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Automated detection of shockable ECG signals: A review

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A B S T R A C T

Sudden cardiac death from lethal arrhythmia is a preventable cause of death. Ventricular fibrillation and tachycardia are shockable electrocardiographic (ECG)rhythms that can respond to emergency electrical shock therapy and revert to normal sinus rhythm if diagnosed early upon cardiac arrest with the restoration of adequate cardiac pump function. However, manual inspection of ECG signals is a difficult task in the acute setting. Thus, computer-aided arrhythmia classification (CAAC) systems have been developed to detect shockable ECG rhythm. Traditional machine learning and deep learning methods are now progressively employed to enhance the diagnostic accuracy of CAAC systems. This paper reviews the state-of-the-art machine and deep learning based CAAC expert systems for shockable ECG signal recognition, discussing their strengths, advantages, and drawbacks. Moreover, unique bispectrum and recurrence plots are proposed to represent shockable and non-shockable ECG signals. Deep learning methods are usually more robust and accurate than standard machine learning methods but require big data of good quality for training. We recommend collecting large accessible ECG datasets with a meaningful proportion of abnormal cases for research and development of superior CAAC systems.

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1. Introduction

Sudden cardiac death (SCD) is an essential preventable natural death cause. It has an estimated annual incidence of up to 5 million cases globally [1]. SCD is defined as a cardiac arrest that occurs within 24 h of symptom onset or when the victim is last seen well [2]. In cardiac arrest, the heart prevents beating or fails to beat effectively, resulting in the cessation of oxygen delivery to the complete body due to the stoppage of blood flow. Ischemic brain injury typically sets in within minutes of cardiac arrest [3], leaving only a small window of opportunity for therapy to abort SCD [4–6].

Most of the SCD cases are caused by ischemic heart disease, but the primary arrhythmic disorder is common in those aged below 35 years [2,7]. Regardless of etiological origin, early electrocardiographic (ECG) diagnosis of shockable versus non-shockable rhythm [8,9] upon circulatory collapse is crucial. The shockable ECG rhythms comprising ventricular fibrillation (VF) and ventricular tachycardia (VT) can potentially revert to normal sinus rhythm with the restoration of adequate cardiac pump function upon emergency administration of electrical shock delivered via implantable cardioverter-defibrillator devices [5] or automatic external defibrillator (AED) [4]. In contrast, shock therapy will neither reestablish sinus rhythm, nor cardiac flow in non-shockable rhythms, which comprise asystole (absent electrical activity in the heart) and pulseless electrical activity, where electromechanical decoupling disables heart contraction despite organized electrical heart rhythm [2,4–7,120,121]. Given that downstream management and prognosis are based on the correct ECG interpretation during cardiac arrest, artificial intelligence (AI) methods have been increasingly incorporated into computer-aided arrhythmia classification (CAAC) systems to enhance the accuracy of real-time detection of shockable ECG rhythms [9–11].

The majority of SCDs occur out-of-hospital without access to ECG diagnosis and resuscitation, resulting in poor survival or neurological outcomes [1–3]. In the setting of cardiac arrest, AED devices are generally used to deliver electrical shocks to the heart to revive normal heart rhythm [12]. Accurate ECG rhythm diagnosis (shockable versus non-shockable) is essential in AED design, which motivates the burgeoning development of novel CAAC systems and related AI-based methods.

2. The morphology of shockable and non-shockable ECG signals

The ECG is the primary and most accessible diagnostic tool for detecting diverse heart conditions, including ischemic heart disease, conduction abnormalities, and arrhythmia [13]. The ECG detects and records the heart rate and rhythm by detecting myocardial electrical activity throughout the cardiac cycle. In designing AED, the accurate identification of shockable versus non-shockable ECG rhythms is vital in order to establish defibrillation parameters [8–11]. Based on ECG signal characteristics, shockable and non-shockable rhythms can be classified using threshold values of heart rate, ECG QRS wave width and height[8]. These details are presented in Tables 1 and 2.

2.1. Shockable rhythms

2.1.1. Ventricular fibrillation (VF)

VF is a fatal arrhythmia that often results in death without timely intervention [14]. It may be due to ischemic heart disease, cardiomyopathy, or primary arrhythmic conditions [15]. During VF, due to rapid fine twitch-like contractions of the myocardium, the heart cannot supply the blood appropriately to get meaningful output. Hence, early identification is critical for the delivery of shock therapy [16,17]. An example of VF signal is shown in Fig. 1 [18].

2.1.2. Ventricular tachycardia (VT)

VT is described as three or more ventricular ectopic beats in a sequence [15]. Ventricular ectopic is characterized by broader ECG QRS morphology. When VT exceeds 30 s, it is termed sustained VT. Unlike VF, VT can sometimes produce reasonable cardiac output and be compatible with life. However, it can also induce hemodynamic compromise, especially at higher heart rates, resulting in cardiac arrest (pulseless VT). Additionally, it can degenerate into VF. Hence, early detection of cardiac arrest is essential. An example of VT signal (Ref. [18]) with a broader QRS duration of individual ECG complexes is depicted in Fig. 2.

Table 1
Classification of shockable and non-shockable rhythms based on width of QRS complex and beats per minute values of ECG signal.

Rhythm	Types of Rhythms	Origin	Width of QRS (ms) and beats per minute (BPM)
Shockable	(i) Polymorphic Ventricular Tachycardia	Ventricular	(i) QRS > 120 & BPM > 150
Non-Shockable	(i) Supraventricular Tachycardia	Supraventricular	(i) 120 < QRS < 150 & BPM < 150.
	(ii) Supraventricular Tachycardia with narrow QRS		(ii) QRS < 120 & BPM > 100.
	(iii) Other non-shockable rhythms with narrow QRS		(iii) QRS < 120
	(iv) (iv) Agonal Rhythms		(iv) QRS > 120 and BPM < 100.
			(v) BPM < 20

Table 2
Classification of shockable and non-shockable rhythms based on amplitude values of ECG signal.

Rhythm	Types of Rhythm	Amplitude (mV)
Shockable	(i) Coarse Ventricular fibrillation	(i) > 0.2 mV
	(ii) Fine Ventricular fibrillation	(ii) Between 0.1 and 0.2 mV.
Non-Shockable	(i) Asystole	(i) < 0.1 mV

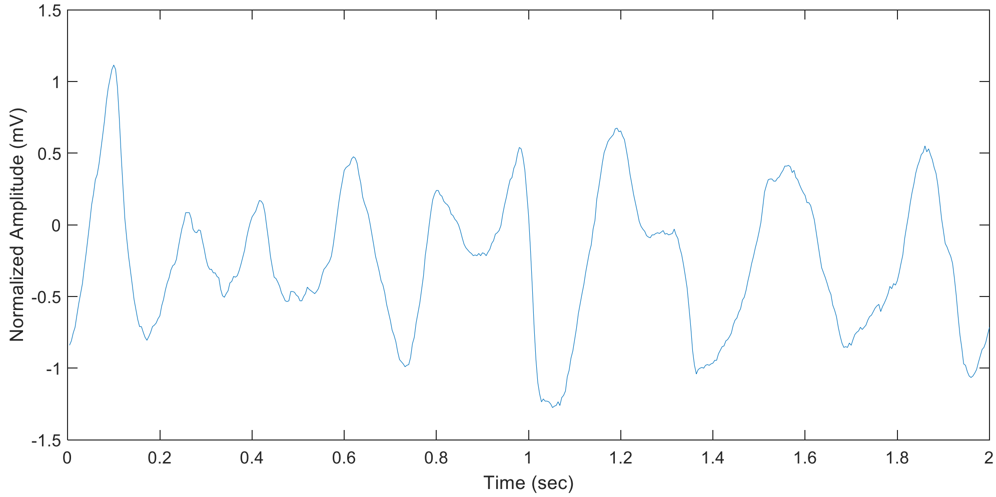


Fig. 1. An example of VF ECG signal.

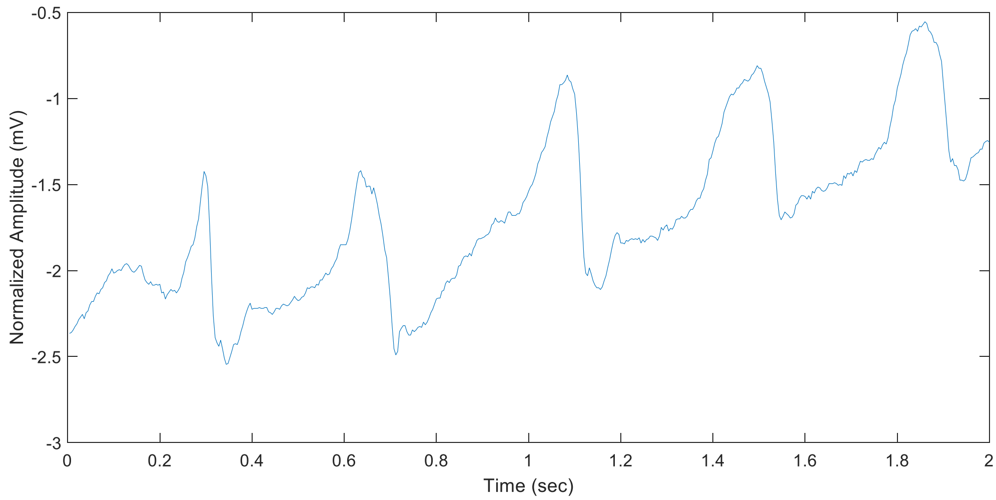


Fig. 2. . An example of VT ECG signal.

2.2. Non-shockable rhythms

2.2.1. Asystole

- There is both an absence of electrical (ECG depolarization and repolarization) and mechanical ventricular activities, which manifest as ''flatline'' on ECG and absent heart contraction. The ECG in systole is never truly ''flat'' due to signal noise. Hence, a threshold value of <0.1 mV is typically applied [8]. An example of an asystole ECG signal (Ref. [18]) is shown in Fig. 3. Note that in addition to the subtle signal variation, there is a broader baseline fluctuation that is probably due to body movement, for instance, during cardiopulmonary resuscitation. The illustration exemplifies the difficulty to differentiate from fine VF, as mentioned above [12].

