on the patient. Patients who don't have symptoms won't be predicted of AF, so it goes untreated and their lives will be under threat. AF can cause severe complication such as stroke or heart failure.

### 2.3. Typical ECG Abnormality Detection Steps

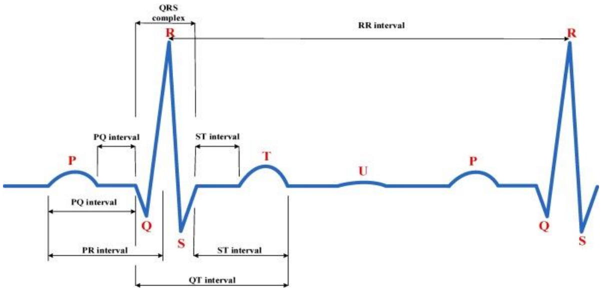


Fig. 1. Diagram of normal ECG signal.

Table 1. ECG Features for lead II in normal adult.

| Feature | Amplitude | Time |
|---|---|---|
| P wave | 0.1 – 0.3 mV | < 120 ms |
| Q wave | < 1/3 of R wave amplitude / lead | < 40 ms |
| T wave | 0.1 – 0.5 mV | - |
| PR interval | - | 120 – 200 ms |
| ST segment | - | 50 – 160 ms |
| QT interval | - | < half RR interval (males < 400 ms; females < 440 ms) |
| QRS complex | < 6 | < 0.12 s |
| RR interval | - | 600 – 1000 ms (60 – 100 bpm) |

Figure 3 shows the flowchart including the main processes for detecting abnormalities in the ECG signals. Preprocessing ECG signals helps in detecting and attenuating frequencies of the ECG signal related to important features in the signal. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. The preprocessing step involves filtering the ECG signal using state-of-the-art methods. Then, the signal will be segmented by detecting the R peaks in the signal since each R peak corresponds to one ECG beat. In the last years, several research and techniques have been developed for the feature extraction of ECG signals. Our proposed method considers the following steps: (1) Detect QRS wave, (2) Determine the location of R points, (3) Obtain the RR intervals, (4) Compute the heart rate, (5) Determine the P-wave duration and the PR interval.

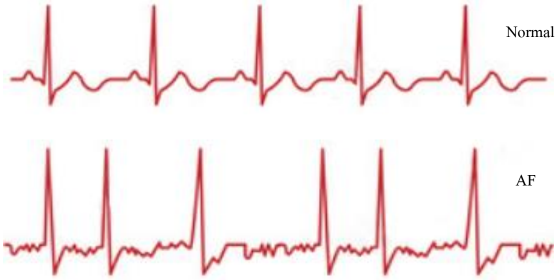


Fig. 2. Comparison between normal & AF ECG rhythms.

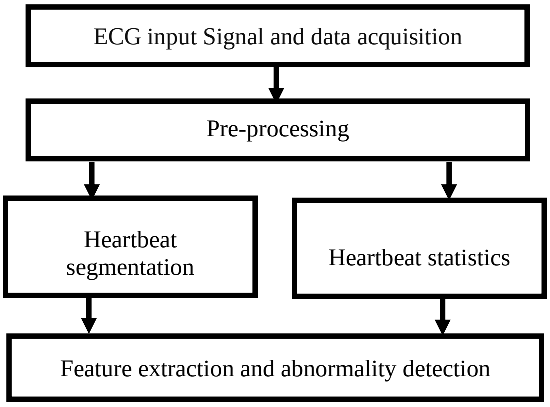


Fig. 4. Main processes for detecting abnormalities in ECG signals

The heartbeat segmentation and statistics computing process is responsible for detecting any deviation from the normal morphology of the ECG signal. In order to be sure if the morphology is normal, the following elements must be checked: 1) The P wave exists and rounded shape, 2) All the P waves should have the same shape, 3) QRS comes after the P wave, 4) The P-R interval should be constant, and 5) The rhythm should be regular (by comparing whether the first three P-P intervals or R-R intervals have the same value).

The feature extraction and abnormality detection process is responsible of analyzing the acquired and extracted information in order to decide abnormalities and whether the patient needs further treatments.

### 2.4. Deep Neural Networks

A neural network is a set of algorithms constructed to imitate the activity of the human brain. It aims to recognize patterns and pass the input through various layers of the simulated neural connections to get useful output. If the neural network contains one layer, we call it a simple neural network. Instead, many experts can consider the network as a deep neural network if at least two hidden layers are there between the input and the output layers. Adding more hidden layers means a deeper neural network. Each layer performs definite types of sorting and ordering in a process that may be specified as “feature hierarchy”. There are many types of deep neural networks depending on the design and learning algorithm used in the network. Each type has its own power and usage.

A Convolutional Neural Network (CNN) is a deep learning algorithm that includes layers performing convolution operations. The two main components of a CNN are: (a) a convolution tool that divides the various features for analysis, and (b) a fully connected layer that takes the output from the convolution layers to make the best prediction.

The strategy and functions of the visual cortex stimulate the designers of CNN architecture in order to create a simulation in relation to the patterns of connectivity within the human brain. In CNN, neurons are structured into 3 dimensions. Each group of neurons has to analyse a tiny feature or region of the signal. The CNN takes these features from layers to produce a final output that gives a vector of probability scores to comment on the possibility that a unique feature is part of a certain class. This architecture constitutes the major factor in determining the performance of a CNN. The layering structure as well as the type of the utilized elements considerably affect the accuracy and speed when performing tasks.

