Sudden Cardiac Arrest Detection Using Deep Learning and Principal Component Analysis

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Abstract. Sudden cardiac arrest (SCA) is mainly caused by ventricular fibrillation and ventricular tachycardia, which are known as shockable rhythms and can be effectively treated with automated external defibrillators (AED). In this study, we propose a novel algorithm with high performance for detecting SCA on electrocardiogram (ECG) signals for use in the shock advice algorithm (SAA) applied in the AED. The algorithm utilizes a combination of principal component analysis (PCA) and convolutional neural network (CNN) model, using 5-fold cross-validation (CV). The PCA algorithm transforms 20 features extracted from ECG signals into 20 component features in different spaces where they are uncorrelated. Our proposed SAA algorithm achieves an accuracy of 99.0 %, a sensitivity of 94.7%, a specificity of 99.4%, and a balanced error rate of 2.9%.

Keywords: Sudden cardiac arrest (SCA) · Principal component analysis (PCA) · Deep learning (DL) · Automated External Defibrillators (AED) · Electrocardiogram (ECG)

1 Introduction

One of the serious health concerns in the world is sudden cardiac arrest (SCA), which also is considered a vital and life-threatening condition. The event appears when the heart experiences sudden, unpredictable electrical disturbances, resulting in the interruption of the pumping of blood. The source of this disease is shockable rhythms including ventricular fibrillation (VF) and ventricular tachycardia (VT), known as the abnormal waveforms of electrocardiogram (ECG) signals [1]. The ECG signals during SCA also include other abnormalities such as a widening of the QRS complex, a decrease in the amplitude of the QRS complex, and changes in the ST segment, for which correct diagnosis is implemented

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for decision support related to relevant treatments. Moreover, patients, who are under the SCA without basic life-support or emergency services in minutes, certainly have a relatively high mortality. Therefore, early prediction of SCA based on ECG signals is crucial for timely intervention, such as immediate treatment with cardiopulmonary resuscitation (CPR) and defibrillation by delivering an electric shock to the heart, which results in survival improvement [2]. In addition, prompt access to emergency medical services and treatment increases the chances of survival and reduces the risk of long-term complications. Currently, automated external defibrillators (AED) are effective portable medical device, which is used for SCA diagnosis and treatment with coutershocks to restore the electrical heart system. The center of the AED is a shock advice algorithm (SAA), which is responsible for quick SCA diagnosis for further decision-making [3].

In recent years, SCA detection has been paid intensive attention from scientists, especially, performance improvement of SAA using intelligent technologies. Correct detection of the shockable or non-shockable rhythm is crucial in providing effective treatment for patients with SCA. Recent advancements in machine learning (ML) [4–6] and deep learning (DL) [7–10] techniques have exposed promising results in ECG signal processing and SCA detection. Indeed, ML and DL techniques have been proposed to improve the performance of the AEDs for the SCA diagnosis with better performance in comparison to conventional methods including thresholds according to American Heart Association (AHA) recommendations [11]. DL-based SAAs have several advantages over ML-based SAAs, such as no feature extraction, better feature selection, and complexity reduction [8]. In addition, the main advantages of DL are automatic feature learning from data and no requirement for feature engineering. This is particularly useful due to complex ECG signals, which demand high-quality signal preprocessing and feature extraction techniques. Furthermore, a large amount of data is necessary for DL training, which allows this method to learn more complex relationships between input features and target outputs. This is particularly important in the case of SCA detection, where access to large and diverse datasets is crucial for achieving optimal performance.

Principal Component Analysis (PCA) is widely used for feature reduction extracted from non-stationary ECG signals containing the rapid changes of the waveform. Therefore, PCA is a useful tool in the development of accurate and efficient SCA detection systems. A key factor of informative feature selection is the correlation between input features, which is simply solved by the PCA. Indeed, this powerful method provides a robust feature estimation by the correlation degrees among the input features [12]. The transformation of the input feature space into a new space is implemented to generate ordered principal components based on their corresponding correlation degrees. As a result, the featured representative comprising a subset of highly uncorrelated input features is highlighted through the PCA transformation for further stages.