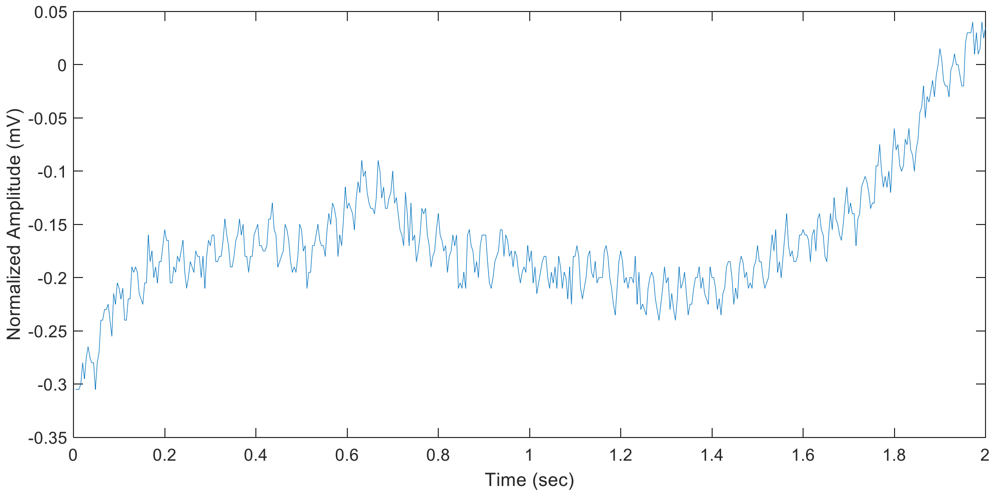


Fig. 3. An example of an asystole ECG signal.

2.2.2. Pulseless electrical activity (PEA)

The presence of an organized ECG rhythm without a detectable pulse is referred to as PEA. It includes normal sinus rhythm, sinus tachycardia, and supraventricular tachyarrhythmias such as atrial fibrillation (AF), atrial flutter, atrioventricular nodal reentrant tachycardia, and atrioventricular reentrant tachycardia [8]. Generally associated with palpable pulses, these ECG rhythms' appearance during cardiac arrest implies electromechanical dissociation where electrical activity is uncoupled from and fails to induce cardiac myofibril contraction. Possible causes, including severe biochemical, metabolic, hemodynamic, and mechanical derangements, should be systemically ruled out and reversed rapidly if possible. Electrical shock therapy is unlikely to restore adequate cardiac output. An example of a PEA signal (Ref. [19]), sinus tachycardia, is shown in Fig. 4.

3. Computer-aided arrhythmia classification (CAAC)

Manual inspection of morphological alterations associated with various shockable and non-shockable ECG rhythms is subjective, qualitative, and error-prone. The discrimination between shockable rhythms from non-shockable must be instantaneous and accurate. The ECG during cardiac arrest can be dynamic. One of the main challenges for detecting actionable shockable rhythm lies with transitional beats, which is when the non-shockable rhythm changes into the shockable rhythm. In such conditions, immediate recognition is required for life-saving treatment [8]. AED devices are embedded with different CAAC algorithms, while the efficiency of the device depends on the type of CAAC algorithm integrated in it.

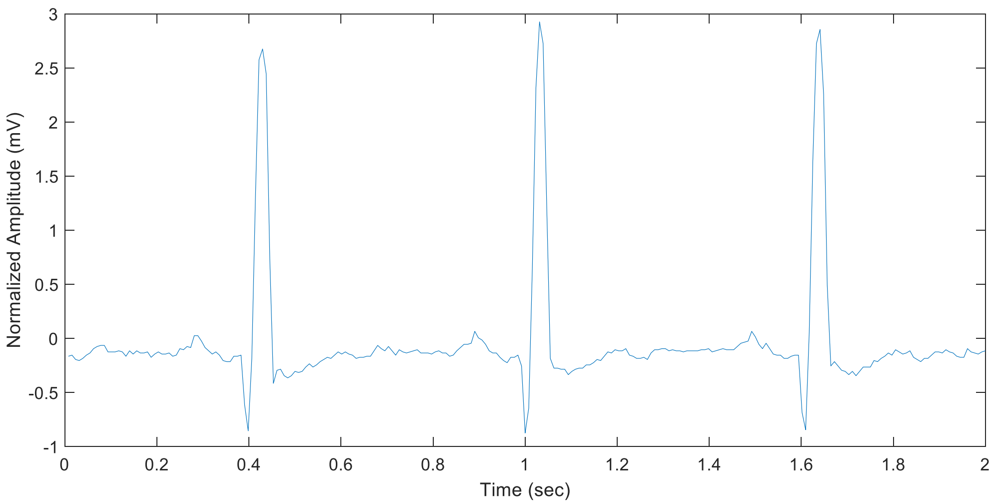


Fig. 4. An example of a sinus tachycardia ECG signal.

This article reviews the state-of-the-art methods developed for shockable arrhythmia detection. The general block diagram of a CAAC system is shown in Fig. 5. A detailed description of each block of CAAC is given in the following sections.

AI is a branch of science involving the design of computer programs that simulate human intelligence methods in extracting and processing information based on previous experience and then making decisions [20]. AI has various applications in many fields, such as healthcare [21,22,116–119], gaming [23], data security [24–26], and others[27–29].

This paper reviews the related studies that have applied AI to shockable rhythm recognition in the literature, from 2015 to 2020. Besides, we are focusing on the effect of nonlinear features in recognizing the shockable rhythms. We carried out the experiments by analyzing the impact of various nonlinear feature combinations in terms of the accuracy, comparing our results with those provided by the state-of-the-art methods. To the best of our knowledge, this is the first comprehensive review focusing on nonlinear features for automated detection of shockable ECG signals.

4. Databases

For ECG-based signal analysis, several databases are publicly available. This section lists the most widely-used databases for shockable rhythms analysis, describes how the database records were obtained, and discusses recorded signals' characteristics.

4.1. MIT-BIH arrhythmia database

This database [19,30] can be downloaded freely from (https://www.physionet.org/content/mitdb/1.0.0/) [19]. The database comprises >4000 long-term ambulatory ECG recordings. There are 48 half-hours, two-channel ambulatory ECG recordings of 47 subjects (male: female 25:22; age range 23–89 years), and two additional recordings (201 and 202) characterizing the same subject. The resolution for digitization is 11 bits over a 10-mV range, and each channel is digitized at 360 samples per second. The lead configuration of the database is as follows: the modified lead II (ML-II), lead V1, was obtained by locating the electrodes on the chest. In ML- II, the normal QRS complexes are notable. In some cases, (as in records 102 and 104), surgical dressings (some of the subjects were inpatients) precluded ML-II, and the alternative lead V5 was used.

The records of the MIT-BIH database, according to the Association for the Advancement of Medical Instrumentation (AAMI), are partitioned into five groups: normal (N), supraventricular ectopic (SVE), ventricular ectopic (VE), fusion (F), and unknown (Q) (see Table 3).

4.2. The Creighton University Ventricular tachyarrhythmia database (CUDB)

The Creighton University Ventricular Tachyarrhythmia Database (https://archive.physionet.org/physiobank/database/cudb/) [31] includes data of 35 subjects with 8-minutes ECG recordings. It concerns patients that have suffered continuous VT, ventricular flutter, and VF seizures. All database records were digitized in real-time analog signals from patient screens except for the first record obtained from a long-term ECG (Holter) recording. The records were digitized at 250 Hz with 12-bit resolution over a 10 V range with 127,232 samples for each record.

4.3. MIT-BIH Malignant Ventricular arrhythmia database (VFDB)

The MIT-BIH Malignant Ventricular Arrhythmia Database (https://archive.physionet.org/physiobank/database/vfdb/) [18] includes data of22 subjects with half-hour ECG recordings who have suffered continuous seizures of VT, ventricular flutter, and VF. All annotations of this database concern rhythm change, most of them are marking changes in cardiac rhythm.

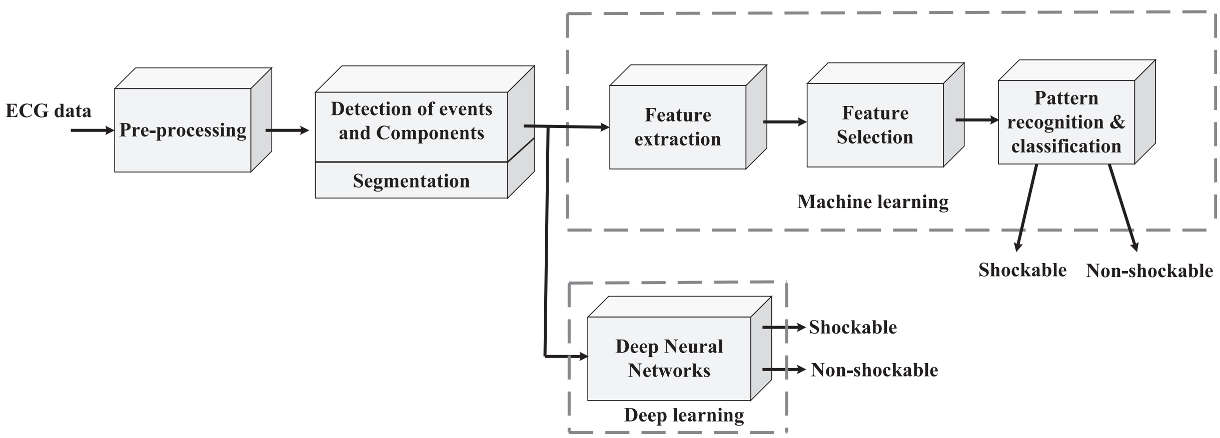


Fig. 5. General block diagram of a CAAC system.

Table 3
Summary of ECG beats presented in the MIT-BIH database according to ANSI/AAMI EC57: 2012 standard classes.