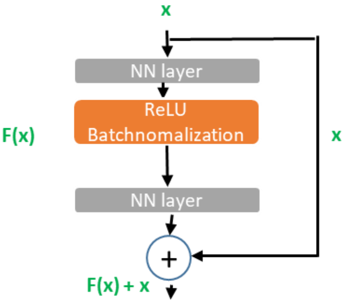


Fig. 3. Illustration of the residual connection concept.

The CNNs have developed rapidly in the last few years and numerous CNNs are proposed. These networks became so deep and it became hard to conceive the whole model. These networks are pre-trained on large image datasets and many researchers use it as a tool for feature extraction.

CNN designers tried to achieve better performance by increasing the number of layers in the deep neural networks. However, when increasing depth, the accuracy gets saturated and degrades fast. To avoid this problem residual neural networks network was used in building deeper models. Residual networks are a type of deep neural network that have been proposed recently for image classification tasks [16]. It is well-known under the name of ResNet and it is commonly used as a pre-trained model in many studies in the literature. The accuracy of deep neural networks become saturated due to the diminishing gradient phenomenon, meaning that the gradient goes to zero during the backpropagation algorithm. Residual networks deal with this problem by using the residual blocks as shown in Fig. 4.

The basic idea is to make a shortcut connection from the input layer to some future hidden layer, where the input x is added to the output from the hidden layer. In other words, the hidden mapping H(x) becomes F(x)+x. Thus, the neural network now maps x to the residual H(x)-x. The idea is that the network learns how to map this residual to 0, that is better and more efficient than learning the mapping between x and F(x).

Furthermore, ResNets were the first deep networks that have used Batch Normalization layers after each Convolutional layer. Normalization means transforming the data so that it follows a normal distribution. Batch Normalization layer will normalize the value of network weights which helps in training it faster.

## 3. Related Work

Two types of atrial fibrillation (AF) can be identified by: 1) Techniques based on atrial activity analysis, or 2) Techniques based on ventricular response analysis. The first type is identified by the absence of P waves or the presence of fibrillatory F waves in the TQ interval. The second form, however, is based on the ability to forecast the intervals between beats (RR intervals) of the QRS complexes in the ECG signal.

Numerous techniques based on atrial activity analysis have been described. They consist of the echo state neural network technology, P-wave-based cardiac monitor application, and wavelet entropy techniques. When the ECG signals are high resolution and contain little noise, these approaches can produce results with a high degree of accuracy. However, in situations of significant noise pollution, their accuracy has a tendency to decline significantly.

The predictability of the inter-beat timing (RR intervals) of the QRS complexes in the ECG is the foundation of ventricular response analysis. Since RR interval identification is based on the detection of the R-peak, the most pronounced characteristic of an ECG heartbeat, it is significantly simpler and more robust to high noise. Therefore, many academics consider this technique to be the best way for automatically and instantly detecting AF. Moreover, it is a more typical strategy in the literature. The additional techniques built on top of this strategy include thresholding on the median absolute deviation (MAD) of RR intervals, Poincare plot analysis and normalized fuzzy entropy of RR intervals, minimum of the corrected conditional entropy of RR interval sequence, Lorenz plot analysis, symbolic dynamics and Shannon entropy, histogram of the first difference of RR intervals, analysis of cumulative distribution functions, and 8-beat sliding window RR interval irregularity detector.

Other researchers have attempted to combine both approaches atrial activity and ventricular response in order to provide enhanced detection accuracies. For example, Babaeizadeh et al. [19] proposed a method that combines RR interval Markov modeling and a P-wave morphology similarity measure. Another method proposed by Petrenas et al. [20] combines P-wave absence, f-wave presence, RR interval irregularity, and noise level to detect AF. The fuzzy logic classifier is used in this method. More recently, machine learning is heavily used in AF detection. Machine learning, especially based on deep learning, can combine all of the above single features automatically, since it is able to acquire the ECG heartbeat as an input and then learn the suitable features automatically. For example, the authors [21] use a Denoising Auto-Encoder (DAE) with sparsity constraint to learn suitable features from an ECG heartbeat, and then they use a deep fully connected neural network for classification.

The Teijeiro et al. method used an abductive framework for time series interpretation to extract morphological and rhythm-related characteristics [5]. Following that, these characteristics were input into two classifiers, one to evaluate the record globally using aggregated values for each feature and the other to evaluate the record as a sequence based on Recurrent Neural Network (RNN) and individual features of the detected heartbeat.

Kropf et al. [6] proposed a classification technique capable of extracting 380 features from the time and frequency domain. They trained a Random Forest-based classifier (bagged decision trees) using these features. A method for extracting fifty different features was proposed by Billeci et al. [22] and can be computed on the ECG signal, extracted from the RR series, or combined with rhythm and QRS morphology. The stepwise linear discriminant analysis is then used to choose a subset of thirty distinguishing features. The least squares support vector machine classifier then completes the classification.

Datta et al.'s top-performing method [23, 24] utilized two layer binary cascaded approaches. First binary classifier divides unlabeled recordings into two intermediate groups (‘normal + others’ and ‘AF + noisy’). Then, a second binary classifier divides each intermediate class into two classes in a subsequent layer. Prior to classification, this method also depends on feature extraction. It extracts over 150 features with various criteria, such as morphological, Prior art AF, frequency, statistical, etc.

For ECGs captured by the AliveCor handheld devices, Zabihi et al. [25] suggest a hybrid categorization strategy. Features from many domains, such as time, frequency, time-frequency, phase space, and meta-level, are combined. It makes use of a random forest classifier-based feature selection strategy. Another random forest classifier then categorizes the chosen characteristics.

An approach to determining AF based on the decision tree ensemble was devised by Bin et al. [26]. To find a point in the QRS complex, the proposed method first used an upgraded Hamilton and Tompkins algorithm. Second, from each ECG record, they extracted thirty features. All of these characteristics can be divided into four major categories: AF characteristics, Morphology characteristics, RR interval characteristics, and Similarity indices between beats. Finally, classification is performed using a binary decision tree-based classifier.