In our work, a novel SAA design is proposed using a convolution neural network (CNN) and principal components transformed from the original features by PCA, which contribute to the performance improvement of the proposed SAA for SCA diagnosis based on the ECG signals. Furthermore, the performance of the DL model using feature transformation is estimated through the 5-fold CV method on the validation set.

The main contribution of this work is the utilization of the PCA algorithm for feature transformation. The original features extracted from ECG signals, which are highly correlated with each other, are transformed into a new space including differently uncorrelated component features. Additionally, the utility of the CNN model with the 5-fold cross-validation method improves the SCA classification performance in the healthcare system, which leads to significantly reliable performance results for practical use in clinic environments.

The rest of the paper is organized as follows: Sect. 2 presents the data used for our method. Section 3 includes a description of the methodology of the proposed technique using feature extraction with conventional techniques, PCA algorithm to transform features, and DL models to diagnose SCA. The performance comparisons of the proposed algorithm with other existing methods are discussed in Sect. 4, followed by a discussion of the results. Finally, The conclusions are presented in Sect. 5.

2 Data

Creighton University Ventricular Tachyarrhythmia Database (CUDB) [13] and the MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB) [14] are used for this work due to its widely spread use in previous studies, which makes it easily compared. The ECG signals in these databases consist of shockable signals containing VF, VT, and ventricular flutter. Other rhythms in the above databases are the non-shockable signals. The CUDB contains 35 single-channel records with a length of 8 min for each record. The VFDB consists of 22 double-channel records of 35 min. For performance improvement purposes, the first channel of the individual is employed. The total of all records is 57, which are then separated into non-overlapping 8-s ECG segments. Therefore, there are 1135 shockable and 5185 non-shockable segments of these databases, which are considered for sampling at a frequency of 250 Hz. We grouped the entire ECG segments into training and testing data corresponding to 70% and 30%, respectively. As a result, 4303 segments of 40 records were used for training and 2017 segments of 17 records were for testing. Here, each record corresponds to a separate patient in the databases. Figure 1 shows the shockable and non-shockable 8 s ECG segments. The ECG signals are preprocessed as following steps:

(i) Implementation of the five-order moving average filtering to achieve signal smooth.
(ii) Removal of the baseline wander by the use of high-pass filtering with 1 Hz cutoff frequency.
(iii) Elimination of high-frequency noise by the 30 Hz low-pass Butterworth filtering.

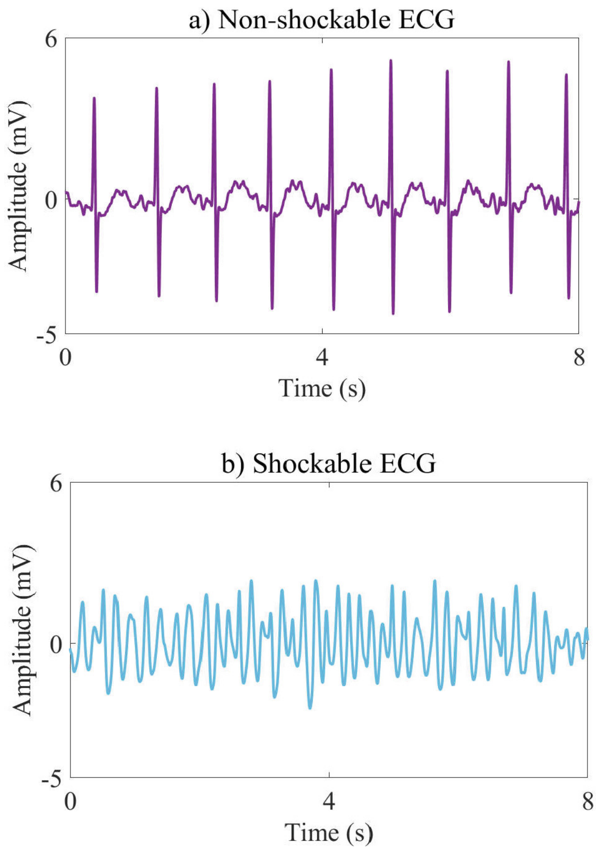

Fig. 1. Waveforms of non-shockable and shockable ECG signals.