MIT-BIH	N	SVE	VE	F	Q
heartbeat types	Normal	Atrial premature	Premature ventricular contraction	Fusion of normal and ventricular	Paced
	Left bundle branch block	Aberrant atrial premature	Ventricular escape		Fusion of normal and paced
	Right bundle branch block	Nodal (junctional) premature			Unclassifiable
	Atrial escape	Supraventricular Premature			
	Nodal (junctional) escape				

4.4. American Heart Association Database (AHADB)

The American Heart Association (AHA) (https://www.ecri.org/american-heart-association-ecg-database-usb) [30] presents information about ventricular ectopy, collected over 40 years, based on its severity. The AHA is a structured dataset used to evaluate ventricular arrhythmia of 82-channel selections of analog ambulatory ECG recordings. These recordings are classified into eight classes. Each class has10recordings, as the most important of which are: 1) Ventricular ectopy, 2) Isolated unifocal PVCs, 3) Isolated multifocal PVCs, 4) Ventricular bi- and trigeminy, 5) R-on-T PVCs, 6) Ventricular couplets, 7) Ventricular tachycardia, and 8) Ventricular flutter/fibrillation. There are two versions of this database; the first one is the short version that includes 30 min of annotated signals and 5 min of unannotated signals. In comparison, the extended version includes two and a half hours of unannotated signals and 30 min of annotated signals. Besides, 75 records are available as the test set for the evaluation.

4.5. The MIT-BIH atrial fibrillation database (AFDB)

The MIT-BIH Atrial Fibrillation Database (https://physionet.org/content/afdb/1.0.0/) [30,32] comprises twenty-five long-term ECG recordings of subjects suffering from atrial fibrillation. Each record contains two ECG signalswith10-hour duration and sampling rate of 250 Hz. In Table 4, we have summarized the number of training and testing data used in this study.

4.6. Cross-validation of data

The k-fold cross-validation is a beneficial technique which can be used to address the overfitting issue [33]. In the k-fold validation, the available n samples are divided into k disjoint subsets each of size n/k. The cross-validation experiment is repeated k-times, using each time one of these subsets for validation, while the remaining subsets are used for training purposes. In our study, a popular 10-fold cross-validation scheme was employed.

5. Methods

Nowadays, AI has been increasingly used in designing CAAC systems. AI methods for ECG analysis can be classified into *two* main approaches: traditional machine learning (ML) and deep learning (DL) methods. In the following sections, we discuss robust ML and DL methods used for classifying shockable and non-shockable rhythms. Furthermore, we discuss in detail the advantages, disadvantages, challenges, and possible future research directions in this relevant field.

Table 4
The total number of 2 s ECG segments (Train + Test) collected from three datasets.

Database	**Class name**	**Train**	**Test**	**Total**
MIT-BIH	Shockable	19,000	4760	23,760
	Non-Shockable	8640	2160	10,800
CUDB	Shockable	1280	320	1600
	Non-Shockable	569	143	712
VFDB	Shockable	2854	714	3568
	Non-Shockable	15,625	3907	19,532
Total		47,968	12,004	59,972

5.1. Machine learning (ML) methods

ML methods used for automated detection of shockable ECG signals include four main steps: preprocessing the input ECG signals, extracting the features (attributes) from the preprocessed signals, selecting the subset of essential features from the extracted features, and feeding these features to the classifiers (Fig. 5).

5.1.1. 1) Preprocessing

Robust preprocessing algorithms are needed to have high classification accuracy. This preliminary step reduces the ECG signal noise by smoothing the ECG signal and reducing drift suppression and baseline wander. This preprocessing step makes the ECG signal suitable for subsequent processes. The most common methods used to reduce signal noise are the following: (i) Second-order low-pass and high-pass Butterworth filtering [9,34–38], (ii) Daubechies wavelet 6 (db6) [39]; and (iii) Orthogonal wavelet filter [11,40]. In addition, many previous works have segmented ECG signals into ECG beats or segments of varying durations (e.g., 2 and 5 s) before extracting the features. The most common algorithm used here is the Pan-Tompkins algorithm [41], which detects the ECG R-peaks for segmentation.

5.1.2. 2) Feature extraction

The next stage is the feature extraction stage, which is considered the most crucial stage in ML. Previous studies have mostly focused on developing optimal feature extraction methods. The common extracted features applied to shockable ECG rhythm diagnosis can beclassifiedinto*four*maincategories:temporal/morphologicalfeatures, spectralfeatures, time–frequency/wavelet features, and complexity features (nonlinear features[42]). The complexity features are the widely-explored feature extraction method [42] used in CAAC systems for shockable diagnosis because of the time-varying and random nature of ECG signals. The details on these features are given below:

a) Temporal/Morphological features

These features are described in the time domain, representing amplitude, slope, and heart rate. The most common features are threshold crossing interval (TCI) [43], threshold crossing sample count (TCSC) [44], mean absolute value (MAV) [45], standard exponential (STE) [46], and modified exponential (MEA) [46].

The TCI is determined as the time interval between sequential pulses that crosses a threshold. The threshold value is set to 20% of the maximum absolute values of each one-second segment. Similarly, the TCSC is an enhanced version of the TCI parameter with some changes consisting in the use of a three-second segment instead of a one-second segment, consideration of both positive and negative thresholds instead of only the positive threshold, and counting samples that meet the preset interval within a given time interval instead of counting pulses. The STE is determined as the number of crossing points of an ECG signal with a decaying exponential curve on both sides. The MEA is the altered version of STE that elevates the curve at the point of crossing onto their lative maximum. This change gives rise to more reliable detection results. Besides, many other temporal and morphological features have been used in other studies, but they are less typical. These features include auxiliary counts (count1, count2, and count3) [47], bCP [48], x1, and x2 [49]. These features are used to decrease the dimension of ECG signals.

b) Spectral features

These features are defined in the frequency domain. They account for spectral concentration, normalized spectral moments, and the corresponding power information in different frequency bands. These features include VF filter (VFleak) [50], spectral algorithm (M, A1, A2 and A3) [51], and median frequency (MF) [52].

The VFleak is a narrow band-stop filter response that determines the mean frequency region of an ECG segment, and its output is the VF filter leakage. The spectral algorithm computes the power information and energy content over different frequency ranges using Fourier analysis. The MF is a central frequency of the spectral mass observed in an ECG segment. In addition, there are some other spectral features used in literature such as spectral characteristics (x3, x4, and x5) presented in [52] or time-domain baseline content (bWT) presented in [48].

c) Time-frequency/wavelet features

These features are based on wavelet analysis of ECG signals such as kurtosis [53], measuring the proportion of outliers inclined to the distribution of a sample data, and skewness[54], measuring the asymmetry of the data around the sample mean, standard deviation, and other features. These features are provided a frequency and amplitude moderated function.

d) Complexity features (nonlinear features)

These features include different measures associated to the complexity of the considered ECG segment [55,56].The most common complexity features extracted from ECG include the recurrence quantification analysis features (RQA) [57], Shanon entropy [58], Renyi entropy [58], sample entropy (SamEn) [59], permutation entropy [60], fractal dimension (FD) [61], approximate entropy (ApEn) [62], higher order spectra (HOS) [63], and the energy [64].

The RQA parameters measure the patterns recurrence and ascertain the complexities in ECG signals [57]. The main RQA features are as follows: Recurrence Rate (RR1, RR2), Determinant (DET1, DET2), entropy (ENTR1, ENTR2), Mean diagonal length (L1, L2), Recurrence time entropy (RP), and Longest diagonal line (DD) [65–68]. The Shannon entropy demonstrates that information obtained from a specific event is inversely proportional [58]. SamEn quantifies the entropy of an ECG segment. A low value of SamEn shows that the signal is more like to itself. A high value of SamEn intimates the chance of shockable rhythms [59]. Renyi entropy (re) has a higher dynamic range compared to Shannon entropy [58]. HOS is a spectral presentation of third and higher-order moments that defines nonlinear correlations of multiple frequency components of an ECG signal [63]. The HOS features extracted are named: HOS Entropy 1, 2, 3, and 4. The features of the HOS are estimated using the bispectrum $B(f_1, f_2)$, which is the Fourier transform of the 3rd order correlation of a signal. In this paper, bicoherence and the normalized bispectrum (in the range from 0 to 1) plots for shockable and non-shockable signals are presented [63,69]. The energy feature (e) is used to estimate the regularity in a signal [64]. In addition, there are other less common complexity features such as covariance (CVbin), area (abin), frequency (Frqbin), kurtosis (Kurt), and sLog Energy [53].

In summary, this paper focuses on the nonlinear features, specifically on the energy and entropy measures. Thus, the following entropy measures were considered in our study: Shanon entropy [58], Renyi entropy [58], SamEn [59], permutation Eentropy [60], and modified multiscale entropy [70]. The entropy of an ECG signal becomes higher as the signal variability and complexity increase.

5.1.3. 3) Feature selection

This step allows one to remove the number of redundant features, reduce the computational cost, and improves the system's overall performance. The *three* primary categories of feature selection methods used on this step are as follows: a) wrapper methods, b) filter methods, and c) embedded methods.

a) **Wrapper**: It is considered the best approach for selecting features in terms of accuracy, but at the cost of computational complexity [71]. This method uses cross-validation by training the model many times using different features and comparing the results. The common methods here are: 1) recursive feature elimination [72], 2) forward feature selection [73], and 3) genetic algorithms [74].
b) **Filter**: This approach uses statistical measures to select the best set of features before the training process. Here, the features are evaluated against a proxy rather than cross-validation accuracy. The common techniques are as follows: 1) correlation, 2) chi-squared [75], 3) analysis of variance (ANOVA) [76], and 4) ReliefF [77].
c) **Embedded**: This approach includes the methods that do not fall into the above-mentioned approaches (wrapper and filter). L1 regularization is an example of such a method [78].

5.1.4. 4) Features reduction

AT this step, a smaller set of new variables is established, each being a mixture of input variables, including the same information as the whole set of input variables. Many feature reduction techniques transform the selected features into low dimensional space. Principal component analysis (PCA) [79], linear discriminant analysis (LDA) [79], and locality sensitive discriminant analysis (LSDA) [80] are examples of feature reduction techniques.

5.1.5. 5) Classification

Classification is the final step used to categorize the input ECG signal class after choosing the vital features. Classification methods can be grouped into two categories: supervised learning and unsupervised learning. In supervised learning, specific outcome labels are predefined, whereas, in unsupervised learning, the class belongings are determined based on a clustering concept. When designing a CAAC system, we are able to get use of previous records with predetermined results (e.g., shockable rhythm versus non-shockable rhythm). Hence, supervised ML methods are widely used in this area.

Supervised ML methods can be broadly categorized into a classification or a regression category. As the output of a CAAC system consists of a discrete set of output labels, many proposed CAACs take advantage of the efficiency of conventional classification algorithms, such as Support Vector Machines (SVMs) [81], Naïve Bayes Classifier [82], k-Nearest Neighbors (k-NNs) [83], Decision Trees (DT) [84],and ensemble classifiers [85–87], in recognizing shockable arrhythmias.