In short-time single-lead ECG records, Behar et al. [27] employed the feature-based machine learning approach to categorize rhythm as a preprocessing step to find and choose the highest quality continuous sub-segment signal. The RR interval is assessed using R-peak detectors, and the signal quality was calculated on a second-by-second basis. The occurrence of ectopic beats, heart rate variability, and ECG shape were among the features that were extracted based on the findings. Support vector machine classifiers were trained using these characteristics using a one-vs.-rest methodology.
According to many sets of well-known AF properties, Bonizzi et al. [28] suggested a two stage ensemble learning method to distinguish the AF from other rhythms. The ECG short-time single-lead records are divided into non-

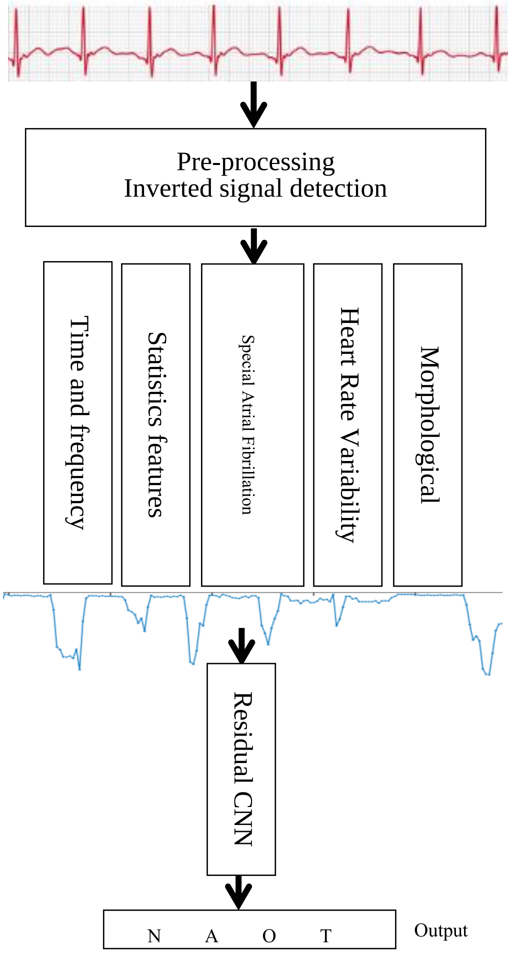


Fig. 5. Architecture of the proposed method. The inputs are short-time single-lead ECG records that have varying length between 9 to 60 seconds (N. Normal, A. atrial fibrillation, O. Other T. Too noisy).

noisy and noisy records in stage one based on the extraction of a collection of features from the ECG signal. The non-noisy records are removed in stage two to obtain the AF features. To classify the records for both stages, an ensemble model with decision tree was used and modified with RUSBoost.

Based on dataset of short-time single-lead ECG records, three CNN suggested solutions are included in the literature. A 16 layer CNN that can accept 5 seconds at a time of the raw ECG signal was proposed by Xiong et al. [29]. The average of each 5-second clip's individual probabilities represents the whole ECG record's final class probability. To learn local and discriminative features on the raw input sequence, Warrick and Homsi [30] employed a one-layer CNN as an auto-encoder. The sequential patterns are then encoded using three layers of LSTMs on top of the previous CNN. The proposed deep network also includes a softmax layer for classification and one fully connected hidden layer. In order to identify rhythms from short ECG segments that are divided into four classifications (AF, normal, other rhythms, or noise), Andreotti et al. [31] compared a feature-based classifier versus a deep learning CNN technique. Both approaches made use of unique tools. The WFDB toolbox was used in MATLAB to implement the feature-based methodology. However, Python 3.5 was used to create the deep learning methodology. The 2017 Computing in Cardiology Challenge database from PhysioNet, together with another database acquired from PhysioNet, were used to train both approaches. Then, a 5-fold cross-validation technique is used to evaluate their performances, and the findings are presented as an F1-score.

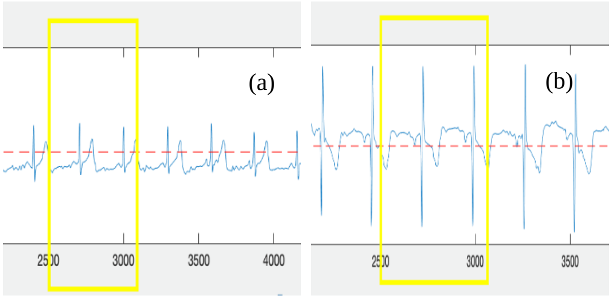


Fig. 6. Illustration of inverted ECG record detection. Sliding window is shown in yellow color. The red dashed line shows the midpoint between maximum and minimum values in window. (a) not flipped (regular) record, (b) flipped (or inverted) record.

## 4. Deep Residual CNN-Based Classification Method

The suggested approach is based on a residual CNN, as depicted in Fig. 5, for the classification of short-time singe-lead ECG records. The preprocessing step of the approach consists of identifying vertically flipped signals. A collection of crucial features is extracted from the ECG records in the second stage. The short-time single-lead ECG records are then classified using the retrieved characteristics by training a residual CNN. The preprocessing, feature extraction, and classification stages utilizing deep residual CNN are covered in depth in the following sections.

### 4.1. ECG Record Preprocessing

The pre-processing phase helps clean the ECG signal and improve the performance of the classification step. The preprocessing phase involves detection and correction of (vertically) flipped signals, resampling and scaling (normalization).