3 Method

The are three steps shown in Fig. 2 for the construction of the proposed SAA. In the first step, the ECG databases are segmented and preprocessed for feature extraction in time and frequency domains. Then, two datasets are generated for training and testing corresponding to 70% and 30% of the total. In the second step, PCA is implemented for the transformation of the extracted features into the component space. Finally, two DL models, which are Long-short term memory (LSTM), and CNN are trained and validated by a 5-fold CV procedure.

3.1 Feature Extraction

The feature extraction is implemented by various conventional techniques. The three main categories of features are extracted temporal, spectral, and complexity features. Table 1 shows a set of 20 features extracted from the 8 s ECG segments [6].

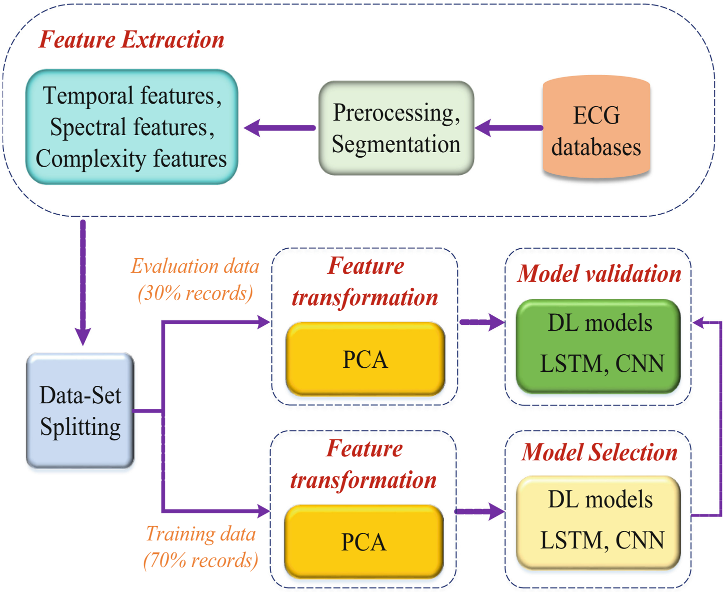

Fig. 2. Steps of method development.

Table 1. Extracted features.

Feature Type	Feature Name
Temporal features	bCP, threshold crossing sample count (TCSC), threshold crossing interval (TCI), modified exponential algorithm (MEA), Count1, Count2, and Count3
Spectral features	spectral analysis (S2), Li, bWT, bW, VF-filter leakage measure (Lk)
Complexity features	phase space reconstruction (PSR), frequency calculation (FB), Kurtosis (Kurt), complexity measure (CM), fuzzy entropy (FE), sample entropy (SE), energy (EN), Renyi entropy (RE)

3.2 Feature Transformation

The feature set is transformed into component space by the PCA technique. More precisely, all of the 20 features, known as observed variable Z_k, are transformed into a new space of 20 principal components F_k, which are independent and uncorrelated variables as follows [12]:

$$Z_k = l_{k1}F_1 + l_{k2}F_2 + ... + l_{kl}F_l + ... + l_{k20}F_{20} \tag{1}$$

Conversely, the components F_j can also be expressed as a linear combination of the original variables as follows:

$$F_j = a_{1j}Z_1 + a_{2j}Z_2 + ... + a_{20j}Z_{20} \tag{2}$$

The component F_j are uncorrelated with each other and ordered by the sample variance λ, that is, the largest sample variance represents F_1, the second largest sample variance is F_2, and so on. The sample variances corresponding to different components are known as eigenvalues, which show the share proportion in the total variance. Particularly, a constituent that holds a greater portion of the overall variation, denoted by a higher eigenvalue, within the initial features, holds more significance compared to those with smaller eigenvalues. The covariance matrix R of the original feature Z is as follows:

$$R = \begin{bmatrix} 1 & r_{12} & ... \, r_{1,20} \\ r_{21} & 1 & ... \, r_{2,20} \\ . & . & ... \quad . \\ r_{20,1} & r_{20,2} & ... \quad 1 \end{bmatrix} \tag{3}$$

where r_{12} represents the correlation between Z_1 and Z_2. The coefficients a_{1j} for component F_j, where j ranges from 1 to 20, encompass the eigenvector associated with the j^{th} largest eigenvalue λ_j. As a result of standardization, the sum of variances across all features is equal to the number of features, demonstrated as follows:

$$\lambda_1 + \lambda_2 + ... + \lambda_{20} = 20 \tag{4}$$

Hence, $\lambda_j/20$ represents the ratio of the entire variation attributed to the j^{th} component.