5.2. Deep learning (DL) methods

In recent years, extended versions of neural networks, called deep neural networks, have attracted much interest in computer-aided diagnosis implementation for almost all diseases [88,89]. Deep networks consist of *two* or more fully connected multilayer perceptrons. Based on their construction, deep learning networks are classified into various classes such as fully connected networks, belief networks, and convolutional networks. One of the main advantages of deep learning networks is that they perform the feature extraction automatically. The common deep learning networks used in ECG signal analysis are convolutional neural network (CNN) [90,91] and recurrent neural network (RNN) [92].

The most critical stage in data classification is the feature extraction stage. It affects the system's overall performance more than other stages. The use of DL network scan improves the robustness of a CAAC system compared to an ML-based system where the features are extracted manually. In general, DL algorithms are more effective than classical ML algorithms for detecting shockable ECG signals. The main shortcoming of DL is the shortage of big data training samples required to train the networks for a better performance.

5.3. Performance evaluation metrics

Various metrics used to evaluate an ECG classification task are given below [93]:

Accuracy(Acc): this is the most widely-used metric for determining the system's overall performance. It is defined as follows:

$$\mathrm{Acc} = (\mathrm{TP} + \mathrm{TN})/(\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}), \tag{1}$$

where, TP, TN, FP, FN represent the number of true positives, true negatives, false positives, and false negatives, respectively.

Sensitivity(Sen): Also known as recall, sensitivity represents the proportion of true positives among the entire set of positive samples:

$$\mathrm{Sen} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{2}$$

Positive Predictivity (Pre): Also known as the precision, it represents the proportion of TP among all classified positive and is defined as follows:

$$\mathrm{Pre} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP}) \tag{3}$$

Specificity (SP): Also known as true negative rate, it represents the proportion of true negatives among all classified negative samples:

$$\mathrm{SP} = \mathrm{TN}/(\mathrm{TN} + \mathrm{FP}) \tag{4}$$

F-measure**:** It is a harmonic mean of positive prediction and sensitivity, defined as follows:

$$\text{F-Measure} = 2\times(\mathrm{Pre} \times \mathrm{Sen})/(\mathrm{Pre} + \mathrm{Sen}) \tag{5}$$

Area under curve (AUC): This metric, computed from receiver operator characteristic(ROC) analysis, is also widely used in ECG-based studies [9].

6. Results and discussion

In this section, we discuss step-by-step machine learning results and describe robust state-of-the-art conventional ML and DL techniques developed for shockable ECG signal detection. We outline the main advantages disadvantages of these methods and provide future recommendations for designers of CAAC systems.

The input shockable ECG signals acquired from publicly available databases, such as MIDB and VFDB, have some high and low frequency noise which may lead to wrong classification of ECG signals. Thus, the data preprocessing step becomes crucial to ensure that the impact of noise in the input ECG signals is minimized. We analyzed various data filtering methods used to preprocess shockable ECG rhythms and found that the Butterworth high-pass filter is performing well in reducing drift suppression and baseline wander [9,35,36,38]. Fig. 6 summarizes the effects of several filtering techniques used for removing the noise from the ECG signals. Fig. 7 shows the ECG signal obtained after applying the Butterworth filtering and high pass filter for baseline wander techniques [9,35,36,38].

6.1. Results of feature extraction

The majority of classifiers used in the literature provide a high detection accuracy of shockable ECG rhythms only if the main features are extracted correctly. It can be noted that linear SVM provided the highest overall classification accuracy compared to other classifiers applied to the same databases (MIDB, CUDB, VFDB, and AHADB). The performance of the three main categories of features extraction methods (mentioned in Section 5) using an SVM classifier (a base classifier for all experiments in this paper) for the common databases for 2 s ECG segments (see Table 4) is shown in Fig. 8. A 10-fold cross-validation technique was used in all our experiments.

As shown in Fig. 8, the complexity (nonlinear) features category of methods provided the highest average accuracy compared to the temporal and spectral categories. Therefore, in this study, we focused on the analysis of nonlinear feature extraction in detecting shockable arrhythmia signals.

In this work, 23 nonlinear features were extracted from ECG signals and fed to SVM classifier for classification. Table 5 reports the average mean and standard deviation values of the extracted nonlinear features for both shockable and non-shockable signal classes of 2-second signals obtained from common ECG databases (i.e. CUDB, MIDB and VFDB).

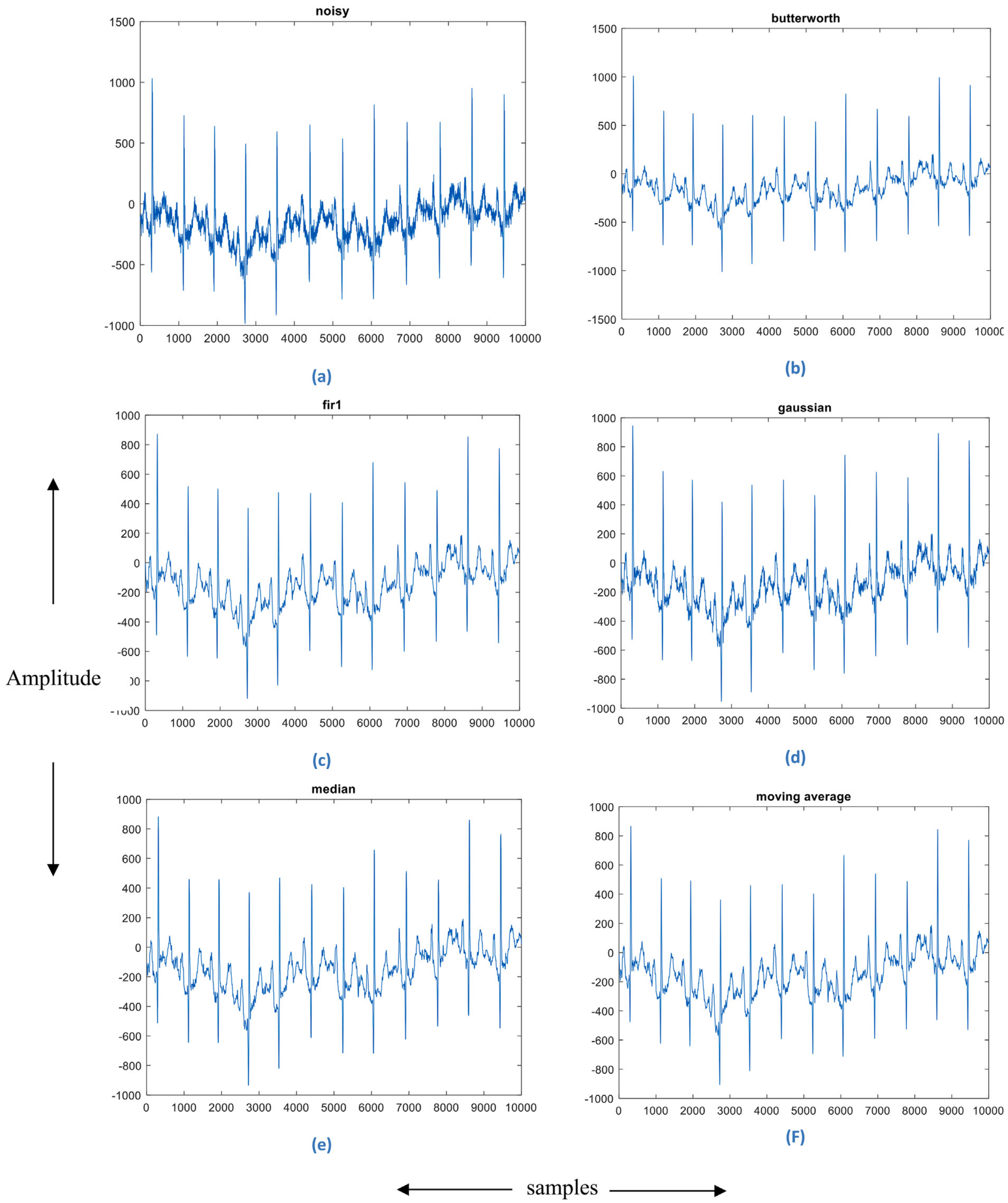


Fig. 6. Effect of using several filtering techniques: a) the noisy signals, b) after applying Butterworth filtering, c) finite impulse response (FIR)filter, d) Gaussian filter, e) Median filter, f) moving average filter.

Table 5, summarizes the average means and standard deviations of the extracted nonlinear features reported for both shockable and non-shockable signal classes. The presented results show the effectiveness of non-linear features in characterizing the shockable rhythms. We then identified 10 most informative combinations of features (using the feature selection