Numerous inverted signals were discovered when the recordings in the short-time ECG dataset were examined [5, 6]. Due to the difficulties in recognizing P waves, a classification system may classify an inverted normal ECG signal as abnormal. Thus, one crucial step in raising classification accuracy is spotting and rectifying inverted signals. Results of our approach for inverted signal detection and correction are shown in Fig. 6. Two instances of typical signals are shown in the picture; one is not flipped (Fig. 6(a)), while the other is flipped (Fig. 6(b)). With a sampling rate of 300 Hz, our algorithm employs a sliding window with a size of 600 samples, or 2 seconds. We calculate the maximum and minimum values for this window. Then, as indicated in Fig. 6's red dashed line, we calculate the midway between the maximum and minimum values.

As can be seen, in the event of an inverted record, the center point should be below the signal mean. A non-inverted record, on the other hand, will have this middle value above the signal mean. As a result, our system simply compares the number of windows that produce points above the signal mean to those that produce points below the signal mean in order to detect inverted signals. The ECG signal is inverted if there are more windows creating middle points below the signal mean.

## 4.2. Feature Extraction

ECG classification is a difficult process since the data include a significant level of inter- and intra-class variability. As a result, a crucial stage in an ECG classification algorithm is feature extraction, which is based on expert knowledge of the primary properties of ECG signals. The QRS complex is one of the primary properties of ECG signals. A well-known technique for identifying the QRS complex and R peaks in ECG signals is Pan-Tompkins. The Pan-Tompkins algorithm that we employed in our study has a MATLAB implementation supplied by the challenge's organizers. The method looks for more ECG waveform main points using the discovered R peaks. Each ECG recording has a collection of 188 features taken from it when the P, Q, R, S, and T points are found [4]. We give a brief description of these features in the following subsections:

### 4.2.1. Frequency features

The Short Time Fourier Transform (STFT) is used to retrieve 39 frequency characteristics. Every 300 samples, a Hamming window of size 2 seconds (600 samples) slides over the ECG recording, resulting in a 50% overlap between the windows. As result, these features are extracted from each sliding window which are named as: mean spectral centroid [18], spectral flux [19], and spectral roll-off [20].

The spectral flux (SF) is a measurement of how fast the power spectrum changes for a signal and provides detection according to energy information or signal amplitude. SF is got by calculating the magnitude of the STFT over two successive frames and comparing these two values by each other. SF is just counting the frequency bins where the energy is increasing. Equation 1 defines the normalized spectral flux as:

$$SF(n) = \frac{\sum_{k=-\frac{N}{2}}^{\frac{N}{2}-1} H(|X(n,k)| - |X(n-1,k)|)}{\sum_{k=-\frac{N}{2}}^{\frac{N}{2}-1} |X(n,k)|} \qquad (1)$$

where H(x) = (x+ | x |)/2 is the half-wave rectifier function.

Although spectral flux is usually used as a function to detect the onset, it can be easily used for transient detection purposes. The more the signal is passing, the greater the value of the spectral flux, and the shorter the time constants necessary to achieve the appropriate compression.

The spectral roll-off point is the frequency in which a specified percentage (95%) of the total signal energy lies below. this value differentiates the abnormal values that could be found in the ECG signal.

### 4.2.2. Heart rate variability (HRV) features

Heart Rate Variability (HRV) is the change in the time intervals between consecutive heartbeats. These HRV features, including SDSD, pNNx, SDNN, and normalized RMSSD, are used in many ECG feature extraction algorithms [21]. We extracted 11 out of a total 188 features defined as follows:

- SDSD: stands for the standard deviation of the consecutive differences for two adjacent intervals (beat-to-beat).
- pNNx: is the portion of adjacent beat-to-beat intervals that differ by more than $x$ ms (we call the beat-to-beat intervals as NN interval). pNN50 and pNN20 are defined.
- SDNN: is the standard deviation of beat-to-beat intervals.
- SDRR: is the standard deviation of RR intervals.
- Normalized RMSSD: is calculated in three steps: (1) measures the difference between consecutive beat-to-beat intervals, (2) compute the squares of successive differences, (3) calculate the square root of the mean of the square series.
- Normalized spectral power of the RR interval time series within the frequency region of 0-0.003 Hz ULF band, 0.04 Hz VLF band, 0.04-0.15 Hz LF band and 0.15-0.5 Hz HF band.

### 4.2.3. Morphological features

The morphological features are considered by doctors as the basic elements used to diagnose ECG abnormalities [22]. They are based on the P, Q, R, S, and T positions within the ECG signal. There are 56 different morphological features (or values) identified as follows:

- 4 features for kurtosis, skewness and variance in amplitude of the QRS.
- 5 features given by the distance of the ST segment among other points.
- 6 features related to the corrected QT interval like mean, median, width and variance
- 6 features inspired from the slope, mean and median of QR, RS, and ST curves.
- features calculating the ratio of depth of S to Height of R.

- features specific to the ratio of depth of Q respected to R.
- features related to QS width and QR width.
- Amplitude difference of TR wave.
- Ratio of the number of P to the number of R.
- features for RS amplitude differences.
- 21 features related to R and P locations.