3.3 Model Selection

LSTM and CNN [15] are optimized models with parameter structures on the training set. Hyper-parameter tuning is crucial to identify optimal models and prevent over-fitting. Additionally, the classification performance of the selected model is estimated on the validation set. To determine the optimal parameter values for the model, we employ a combination of grid search and the 5-fold CV method in this work.

Convolutional Neural Networks: The most important element of the CNN is the neurons, which construct the layers within the CNN. The neurons are organized with three dimensions such as spatial dimensionality of the input including height width, and depth. There are three main layers of the CNN structure, which are the convolutional, pooling, and fully connected layers.

Convolutional Layer: This layer computes the output of neurons connected to local regions of the input by calculating the scalar product between their weights and the corresponding region within the input volume. The rectified linear unit (ReLu) is employed to introduce a wise activation function, such as the sigmoid, to the output generated by the preceding layer.

Pooling Layer: The layer simply performs downsampling along the spatial dimensionality of the given input, further reducing the number of parameters within that activation.

Fully-Connected Layer: This attempts to produce class scores from the activations, which are used for classification. The ReLu can be placed between the fully connected layers for performance improvement.

Long Short Term Memory: Vanishing gradients, which arise when learning long-term dependencies, even when the minimal time lags are very long, are serious problems. The LSTM model is one of the effective methods to overcome such problems. In general, a constant error carousel is used to prevent such a problem, which remains the error signal inside each cell of the unit. The LSTM architecture consists of a set of recurrently connected sub-networks, also known as memory blocks. The block functions to preserve the state across time and control the passage of information through nonlinear gate elements. The output of the block is cyclically linked back to its input and all of the gating components.

3.4 Model Validation

The 5-fold CV procedure is employed by the division of the ECG dataset into 5 parts. Each part is considered as testing data, while the remaining parts are arranged for training data. Hence, the procedure includes 5 run to complete an entire process. Moreover, the models are trained and tested repeatedly five times so that each subset serves as the testing data in the latter iterations to increase reliability. The mean and standard deviation of the classification performance are calculated for further estimation. Additionally, LSTM and CNN are optimized with parameter structures on the training set. Hyper-parameter tuning is crucial to identify an optimal model and prevent over-fitting. Then, the classification performance of the optimal model is estimated on the validation set. To determine the optimal parameter values of the model, we employ a combination of grid search and the 5-fold CV procedure in this work. The optimal model with the highest detection accuracy among others is selected as the final model for practical AED applications.

4 Results and Discussion

4.1 Results

The measured parameters are used in this work to estimate to diagnostic performance of the DL models. They are accuracy (Acc), sensitivity (Se), specificity (Sp), and Balanced Error Rate (BER). The Acc shows the proportion of ECG segments identified correctly. The accuracy of correctly identifying shockable and non-shockable ECG segments is represented by Se and Sp, respectively. The BER is calculated as $1 - 0.5.(Se + Sp)$.

Model Selection: The 20 features extracted from the ECG segments are transformed into a different space using the PCA transformation technique. They are used as the input features of DL models for searching for optimal structures.

Model Validation: The performance of two optimal DL classifiers is presented in Table 2. Generally, the CNN model is marginally more efficient than the LSTM model, achieving Acc of 99.03 %, Se of 94.74%, Sp of 99.37% and BER of 2.94%. On the other hand, the LSTM model has Acc of 98.50 %, Se of 88.74%, Sp of 99.07%, and BER of 6.09%. Therefore, in this work, we chose the CNN model for proposing the SAA algorithm.