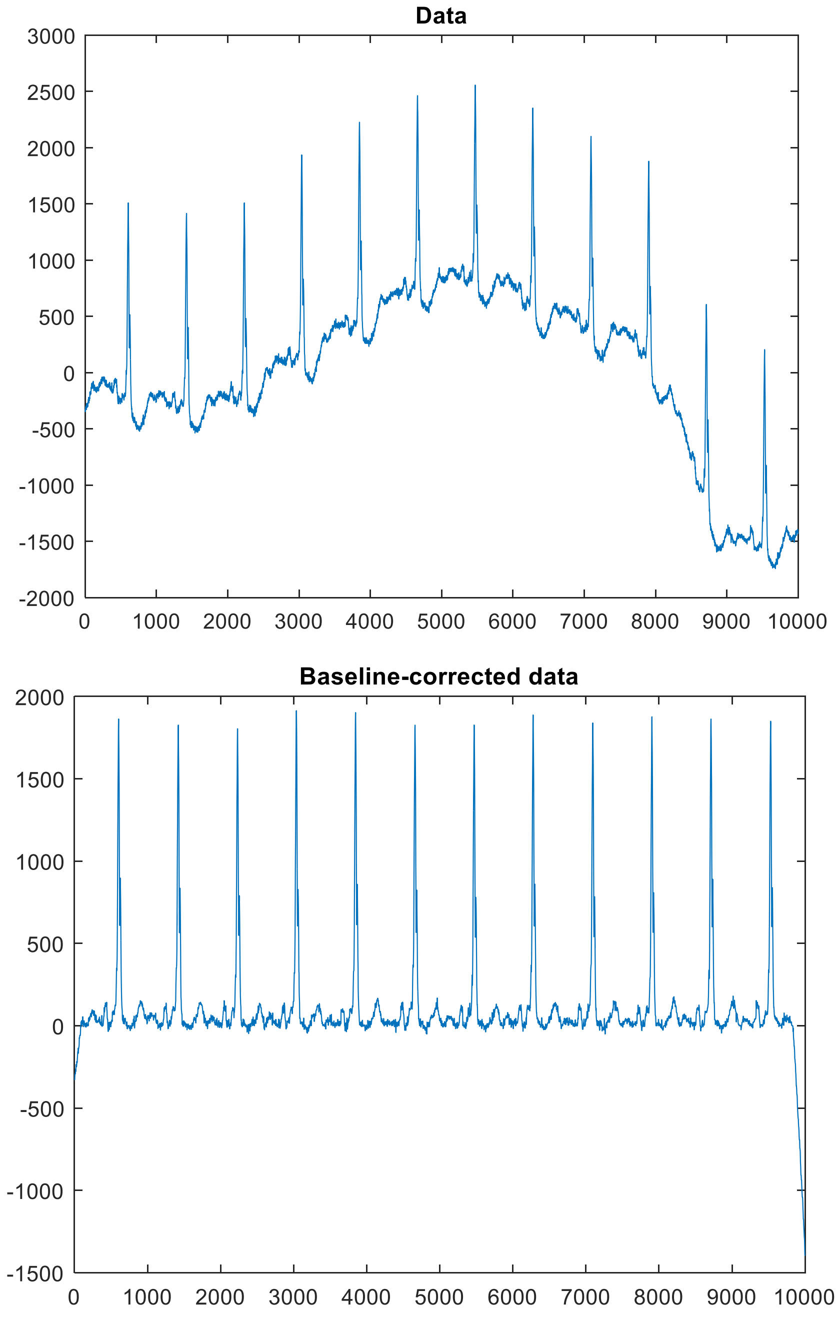


Fig. 7. Elimination of baseline wander using filtering methods.

algorithms, see Section 5, that provided the highest average accuracy over all datasets). These combinations of features are reported in Table 6.

It is worth noting that the use of a single feature led to a low performance compared to combinations of features. For instance, when using only ApEn, we obtained the accuracy of 70.78% only, whereas combing it with other nonlinear features, such as ApEn, FD, and hurstExponent, helped us increase the accuracy to 86.54%. Also, we can observe that combining more non-linear features leads to increase in the accuracy; we obtained the highest accuracy when combining all non-linear features together.

Fig. 9 presents typical bispectrum contour plots for shockable and non-shockable ECG signals collected from FVDB. From a visual inspection of the figures, we can discriminate between shockable and non-shockable subjects. In the non-shockable

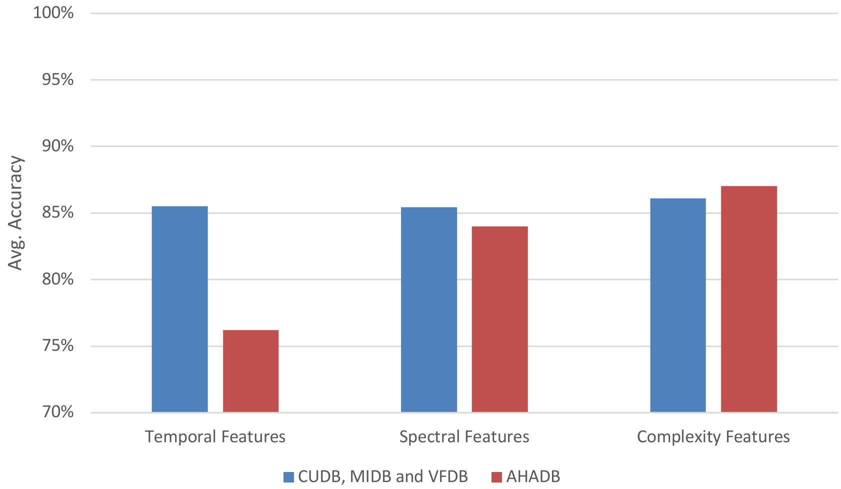


Fig. 8. Average accuracy (%) of the feature extraction methods for all common ECG databases.

Table 5
Summary of the average mean and standard deviation (Std) values of the extracted nonlinear features reported for both shockable and non-shockable signal classes.

Feature	Nonlinear Features			
	Non-Shockable		Shockable	
	Mean	Std	Mean	Std
ApEn	0.4974	0.2609	0.5761	0.2896
FD	1.2412	0.1042	1.3353	0.1203
HOS entropy 1	0.2862	0.1133	0.3020	0.1069
HOS entropy 2	0.1260	0.1251	0.1300	0.1000
HOS entropy 3	0.0835	0.1207	0.0857	0.0951
HOS entropy 4	2.7502	0.5597	2.8301	0.5188
Hurst exponent	0.8935	0.0874	0.9179	0.0699
modifiedMultiScaleEntropy	0.1395	0.1112	0.2053	0.1697
Permutation entropy	0.6906	0.0059	0.6920	0.0018
Renyi entropy	−23.5925	1.8065	−23.6152	1.6079
Sample entropy	0.5163	0.0982	0.5781	0.1167
Shanon entropy	−1.9904	4.3479	−1.6275	2.8209
sLogEnergy	23.5590	1.9834	23.1670	1.9447
RR1	0.0106	0.0012	0.0106	9.7414
RR2	0.1747	4.4533	0.1747	8.3925
L1	2.2693	0.1031	2.2637	0.1111
L2	5.3439	5.3439	6.7125	1.7904
DET1	0.3647	0.0485	0.3529	0.0422
DET2	0.9595	7.7932	0.9595	1.3428
ENTR1	0.4442	0.0527	0.4322	0.0476
ENTR2	1.7556	5.1213	1.7556	1.3428
RP	0.1056	0.3081	0.1162	0.3205
DD	1.6765	1.3557	1.5837	1.3326

ECG plots (Fig. 9(a,c)), there are connections between two-frequency spectrums, and the peaks are concentrated in the center. In the non-shockable ECG plots (Fig. 9(b,d)), there are spectrum connections and the peaks are present entire plot and spread throughout the frequency spectrum. Fig. 10 presents a typical recurrence plot(RP) of non-shockable (Fig. 10(a,b)) and shockable signals (Fig. 10(c,d)). More dots (changes) could be observed in the non-shockable signals compared to the shockable ones. Also, a more regular pattern in the recurrence plot of a shockable ECG could be observed, indicating a higher rhythmicity compared to a non-shockable ECG.

The confusion matrix plots for shockable and non-shockable ECG signals without using the PCA strategy, and using this strategy, for the three datasets (CUDB, MIDB and VFDB) are shown in Fig. 11(a) and (b), respectively, where the average accuracy of 87.95% was obtained without using PCA, and that of 91.14% when using PCA. The discussed algorithm used without PCA provided the sensitivity of 82.8%, positive predictivity of 94.6% and specificity of 94.3%, whereas, when using PCA, the sensitivity of 83.7%, positive predictivity of 98.7% and specificity of 98.6%, were achieved.

Table 6
Accuracy results obtained using 10 most informative ECG signal features.

Order number	Selected combinations of features ordered according to their accuracy	Acc (%)
1	Renyi entropy + Shanon entropy + permutation entropy + sample entropy + ApEn + FD + RQA + HOS + modifiedMultiScaleEntropy	87.95
2	Renyi entropy + Shanon entropy + permutation entropy + sample entropy + ApEn + FD + RQA + HOS + sLogEnergy + Hurst exponent	87.95
3	Renyi entropy + Shanon entropy + permutationEntropy + sample entropy + ApEn + FD + RQA + HOS + modifiedMultiScaleEntropy + Hurst exponent	87.54
4	Renyi entropy + Shanon entropy + permutation entropy + sample entropy + ApEn + FD + RQA + HOS + modifiedMultiScaleEntropy + sLogEnergy + Hurst exponent	87.13
5	Renyi entropy + Shanonentropy + permutation entropy + sample entropy + ApEn + FD + RQA + HOS	86.70
6	ApEn + FD + Hurst exponent	86.54
7	Renyi entropy + Shanonentropy + permutation entropy + sample entropy + ApEn + FD + RQA + HOS + modifiedMultiScaleEntropy + sLogEnergy	86.31
8	ApEn + FD + sLogEnergy	85.72
9	ApEn + FD + RQA	85.31
10	ApEn + FD + permutation entropy	85.31

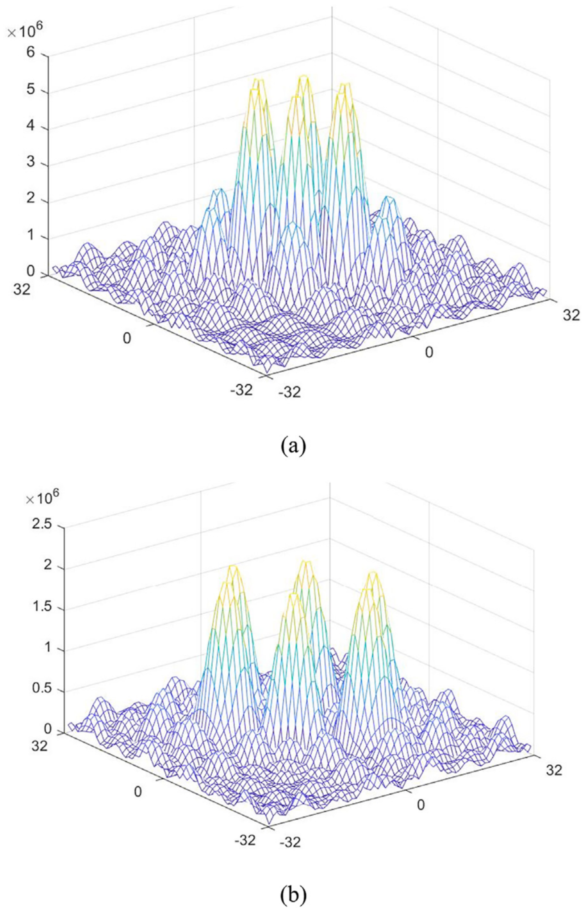
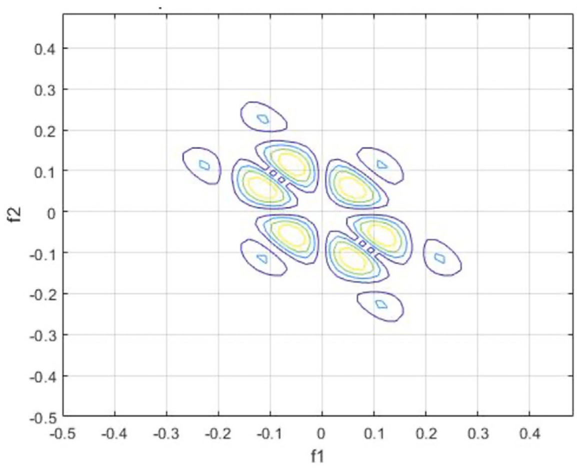