### 4.2.4. Special AF features

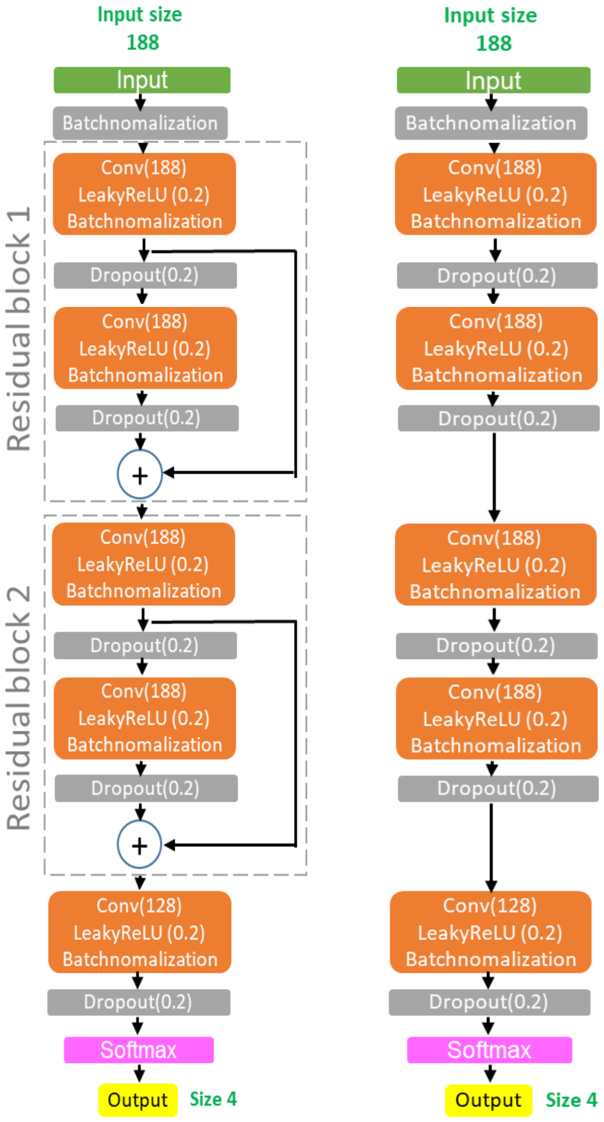
In the literature, many researches have proposed special features for AF detection. In our work, we extracted 30 special AF features including:

- Features that measure the RR intervals variance correlated with the presence of AF.
- 8 features including Evidences of AF, Original Count, Irregularity, Pace, Density, and Anisotropy, where AF Evidence from Lorentz plot of RR intervals, were proposed by Sarkar et al. [23].
- Entropy-based characteristics are additional features that have been mentioned in the literature to improve AF identification [24, 25]. We extracted 15 different entropy-based features.
- 5 features, inspired from Poincare plot [26], are related to inter-beat intervals.

### 4.2.5. Statistical features

All features that can be calculated using statistical analysis are named statistical features. We extracted 21 different statistical features, including:

- 8 features computed from the RR intervals are: the maximum, minimum, median, mean, variance, range, kurtosis, and skewness.
- Entropy related-features defined by Shannon, Tsallis, and Renyi entropy.
- 7 features are used to estimate the probability density of the RR and delta RR intervals as well as the number of peaks
- Features corresponding to the linear predictive coefficients of the raw time series data.
- 1 feature for the variance of energy between R peaks.



(a) (b)

Figure 6. CNN architecture proposed for short-time single-lead ECG records classification. (a) 5-layer CNN with residual connections, (b) same CNN without residual connections.

### 4.2.6. Other features

A total of 30 features are extracted to detect noisy ECG signals similar to those that have been specified in the literature. They include statistical features considering the ECG signal morphology [27] as well as special features described in [28] and extracted from frequency and time domains.

## 4.3. Classification Using Residual CNN

In the literature, a variety of techniques for classifying ECG signals have been proposed and developed. To categorize recent single-lead ECG records, none of them have used residual networks. The proposed deep residual CNN is shown in Fig. 7(a). It employs two residual blocks. Two convolutional layers with a Leaky ReLU activation function, followed by a Batch Normalization layer, build each residual block. It is well established that normalization is an important requirement for neural networks, in order for them to avoid overfitting and converge during training to an optimal or near optimal solution. Szegedy et al. [29] have also shown the normalization of the data between layers of the network also helps the network converge quicker. Thus, they have introduced the Batch Normalization layer in their

GoogLeNet CNN architectures (in particular in the InceptionV2 model).

We have also added a dropout layer in between the two convolutional layers. The dropout layer, basically, drops out or excludes, some neurons from the previous layer in the feed-forward computations. In other words, the dropped neurons do not get used in the computations of the neurons of the current layer. The dropout layer has been shown to combat overfitting in neural networks. The convolutional layers are characterized by a size of 188, an activation function based on LeakyReLU and alpha fixed to 0.2. Our model includes after each convolutional layer a batch normalization layer and a dropout layer with a drop out of 0.2.

The proposed model is characterized by additional residual connections (Fig. 7(a)) compared to the base model. To evaluate the efficiency of our model, we have implemented a similar 5-layer CNN without residual connections as given in Fig. 4(b). Then, we established a comparative study of the two models to demonstrate the effectiveness of the residual connections.

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## 5. Experimental Work

The experimental work has been performed in a specific simulation environment. For more details, this environment is described in the following paragraphs in terms of structure of the dataset and the experimental setup.

### 5.1. Dataset Description

The 2017 PhysioNet Computing in Cardiology Challenge [2] featured the relatively new dataset of short-time single-lead ECG recordings. There are 12,186 records. This dataset has been made available for the challenge by AliveCor known as manufacturer of handheld ECG equipment. Each sample was recorded using one of the three single-channel ECG devices. Theoretically, the user gripped each of the two electrodes in each hand to create an ECG equal to lead I (LA-RA). The recording lasted, on average, 30 seconds.

The equipment then used a 19 kHz carrier frequency and a 200 Hz/mV modulation index to acoustically send the data to a wireless device into the microphone over the air. Software demodulation was used to digitize the data in real time at 44.1 kHz and 24-bit resolution. The data were finally saved as 300 Hz, 16-bit files with a bandwidth of 0.5-40 Hz and a dynamic range of 5 mV.

