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A REVIEW OF SHOCKABLE ARRHYTHMIA DETECTION OF ECG SIGNALS USING MACHINE AND DEEP LEARNING TECHNIQUES

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An electrocardiogram (ECG) is an essential medical tool for analyzing the functioning of the heart. An arrhythmia is a deviation in the shape of the ECG signal from the normal sinus rhythm. Long-term arrhythmias are the primary sources of cardiac disorders. Shockable arrhythmias, a type of life-threatening arrhythmia in cardiac patients, are characterized by disorganized or chaotic electrical activity in the heart's lower chambers (ventricles), disrupting blood flow throughout the body. This condition may lead to sudden cardiac arrest in most patients. Therefore, detecting and classifying shockable arrhythmias is crucial for prompt defibrillation. In this work, various machine and deep learning algorithms from the literature are analyzed and summarized, which is helpful in automatic classification of shockable arrhythmias. Additionally, the advantages of these methods are compared with existing traditional unsupervised methods. The importance of digital signal processing techniques based on feature extraction, feature selection, and optimization is also discussed at various stages. Finally, available databases, the performance of automated algorithms, limitations, and the scope for future research are analyzed. This review encourages researchers' interest in this challenging topic and provides a broad overview of its latest developments.

Keywords: deep learning, defibrillation, electrocardiogram, feature extraction, shockable arrhythmias, ventricular fibrillation, ventricular tachycardia.

1. Introduction

Cardiovascular diseases (CVDs) are the leading cause of high mortality rates, accounting for an estimated 17.9 million deaths each year. The World Health Organization (WHO) ranks CVD mortality as the highest among all causes of death (WHO, 2021). Cardiac arrhythmias, deviations from the heart's normal rhythm, present a significant clinical challenge. Of particular concern are

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shockable arrhythmias. CVDs occur when the blood supply to the heart muscle is obstructed or diminished in the coronary artery, which supplies blood to the heart. Heart disease, a type of CVD, refers to a wide range of disorders that impair the anatomy and functioning of the heart. However, not all heart diseases are cardiovascular diseases.

Arrhythmia, an irregular heartbeat, can be caused by heart disease in the atrium or ventricular region, and known as is a supraventricular (atrium) or ventricular arrhythmias, respectively (Kandukuri *et al.*, 2023). A complex electrical conduction system governs the rhythmic beating of the heart. Shockable arrhythmias result from severe heart electrical system disruptions, causing chaotic or excessively rapid signals in the ventricles. When these abnormal electrical patterns prevent the heart from contracting effectively, the result is a sudden loss of blood flow and, consequently, cardiac arrest. The only definitive treatment for shockable arrhythmias is defibrillation, the delivery of a controlled electrical shock to reset the heart's rhythm. Shockable arrhythmias represent a true medical emergency. The rapid deterioration from a chaotic or excessively fast heart rhythm to full cardiac arrest underscores the importance of swift diagnosis and intervention. Each minute that passes without treatment significantly decreases the chance of survival. For this reason, early recognition of shockable arrhythmias and the immediate availability of defibrillators are crucial in both healthcare settings and the community.

1.1. Background and motivation. Ventricular arrhythmias (Marsman *et al.*, 2014), VT and VF are recognized as lethal cardiac irregularities that can precipitate SCA, a condition resulting in sudden cardiac death within minutes if left untreated (John *et al.*, 2012). Globally, SCA accounts for approximately five million fatalities annually (de Luna *et al.*, 1989). Prompt intervention is paramount during SCA, with time being of the essence. Immediate treatment options such as CPR (Fumagalli *et al.*, 2018), AEDs, and implantable cardioverter-defibrillators (ICDs) (Josephson and Wellens, 2004) are most effective in restoring normal cardiac rhythm (Nichol *et al.*, 2017). AEDs and ICDs, capable of analyzing the heart's rhythm and delivering electrical shocks if necessary, are pivotal life-saving technologies (Didon *et al.*, 2021).

Ventricular arrhythmias may deviate from the typical sinus node initiation (Islam, 2021), possibly originating from Purkinje fibers, leading to premature ventricular contractions (PVCs) (Krause, 2023). In some instances, PVCs progress to sustained VT, a precursor to VF (Boston Scientific, 2024), which induces ineffective ventricular contractions and impedes sufficient blood circulation. The utilization of the ECG for arrhythmia analysis is common practice, but identifying shockable rhythms presents challenges to clinicians (Huang *et al.*, 2019), necessitating meticulous examination of ECG recordings. This process, often conducted over extended periods using devices like Holter monitors, is susceptible to human error due to fatigue, prompting the exploration of computational methods for automated classification. Timely recognition of shockable arrhythmias via the ECG holds promise in saving lives.