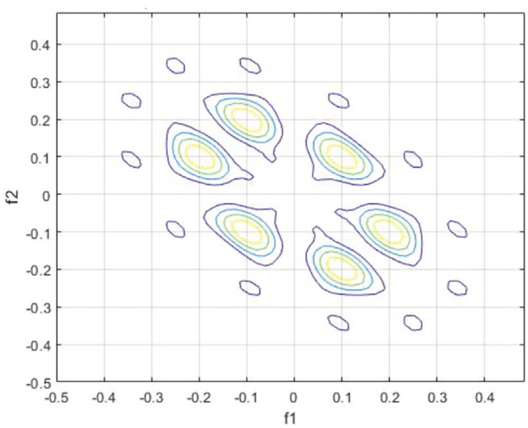
Fig. 9. Typical bispectrum and its contour plots for non-shockable (a,c) and shockable(b,d)ECG signals.

Table 7 presents the summary of main experimental results provided by conventional ML methods used for automated detection of shockable ECG signals.

Many ML methods focus on the improvement of the results of the feature extraction step. There are also a few drawbacks related to morphological feature methods such as TCI, TCSC, etc. The main limitation of the TCI method is the choice of one-



(c)



(d)

Fig. 9 (*continued*)

second analysis window, which may miss the R peak when the heartbeat rate is <60 bpm (a not uncommon occurrence among normal subjects as well as in the database records) or when there is a post-ectopic pause. When this happens, the method will make a wrong decision. The TCSC method does not consider the shape of the ECG signal, and therefore may fail to recognize some shockable cases.

We recommend using the complexity measure method [55,56] for feature extraction because of its ability to work with non-uniformly-spaced trajectories. Also, we recommend using agenetic algorithm with sequential forward feature selection for feature extraction. These two methods have achieved the highest accuracy compared with other method [36].

The performance of the presented ML methods depends on the selection of robust features extracted using advanced non-linear signal processing techniques. Hence, it depends on the expertise of the practitioner carrying out this selection (very subjective). Most of the methods perform well on smaller datasets and the prediction accuracy falls gradually as the size of dataset grows. In order to overcome these limitations, the appropriate DL models should be implemented, tested and used in practice.

6.2. Deep learning

Several deep learning models have been proposed in the literature to overcome the problems of traditional machine learning technique s[100–108]. Fig. 12 reports the classification accuracies obtained for the MITDB data using various deep learning models of automated detection of shockable ECG signals. It can be observed that the use of a single CNN model led

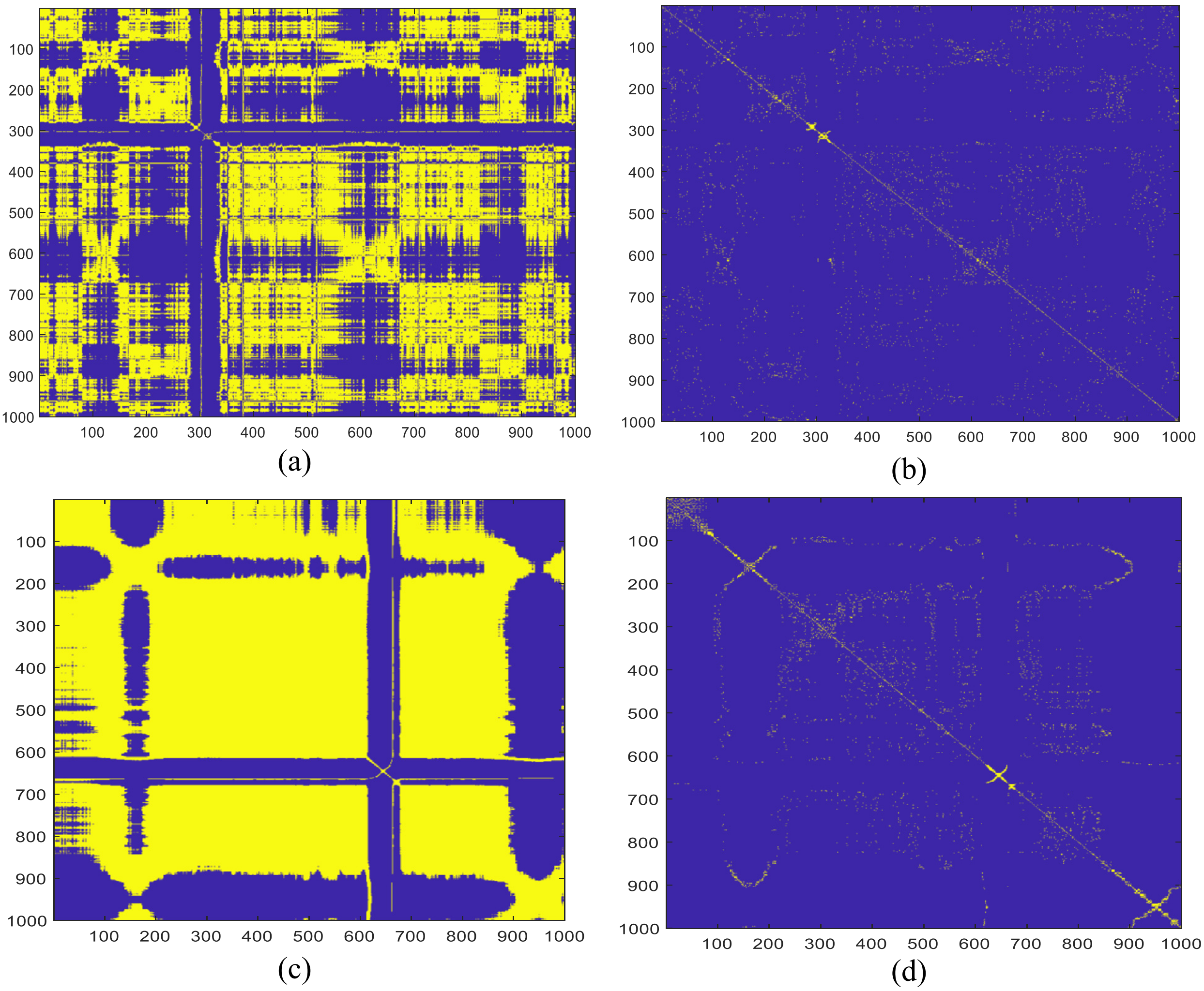


Fig. 10. Typical recurrence plot for non-shockable (a,b) and shockable (c,d) ECG signals.

the highest accuracies comparing to the other models. As a result, this model is widely used for automated shockable ECG detection. The use of RNN with CNN has boosted the sensitivity of the model, compared to CNN alone. However, the obtained accuracy is still lower than that provided by CNN on this database. The use of the other models with CNN, such as SWT and LSTM, also leads the increase of their accuracy.

Fig. 13 reports the classification accuracies obtained using various deep learning models for automated detection of shockable ECG signals on the three common databases (CUDB, MITDB and VFDB). In this case, the use of CNN only led to a low performance compared to the other models. When hybrid features were used with CNN, the best overall performances were achieved. In addition, the use of CNN with LSTM and RNN has boosted the performance of the model compared to CNN alone.

Table 8 presents the summary of main experimental results provided by DL methods used for automated detection of shockable ECG signals.

Many DL methods make use of CNNs, which provided the highest performance compared to the other DL models. We recommend using CNNs with wavelet transform, which can ensure a good accuracy even for small datasets. The major drawbacks of most of these DL models are a possible overfitting and high computational complexity, which may result in unreliable performance. Overall, we can observe that DL methods are more robust than classical ML prediction models in most cases. However, most DL approaches require big data for an effective model's training and are usually very time-consuming.

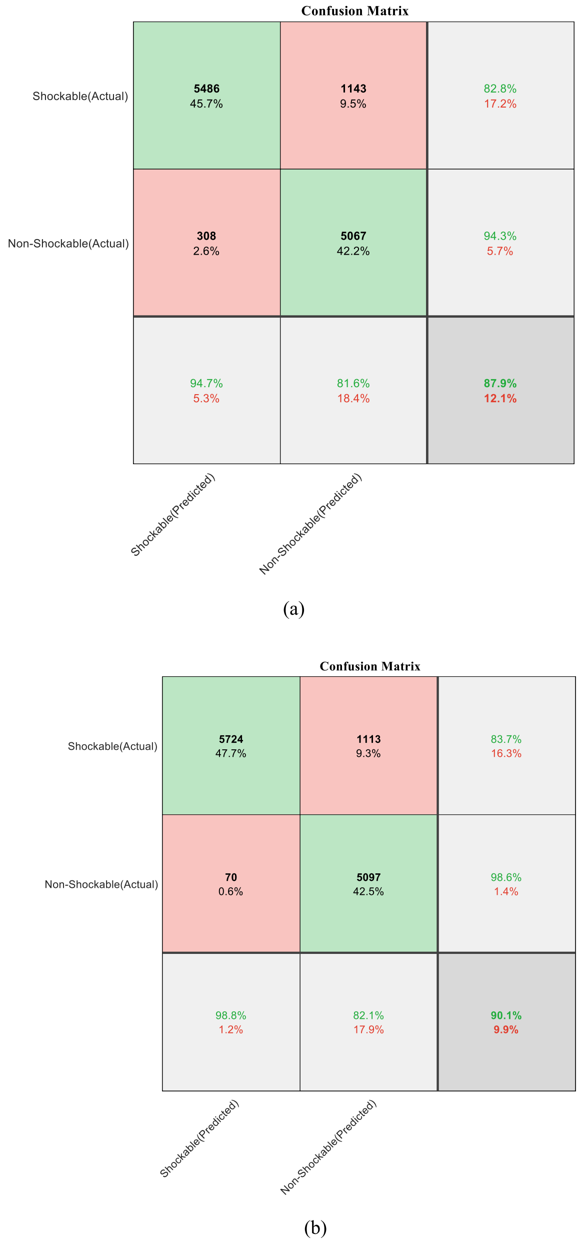


Fig. 11. Confusion matrix for shockable and non-shockable ECG signals: (a) without using the PCA strategy, and (b) using the PCA strategy.