The data was then divided into training and test data sets and transformed into Matlab V4 files according to WFDB. The test set contains 3,658 recordings with identical lengths and class distributions. However, the training set inludes 8,528 samples ranging from 9 to 60 seconds. In our work, 300 records are selected for testing.

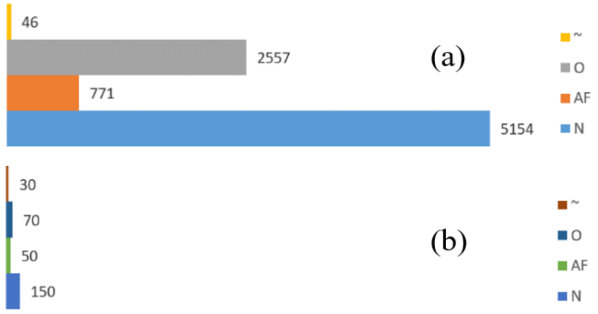


Fig. 7. Composition of short-time single-lead ECG dataset. (a) Training set with 8,528 samples, (b) Testing set with 300 samples

Table 2. Definition of parameters used in score formulas in Eq. (2), (3), (4), and (5).

| | | **Predicted Classification** | | | | |
|---|---|---|---|---|---|---|
| | | **Norma** | **A** | **Othe** | **Nois** | **Tota** |
| **True classificatio** | Norm | Nn | Na | No | Np | ∑ N |
| | AF | An | Aa | Ao | Ap | ∑ A |
| | Other | On | Oa | Oo | Op | ∑ O |
| | Noisy | Pn | Pa | Po | Pp | ∑ P |
| | Total | ∑ n | ∑ | ∑ o | ∑ p | |

Fig. 8. shows the composition of the dataset in terms of samples per class, where N, A, O, and ~, represent the Normal, AF, Other, and Noisy classes respectively.

### 5.2. Experimental Setup

The proposed deep residual CNN has been implemented using the Python-based TensorFlow environment through a high-level neural network API. We set the batch size to 250 samples, because the computer RAM can handle 250 ECG features at a time. In addition, we set the Adam optimization method's learning rate to 0.0001. We utilize the default values of 0.9, 0.999, and 1e-8 for the exponential decay rates for the present, estimations, and epsilon. The HP-station used for all studies has an Intel Xeon CPU clocked at 2.40 GHz, 24.00 GB of RAM, and an 11 GB GEForce GTX1090 GPU.

The performance evaluation of the proposed model has been performed using F1-score metric for each class as well as over all classes. Given a confusion matrix as shown in Table 2, these scores are computed, as presented in Eq. (2), (3), (4), and (5). Finally, the overall F1-score is computed using FN, FA, and FO as shown in Eq. (6) and according to the guidelines of the PhysioNet/Computing in Cardiology challenge.

$$F_N = \frac{2 \times N_n}{\sum N + \sum n} \tag{2}$$

$$F_A = \frac{2 \times A_a}{\sum A + \sum a} \tag{3}$$

$$F_O = \frac{2 \times O_o}{\sum O + \sum o} \tag{4}$$

$$F_\sim = \frac{2 \times P_p}{\sum P + \sum p} \tag{5}$$

$$F1_{overall} = \frac{F_n + F_a + F_o}{3} \tag{6}$$

## 6. Results and Discussion

### 6.1. Results with the Base CNN (Without Residual Connections)

In this section, we present the results obtained by the base CNN model without residual connections. This model is characterized by the following parameters: convolutional layers with 188 filters of size 3 each and a stride of 1. Stride specifies the step size between each convolution of the signal with the filter. In other words, the convolution is not computed at every value of k, instead k moves by step equal to s. as illustrated by the following formula for the convolution between x[n] and the filter h[n]:

$$(h * x)[n] = \sum_{k=0}^{N} h[n-k] \times x[k] \tag{7}$$

In this first experiment, we set the learning rate of the Adam optimization algorithm to the low rate of 0.0001 to start with. The categorical cross entropy loss function is used when the data point belongs to one category. In other words, it is used in classification problems where only one result is correct. Categorical cross entropy loss can be represented by Eq. (8).

$$L(y, \hat{y}) = -\sum_{i=1}^{S} \sum_{j=1}^{C} \left( y_{i,j} \times \log(\hat{y}_{i,j}) \right) \tag{8}$$

where $\hat{y}$ is the predicted probability that observation i is of class j. y is binary indicator (0 or 1) if class label j is the correct classification for observation i, S is number of samples, and C is the number of classes.

Based on the initial loss and accuracy curves shown in Fig. 9, we notice that the CNN converges around training epoch 200. Thus, we settle on 200 for the number of epochs parameter. However, we implemented the following improvement. For the first 150 epochs, we set learning rate to a higher value, namely 0.001, to speed up convergence. Then, for the training epochs between 150 and 200, we reset again to 0.0001, so that the network fine-tunes its final result.

Furthermore, we notice also from Fig. 9 that there are small fluctuations in the loss value even when the CNN reaches convergence. Thus, we have implemented a solution that keeps track and saves the model with the lowest loss value during the epochs 150 to 200. The model with the lowest loss value is the best model that we expect to give us optimal results when we apply it to the testing set.

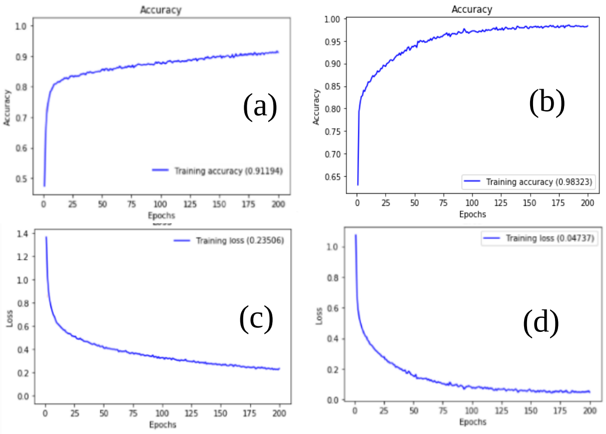


Fig. 8. Loss and accuracy curves results. (a) and (b) CNN without residual connections. (c) and (d) CNN with residual connections.