Table 2. The detection performance of the model on the evaluation data.

Model	Acc (%)	Se (%)	Sp (%)	BER (%)
CNN	99.03 ± 0.19	94.74 ± 2.03	99.37 ± 0.23	2.94 ± 1.12
LSTM	98.50 ± 0.17	88.74 ± 4.43	99.07 ± 0.37	6.09 ± 2.04

Proposed Algorithm of SAA for SCA Detection. The SAA design, which is proposed for the AED in this study, includes a CNN model and 20 extracted features from the 8 s segment length of the ECG signals.

4.2 Discussion

Currently, the most effective way to treat cardiac arrest is using an affordable, reliable electronic device called an AED. The AHA recommends relatively high sensitivity and specificity for designing the SAA, but improving the detection performance is crucial to avoid incorrect diagnoses and increase the chance of survival.

The degree of correlation between features is important for determining their quality in classifying shockable and non-shockable rhythms on ECG signals. Feature correlation measures how much information is shared between features. Therefore, each feature should contain distinct information that can accurately distinguish between shockable and non-shockable ECG segments. The generation of the feature correlation is implemented by the PCA transformation. Indeed, the transformed features resulting from the PCA technique are highly uncorrelated and referred to as principal components, as shown in Eq. 2.

LSTM models are well-suited for modeling sequential data, which have a time-varying nature. They can capture long-term dependencies in the signal and can remember information from previous time steps, making them effective at predicting future events based on past events. Besides, CNN models are good at identifying patterns in time-series data, which is important for ECG analysis. They can identify important features in the ECG signal, such as the QRS complex or the ST segment, which are used to diagnose heart conditions. Therefore, LSTM and CNN models have been widely used for analyzing ECG data. They can capture temporal patterns, identify important features in the signal, and achieve high accuracy in predicting cardiac events. Indeed, Table 2 shows

Table 3. Performance comparison of the proposed algorithm to existing methods.

Ref	Database	Methods	Acc (%)	Se (%)	Sp (%)
This work	**CUDB, VFDB**	**PCA, CNN**	**99.03**	**94.74**	**99.37**
[16]	CUDB, VFDB	KNN, fuzzy C-mean clustering	99.01	99.14	98.97
[4]	MITDB, CUDB, VFDB	SVM, adBoost, Differential Evolution	98.2	98.25	98.10
[17]	CUDB, SDBB	CNN, LSTM	NA	92.71	97.6

the high performance of the DL models. The performance of the CNN model is higher than that of the LSTM.

In our work, a novel SCA detection algorithm based on PCA transformation and CNN technique is proposed that can be applied to the AED. To avoid overfitting problems caused by the small size of the public CUDB and VFDB databases, which are used in the training and validation data of the proposed SAA, the 5-fold CV method is applied to compute statistical performance results in both training and validation phases. The performance of proposed SCA detection in this work meets the AHA's requirement for accuracy Acc (≥90%), sensitive Se (≥90%), and specificity Sp (≥95%) [6].

Table 3 presents a comparison of our proposed SCA detection performance among recent publications using different methods. The results demonstrate that our proposed algorithm outperforms existing methods, making it suitable for use in the SAA algorithm for AED applications.

5 Conclusion

The timely and accurate detection of SCA plays a critical role in increasing the chances of survival. Therefore, the development of an SAA algorithm for SCA diagnosis that can achieve highly reliable detection performance is paramount to ensuring safe and effective diagnosis in AED applications. In our work, we proposed an effective SAA algorithm for AED that utilizes the PCA technique to transform the features into a different space where they are uncorrelated and independent variables. Additionally, we utilized a CNN model for diagnosis. The CNN model is carefully optimized using the 5-fold CV approach to increase the model's reliability and accuracy, making it suitable for practical healthcare systems. The combination of PCA with CNN achieves the high performance of SCA detection. Indeed, the proposed SAA demonstrates high performance on the evaluation data, with Acc of 99.03 %, Se of 94.74%, Sp of 99.37% and BER of 2.94%, which are higher than that existing using others DL and ML algorithms.

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