Overall, the weaknesses of the existing CAAC systems are as follows:

i. **More data are needed.** Most of previous studies collected ECG signals from small databases, such as the MIT-BIH database, which led to a low classification performance especially using DL methods.
ii. **Collecting the data.** There is no standard methodology for collecting and organizing the data, which makes it difficult to compare them among different databases. In addition, the quality of ECG data used is generally low in most of the works focusing on short-term ECG recordings.
iii. **The complexity of deep learning models.** Most of DL models are complex, which hinders their deployment in real applications (e.g. portable healthcare devices). Moreover, the hardware used are generally very expensive.
iv. **Imbalanced data.** Most of the datasets considered in this field are imbalanced; the number of normal cases is usually much larger than the number of anomalous cases. This may affect the efficiency of DL models.
v. **Robust models need to be developed.** Many ML models are not robust and suffer from overfitting, which makes the models unsuitable for real applications.

Table 7
Summary of the main results provided by state-of-the-art machine learning methods used for detecting shockable ECG rhythms.

Author/Year	Methods	Database	Advantages	Disadvantages	Performance	Future works and suggestions
Nguyen et al. [34], 2018	Count2 VF-filter Leakage Measure (Lk) Threshold Crossing Interval (TCI) CentroidFrequency (CF) binary genetic algorithm SVM	CUDB VFDB	Overcome overfitting Less complex Obtained high accuracy with small features	Working on public database without clinical setting Low performance	Acc = 95.9% SP = 96.8% PPV = 87.6%	1. Try to work on other big databases 2. Try to apply this method to different kinds of ECG signals
Cheng and Dong [35], 2017	Personalized features SVM	MIT-BIH arrhythmia CUDBVFDB	Low complexity Fast	The design of QRS-complex template is not adaptive in this method	Acc = 95.5% SP = 95.6% AUC = 98.9%	Try to update the template for real-time ECG
Nguyen et al. [36], 2017*	GA SFFS with modified VMD SVM	CUDB VFDB	Obtained high performance with small features Overcome overfitting	Time consumed	Acc = 99% Sen = 97.36% SP = 99.61%	Try to apply this method to other ECG signals
Kong *et al.* [94], 2019	Integrated radial basis function (IRBF) and relevance vector machine (RVM)	MIT-BIHarrhythmia	1. Used for rapid modeling without parameter optimization 2. Used for fast modeling and recognition 3. Its prediction has probability significance	Data not suitable for real applications	Acc = 98.16%	Applied to consumer products, such as household or commercial massage chairs
Buscema*et al.* [95], 2020	Artificial adaptive systems and fuzzy transformation	AFDB MITBIH arrhythmia	1. Fast processing and suitable for real applications 2. Computationally highly efficient	The data not suitable for real applications	Acc = 95%	1. Remote monitoring of ECG over a novel device 2. Try to present new wearable photo-plethysmograph [PPG] wrist-watch sensor.
Kumar et al. [96], 2018	Flexible analytic wavelet transform (FAWT) Log energy entropy (LEE) Permutation entropy (PEn) Random forest (RF) classifier	MIT-BIH AFDB	1. No need for R-peak and P-wave detection 2. Robust system	Sensitive to the R-peak detection errors	Acc = 96.84%	Try to diagnose other cardiac diseases
Islam et al. [97], 2016*	HBD-irregularity Affine normalization	MIT-BIH AF and MIT-BIH Arrhythmia	1. Needs a minimum preprocessing and training 2. Robust to different kinds of noise 3. Applicable to different technologies	1. Overfitting problem 2. Low accuracy on big data	Acc = 96.38%	1. Try to develop a robust AF detection process 2. Try to use data augmentation technique
Asgari et al. [98], 2015*	Stationary wavelet transform SVM	MIT-BIH AFIB	1. Reduces the need for the detection of P-peak or R-Peak 2. High accuracy using short data segment 3. Does not depend on 4. R peak locations for the detection of AF	1. The method does not choose the most effective wavelet scale for denoising 2. Work on small data set	Acc = 96.9%	1. Further enhancement in terms of specificity 2. Try to enhance the method using multi-resolution analysis 3. Try to work on big data

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Table 7 (*continued*)

Author/Year	Methods	Database	Advantages	Disadvantages	Performance	Future works and suggestions
Ladavich et al. [99], 2015	Gaussian mixture model (GMM) Expectation–Maximization (EM) P-wave absence (PWA)	MIT-BIH AF	1. Robust to noise and artifacts 2. Can detect shorter AF episodes and AF episode endings with high accuracy 3. Rate independent	1. Cannot detect short episodes in large data sets 2. Depend on the absence of P-waves	Acc = 93.12%	1. Try to use this method with another kind of ECG signal 2. Try to use data augmentation technique
Tripathy et al. [37], 2018	Digital Taylor-Fourier transform (DTFT) Phase difference (PD) Least square support vector machine (LS-SVM) classifier with linear and radial basis function (RBF)	CUDB VFDB	Can be used for the detection of other pathologies from ECG signals	Complexity Time-consuming	Acc = 89.81% Sen = 86.38% SP = 93.97%	Evaluated the method for detection of other heart ailments
LIH et al. [9], 2017*	DWT nonlinear features Sequential forward feature selection (SFS) kNN	MIT-BIH arrhythmia CUDBVFDB	Highly sensitive in capturing the shockable rhythms Cost-effective	Complex	Acc = 98.34% Sen = 95.49% SP = 99.14%	Try to implement deep learning methods to increase the accuracy
Sharma et al. [11], 2019	Wavelet-based features Fuzzy entropy (FE) Renyi entropy (RenE) SVM	MIT-BIH arrhythmia CUDBVFDB	No need for pre-processing on ECG signals No need for R-peaks detections	Working on small data	Acc = 97.8% Se = 93.42% SP = 98.35%	Try to extract other nonlinear features to improve the performance
This Study 2020	Preprocrssing + renyiEntropy + shanonEntropy + permutationEntropy + sampleEntropy + ApEn + FD + RQA + HOS + modifiedMultiScaleEntropy + SVM	MIT-BIH arrhythmia CUDBVFDB	1. No need for detecting R peaks 2. Can be used for the detection of other pathologies from ECG signals 3. Robust system	1. Complex 2. Low accuracy with big features number	Acc = 87.95%	Using these features on other physiological signals (e.g. EEG) Using feature reduction techniques to improve the performance
This Study 2020	Preprocrssing + PCA + SVM	MIT-BIH arrhythmia CUDBVFDB	1. No need for detecting R peaks 2. Can be used for the detection of other pathologies from ECG signals 3. Robust system 4. Achieved high accuracy with low features number	Time consumed	Acc = 90.14%	Using these features on other physiological signals (e.g. EEG)

* RecomSmended.

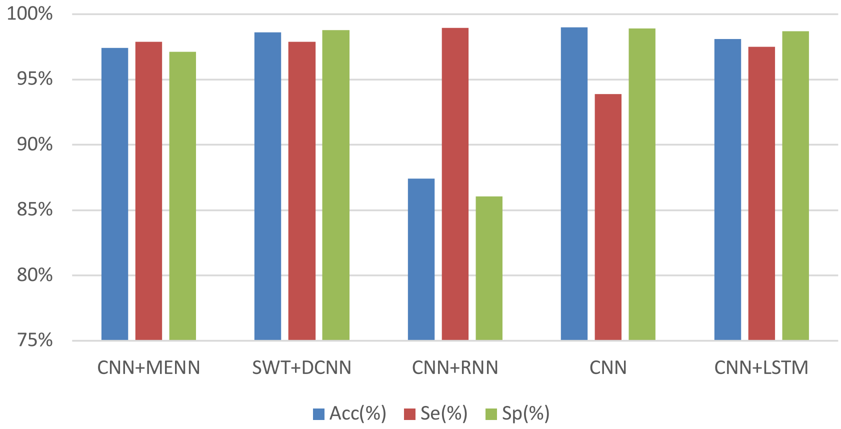

Fig. 12. Classification accuracies obtained using various deep learning models on MITDB.

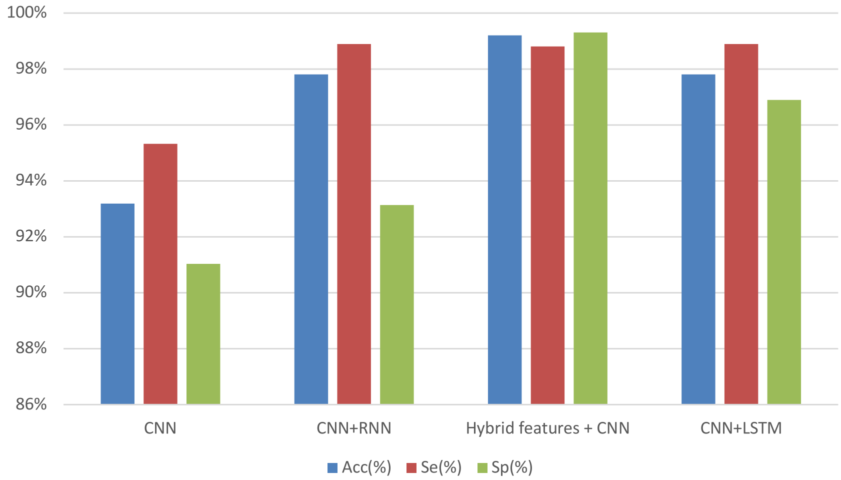

Fig. 13. Classification accuracies obtained using various deep learning models on CUDB, MITDB and VFDB databases.