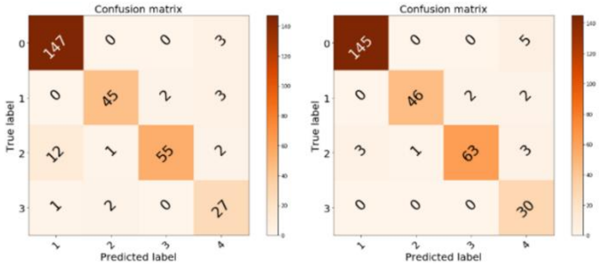
Table 3. Effect of adding residual connections to our proposed deep CNN model.

| | F1 Score per class | | | | F1 score |
|---|---|---|---|---|---|
| **Method** | **N** | **A** | **O** | **~** | **Overall** |
| 5-layer CNN [ours] | 96.71 | 90.52 | 86.13 | 83.71 | 91.76 |
| Residual CNN [ours] | 97.10 | 94.85 | 93.33 | 85.58 | 95.09 |

### 6.2. Effect of Residual Connections

In the second set of experiments, we compare the base model (without residual connections) to the proposed model of the residual CNN. For these experiments we fix the parameters to the same values as in the experiment of the previous section, including the idea of setting the learning rate to 0.001 during the first 150 epochs and then reducing it to 0.0001 thereafter. In addition to saving the best model that reaches the lowest loss value on the training data. We obtain the results shown in Table 3, which clearly show the effectiveness of introducing residual connections to the model. In particular, the overall F1-score has increased from 91.76% to 95.09%. In addition, the F1-score has improved across all classes. In particular, the improvement was pretty significant for the minority classes which are the A and O classes. This shows that residual connections were instrumental in helping the model focus on important features that helped identify these classes.

Figure 10 shows the confusion matrix on the test set for both models, in which we can see that the main difference is in the minority classes, especially the "O" class (class two). For this class the base model wrongly classifies more (exactly 12) ECG records as normal records compared to the residual CNN.



(a) (b)

Fig. 9. Confusion matrix for (a) CNN without residual connections and (b) CNN with residual connections.

Finally, we plot the loss and accuracy curves for both models in Fig. 11. We notice here that initial loss of the residual networks is (around 0.9) which is lower than the initial loss of the base network without residual connections. Also, we notice the CNN with residual connections converges faster. This clearly shows the effectiveness of residual connections in deep CNN models.

### 6.3. Effect of Inverted Signals Detection

The impact of inverted signals detection on the classification accuracy for both types of CNN is shown in Table 4. The classification accuracy increases greatly by identifying and correcting inverted signals, as shown in the table. When using the 5-layer CNN model, the accuracy increases from 87.58 to 91.76%. however, when using the 5-layer CNN with residual connections the accuracy is much better which incrases from 89.09 to 95.09%. These results show how correcting inverted ECG signals can be effective before classification to produce precise results.

We also present the confusion matrix for both scenarios in Fig. 12. An interesting observation here is that the inversion detection pre-processing step had a higher positive effect on the minority classes compared to the normal class (or class zero). In particular, the "O" class (or class two) is the one most affected. It is confused with the "N" class (or class zero) which is the "Normal" class.

Table 4. Effect of inversion detection on classification accuracy.

| | F1 score per class | | | | F1 score |
|---|---|---|---|---|---|
| **Method** | **N** | **A** | **O** | **~** | **Overall** |
| **5-layer CNN** | | | | | |
| No correction of inverted signal | 95.42 | 93.75 | 84.21 | - | 87.58 |
| with correction of inverted signal | 96.71 | 90.52 | 86.13 | - | 91.76 |
| **5-layer CNN with residual connections.** | | | | | |
| No correction of inverted signal | 93.89 | 92.63 | 83.72 | - | 89.09 |
| with correction of inverted signal | 97.10 | 94.85 | 93.33 | - | 95.09 |

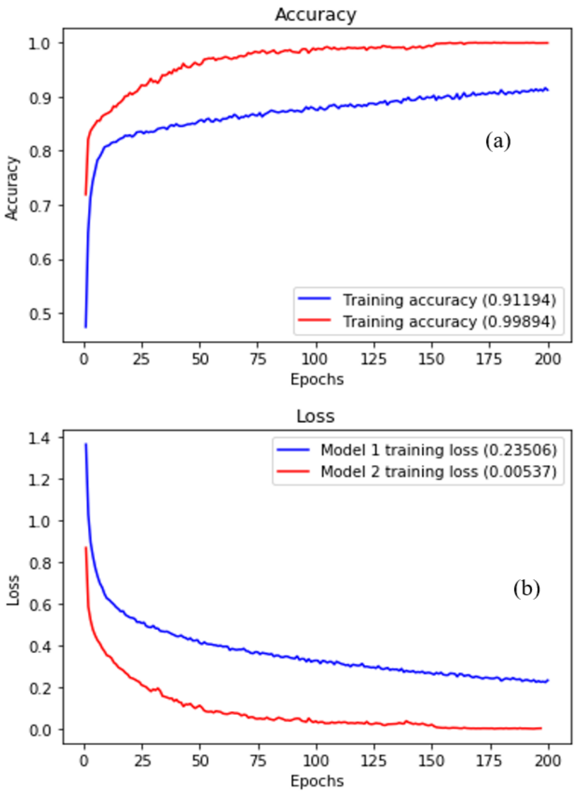
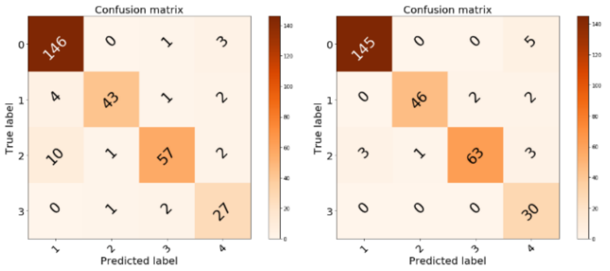