The proposed solutions to overcome these limitations are as follows:

i. We recommend applying the existing state-of-the-art methods on big data, such as MWM-HIT database [109] and PTB-XL database [110], or constructing new large ECG datasets.
ii. We recommend collecting and working on new high-quality and long duration ECG data.
iii. We recommend using one of the compression techniques to convert the complex deep learning models into simpler models or building a deep learning model with fewer layers and activation functions.
iv. We recommend using data augmentation methods to increase the size of data sets, or designing a new training model [111], or new loss function such as the focal loss function, as discussed in [112].

We recommend using cross-validation techniques (e.g. 10-fold cross-validation [113]) to make the considered machine learning model more robust. In addition, we also recommend using optimization algorithms, such as a genetic algorithm for features optimization [114], in order to improve the overall performance of the models.

7. Future work

The cloud-based system linked to mobile and wearable devices for shockable arrhythmia detection could be proposed in the future. An example of such a system is shown in Fig. 14. The input ECG signals obtained from a wearable device are communicated to a smartphone and stored on a local server located in the hospital. After that, the data is sent to the cloud service, where a trained deep learning model is deployed and maintained to make the diagnosis. Finally, the diagnostic decision

Table 8
Summary of the main results provided by state-of-the-art deep learning methods used for automated detection of shockable ECG signals.

Author/Year	Methods	Database	Advantages	Disadvantages	Performance	Future works and suggestions
Andersen *et al.*[100] 2019	CNN RNN	AFDB MITDB NSRDB	1. Faster 2. classification of long-term recordings 3. The features are learned directly from the data	1. Problem with detection of the noisy ECG segments	Acc = 89.30%	1. Try to recognize the noise level in each ECG segment
Baalman*et al.* [101] 2020	Morphology based deep learning	Private AF data	Unique to classic rule-based algorithms No feature extraction stage	1. Low incidence of AF 2. Used limited information from single cardiac cycles of one single lead 3. Complexity	Acc = 96%	1. Try to use the Fourier cosine series as input for a neural network 2. Need improvements in visualization techniques
Panda et al. [102] 2020*	Fixed frequency range empirical wavelet transform (FFREWT) Filter-bank convolutional neural network	CUDBVFDB	Can used for the multiscale analysis of ECG signal. No feature extraction stage	Working on small number of subjects to develop the model	Acc = 99.03%	Try to use more training data
Acharya et al. [103] 2018	CNN	MITDB VFDB CUDB	Invariant to translation No need handcrafted feature for the classification No need R peak detection	Need a big data to train Training time of CNN is longer compared to models	Acc = 93.2% Se = 95.32% SP = 91.04%	Try to improve the performance by performing bagging algorithm and data augmentation
Xia *et al.* [92] 2018*	Short-term Fourier transform (STFT) Stationary wavelet transform (SWT) Deep convolutional neural network (DCNN)	MIT-BIH AFIB	1. Does not rely on peak detection 2. Can achieve good accuracy on a small data segment	1. Work on small data 2. Problem with detection of some signals 3. Time cost	Acc = 98.63%	1. Try to work on ECG signal directly 2. Try to work on big data 3. Try to work on other datasets
Dang *et al.* [105] 2019	CNN-BLSTM	MIT-BIH AF	1. Does not consume a large amount of time and energy for selecting and extracting features 2. Real-time speed 3. Low cost	1. Overfitting problem 2. The model is not employed for genuine clinical diagnosis	Acc = 96.59%	1. Try to use all the points of RR intervals 2. 2 Genuine clinical contributions needed 3. Classification of multiple arrhythmia signals 4. Try to work on other data
Li *et al.* [106] 2019	CNN-SVM method	Private AF data	1. High accuracy on big data 2. Overcome the overfitting	1. Low accuracy on small data 2. Complex	Acc = 96%	1. Try to establish a follow-up system 2. Try to work on big data
Faust *et al.* [95] 2018*	RNN	MIT-BIH Atrial Fibrillation Database	1. No feature extraction method 2. Can used for long-term monitoring 3. Cost effective	1. Using short segment 2. Working on limited data 3. Time cost	Acc = 99.72%	1. Try to use this algorithm in Internet of Things (IoT) technology 2. Try to detect different AF types 3. Try to work on different heart diseases 4. Try to work on different dataset
Wang Jibin [96] 2020	CNN and the improved Elman neural network (IENN)	AFDB MIT-BIH	1. End-to-end classification mechanism 2. The convergence rate of the model is also accelerated to some degree	Only focused on AF detection and needs more large and diverse data set	Acc = 98.8% Sensitivity = 98.6% Specificity = 98.9%	Try to combine more modified ENN structures with deep learning frameworks for analysis more types

* Recommended.

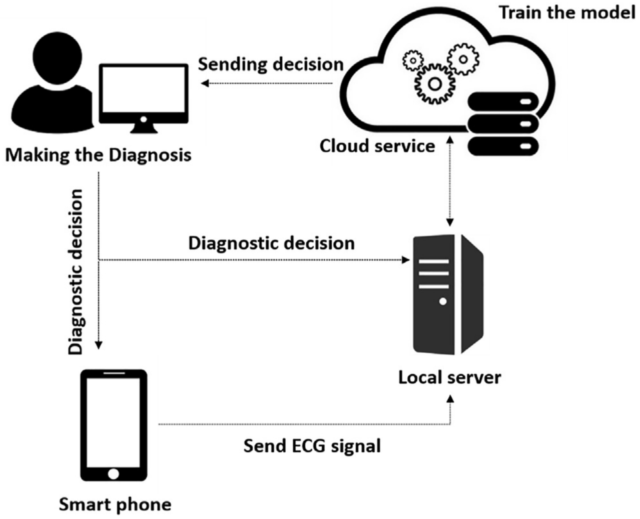

Fig. 14. Cloud-based system with mobile and wearable devices for shockable arrhythmia detection.

is sent back to the local server and the patient via a smartphone. Such a system processes the diagnosis automatically and could serve as triage to decrease the workload of healthcare specialists in hospitals. Most of the previous studies used CNN-based deep learning models; here, in addition, we recommend using other deep learning models, such as long short-term memory (LSTM) and autoencoders, and evaluating the required performance metrics.

Moreover, the use of non-linear features, such as Hurt and Lyponev exponents, and the proposed unique bispectrum and RP plots, can improve the classification performance. Besides, it would be also important to tackle the data imbalance problem by using one the existing data balancing procedures, e.g. the focal loss technique [115]. Furthermore, exploring some lightweight transfer learning models is also a possible solution to enhance the prediction accuracy. Finally, the impact of uncertainty, while building traditional machine learning and deep learning models needs to be investigated and evaluated [122].

8. Conclusions

Ventricular tachyarrhythmia is a preventable cause of sudden cardiac death. Early detection of shockable ECG rhythms, followed by emergency shock therapy, can save lives. The manual reading of ECG signals remains, however, a challenging task in the acute setting. Thus, the development of effective CAAC systems would help clinicians screen and recognize accurately shockable arrhythmias cases. In this paper, we have comprehensively reviewed recent CAAC systems for shockable arrhythmia detection developed from 2015 to 2020 and based on conventional ML and DL methods.

Furthermore, we have presented unique bispectrum and recurrence plots for visualization of shockable and non-shockable ECG signals. We have discussed the main advantages and drawbacks of the state-of-the-art CAAC systems and compared various conventional ML- and DL-based techniques for automated detection of shockable ECG signals. We found that DL methods generally provide more reliable performance in ECG modeling than conventional ML techniques. Unfortunately, the computational cost remains one of the main limitations of DL methods. Therefore, we are focusing on the effect of nonlinear features in recognizing shockable rhythms. Hence, we carried out the experiments by analyzing the impact of various nonlinear feature combinations in terms of accuracy, comparing our results with those provided by the state-of-the-art methods. We have obtained an average accuracy of 87.95% without using PCA, and of 91.14% when using this technique.

Several unresolved challenges related to the effective use of deep learning methods in shockable ECG modeling remain relevant. We have provided a few recommendations for tackling these challenges and improving a CAAC system's overall performance. We conclude that large public databases need to be created to classify shockable ECG detection data accurately.

CRediT authorship contribution statement

Mohamed Hammad: Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper. **Rajesh N.V.P.S. Kandala:** Conceived and designed the analysis, Wrote the paper. **Amira Abdelatey:** Wrote the paper. **Moloud Abdar:** Wrote the paper. **Mariam Zomorodi-Moghadam:** Wrote the paper. **Ru San Tan:** Wrote the paper. **U. Rajendra Acharya:** Wrote the paper. **Joanna Pławiak:** Wrote the paper. **Ryszard Tadeusiewicz:** Wrote the paper. **Vladimir Makarenkov:** Wrote the paper. **Nizal Sarrafzadegan:** Wrote the paper. **Saeid Nahavandi:**Wrote the paper. **Ahmed A. Abd EL-Latif:** Wrote the paper. **Paweł Pławiak:** Conceived and designed the analysis,Wrote the paper, Other contribution and supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary Material

Access to source code mentioned in the article:

1. Temporal/Morphological features and Spectral features

   https://github.com/FelipeURJC/ohca-vs-public-dbs.

2. Time-frequency/wavelet features:

   https://in.mathworks.com/help/stats/skewness.html.
   https://in.mathworks.com/help/stats/kurtosis.html.

3. Complexity features (nonlinear features):

   https://in.mathworks.com/matlabcentral/fileexchange/46765-recurrence-quantification-analysis-rqa.
   https://in.mathworks.com/matlabcentral/fileexchange/50289-a-set-of-entropy-measures-for-temporal-series-1d-signals.
   https://in.mathworks.com/matlabcentral/fileexchange/3013-hosa-higher-order-spectral-analysis-toolbox.
   https://www.mathworks.com/matlabcentral/mlc-downloads/downloads/submissions/13063/versions/1/previews/box-count/html/demo.html#:~:text=A%20possible%20characterisation%20of%20a,1%2C%202%2C%203).

4. Feature selection:

   https://in.mathworks.com/help/stats/feature-selection.html.

5. Classification and feature extraction:

   https://in.mathworks.com/help/stats/index.html?s_tid=CRUX_lftnav.

6. Deep learning:

   https://in.mathworks.com/help/deeplearning/ug/deep-learning-in-matlab.html#:~:text=What%20Is%20Deep%20Learning%3F&text=Deep%20Learning%20Toolbox%E2%84%A2%20provides,vision%20algorithms%20or%20neural%20networks.

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