Fig. 10. Loss and accuracy curves results. Model 1 is CNN without residual connections, while model 2 is CNN with residual connections. (a) Loss curves. (b) Accuracy curves.



(a) (b)

Fig. 11. Confusion matrix for CNN with residual connections. (a) ECG records without inversion detection and (b) ECG records with inversion detection.

### 6.4. Comparison to State-of-the-Art Methods

Table 5 establishes a comparative study, based on the F1 scores, between our work and the top-performing deep learning methods proposed for this problem. These include the methods proposed in [5, 6, 7, 8, 30]. In addition, we included three more studies that are similar to our method because they are based on deep neural networks. Specifically, we used the research developed in [13, 14, 15].

Our residual CNN model performs better than six methods out of eight. Only two methods developed by

Kropf et al. [6] and Datta et al. [8] surpassed our method by achieving an overall F1-scores of 95.62 and 99.02, respectively.

In terms of the feature extraction phase, while more than 150 features are extracted, our methodology is similar to Datta et al. [8] research work. However, the last employs a binary cascaded technique with two stages. The recordings are split into the "normal+others" and "AF+noisy" intermediate classes by the first binary classifier. The final classes "normal", "others", "AF", and "noisy" are the result of splitting each intermediate class into two groups using a separate binary classifier in an additional stage. This idea represents the main cause of their method's successful application. We therefore believe that further research into this cascaded method can lead to better performance.

The work achieved by Kropf et al. [6] initiates ECG record processing by extracting 380 features used for classification. This number is significantly larger than the number of features extracted in our method (188 features). Moreover, they used a bagged decision trees method based on random forest classifier. As result, when comparing the number of features in one hand and the obtained results in another hand, we can conclude that more complexity is introduced in their model without significant improvement in the classification accuracy.

Table 5. Classification accuracy: Comparative study with state-of-the-art methods.

| | F1 Score / class | | | | F1 score |
|---|---|---|---|---|---|
| **Method** | **N** | **A** | **O** | **~** | **Over all** |
| **Top 5 methods** | | | | | |
| Billeci [7] | 92.72 | 94.62 | 83.2 | | 90.18 |
| Teijeiro [5] | 93.29 | 95.74 | 84.62 | | 91.22 |
| Plesinger [30] | 95.30 | 95.83 | 85.94 | | 92.36 |
| Kropf [6] | 95.50 | 98.95 | 92.42 | | 95.62 |
| Datta [8] | 99.66 | 98.95 | 98.46 | | 99.02 |
| **Other deep NN** | | | | | |
| Xiong [13] | 92.31 | 96.91 | 82.17 | | 90.46 |
| Warrick [14] | 89.93 | 89.36 | 70.07 | | 83.12 |
| Andreotti [15] | 96.35 | 84.71 | 89.05 | | 90.03 |
| 5-layer CNN [ours] | 96.59 | 90.7 | 86.79 | 84.11 | 91.36 |
| Residual CNN [ours] | 97.21 | 94.96 | 93.15 | 85.58 | 95.11 |

## 7. Conclusion

In this work, we proposed a deep learning-based method to classify short-time single-lead ECG signals. These signals constituted a dataset presented during the 2017 PhysioNet Computing in Cardiology Challenge. Our proposed method operates through three main phases: preprocessing, feature extraction, and deep residual CNN-based classification. In the preprocessing phase, the method performs detection and correction of inverted signals. The proposed inversion detection algorithm is our first contribution in this work. In the second phase, we have combined a wide range of feature extraction algorithms, including morphological features, Heart Rate Variability (HRV) features, special AF features, statistical features and time and frequency features. The 3rd phase constitutes the main contribution of this paper, which resides on investigating deep residual CNN to classify short-time single-lead ECG signals.

We have carried out several experiments to study the proposed method. The experimental results show the effectiveness of the algorithm to detect and correct inverted signals. This algorithm led to significant improvements in the classification accuracy. As result, the proposed residual CNN model demonstrates better performance, especially compared many existing state of the art researches. In perspective, we are interested to extract, from both time and frequency domains, additional features that can improve the classification performance. In addition, the cascaded classifier approach can be another direction, where the first classifier divides the ECG signals into two classes, and then each class is further split into two sub-classes using other classifiers.

### Contributions

The main contributions of this paper are the following:

- Automatic mechanisms for detection of inverted signals.
- Proposing an algorithm for extracting a wide range of ECG features to be used jointly with a convolutional neural network classifier.
- Designing a lightweight CNN model based on the idea of residual connections for effective classification of short-time single-lead ECG signals.
- Validating the proposed methods on short-time single-lead ECG dataset presented in the 2017 PhysioNet Computing in Cardiology Challenge.

### Declaration of Interest

The authors have no relevant conflicts of interest to disclose.

### Data Availability Statement

The data supporting the findings of this research are freely available in the 2017 PhysioNet Computing in Cardiology Challenge at [*https://archive.physionet.org/challenge/2017/*], given in reference [2].

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