Moreover, VF waveform characterization, noted for its nonlinear, nonstationary, and chaotic nature, has been the focus of extensive research efforts aimed at enhancing detection algorithms for VT and VF (Small *et al.*, 2000; Patro *et al.*, 2022). Improving the accuracy of these algorithms, particularly in distinguishing shockable arrhythmias from non-shockable ones such as asystole, has emerged as a significant research endeavour (Hajeb-M *et al.*, 2022; Lu *et al.*, 2022). This motivation underscores the exploration of ventricular arrhythmias in the present survey, which delves into methodologies for examining VF waveforms. The survey encompasses a comprehensive review of techniques ranging from traditional signal processing methods to advanced machine learning (ML) and deep learning (DL) models, including HPO algorithms. These techniques are instrumental in the classification of shockable arrhythmias against non-shockable ones. Figure 1 illustrates a generalized block diagram derived from the literature, offering insights into the development of autonomous systems for arrhythmia identification using ECG signals. This entails preprocessing and segmentation of signals, feature extraction, feature selection for ML and DL models, and, ultimately, arrhythmia classification.

1.2. Pre-processing. The frequency range of the ECG signal is around 0.5–100 Hz. Most of the relevant information on heart functioning is located in this complex. In many cases, the QRS complex is corrupted by noise, making pre-processing crucial to eliminate the contaminated noise before classification (Shi *et al.*, 2021; Wang *et al.*, 2022; Shridhar *et al.*, 2019). Familiar noise sources include muscular artifacts (MAs), baseline wander (BW), and electrode motion (EM), which can be both low-frequency and high-frequency noises. Various established techniques for denoising ECG data include adaptive Fourier decomposition (Wang *et al.*, 2016), the S-transform (Ari *et al.*, 2013), the wavelet transform (WT), and empirical mode decomposition (Kabir and Shahnaz, 2012). Additionally, wavelet Wiener filtering (Smital *et al.*, 2013) is used to decrease electromyography noise in ECG readings.

In the literature on shockable arrhythmia classification, specific filters are used to remove noise from the ECG signal. To remove power line interference, fifth-order moving average filters (Amann *et al.*, 2007;

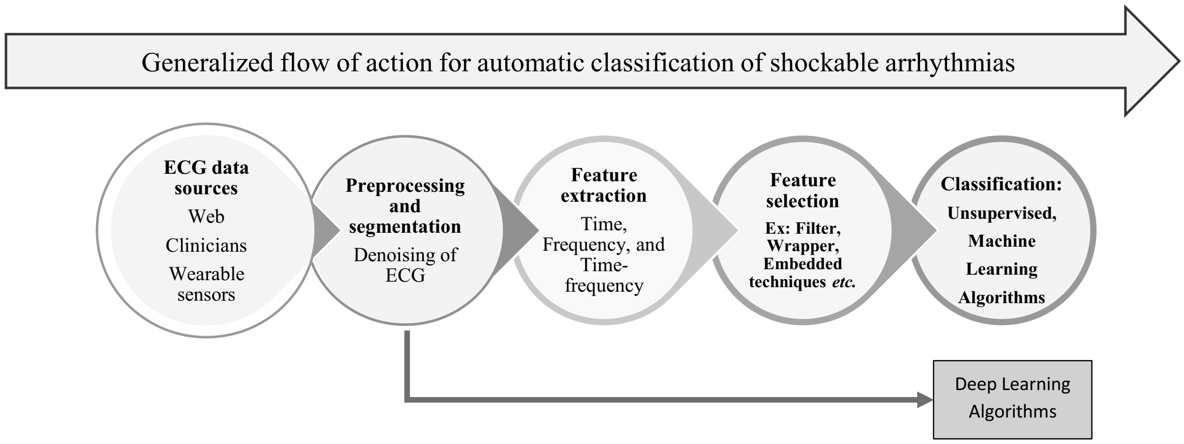

Fig. 1. Classification of shockable arrhythmias.

2005b; 2005a; Arafat *et al.*, 2011; Sinha and Das, 2021) and notch filters (Thakor *et al.*, 1990; Zhang *et al.*, 1999; Krasteva and Jekova, 2005) are commonly used. To suppress BW, a high-pass filter (HPF) with a 1 Hz cut-off frequency (Jekova and Krasteva, 2004; Clayton and Murray, 1999; Figuera *et al.*, 2016; Wang *et al.*, 2001; Noruzi *et al.*, 2017) is applied. A Butterworth low-pass filter with a 30 Hz cut-off frequency (Myers *et al.*, 1986; Selvakumar *et al.*, 2007; Li *et al.*, 2012; Okai *et al.*, 2018; Mohanty *et al.*, 2019; Ibtehaz *et al.*, 2019; Noruzi *et al.*, 2017) is used to suppress MA. Furthermore, Daubechies wavelets (Oh *et al.*, 2017) and orthogonal wavelet filters (Sharma, 2020; Sharma *et al.*, 2019) are also employed.

CPR can corrupt the morphology of the ECG signal, resulting in false decisions in AED rhythm analysis. To address this issue, researchers have used condition-based filtering algorithms (Hajeb-Mohammadalipour *et al.*, 2021) and adaptive filtering methods (Gong *et al.*, 2017) to enhance ECG signals. In addition, they have implemented new algorithms (Hu *et al.*, 2019; Didon *et al.*, 2011) and employed the frequency of compressions to gauge the CPR artifact (Irusta *et al.*, 2009). A least mean squares (LMS) filter has been used to dynamically adapt and estimate CPR artifacts (Eilevstjønn *et al.*, 2004), and a multichannel adaptive filter, precisely the multichannel recursive adaptive matching pursuit (MC-RAMP) algorithm, has been utilized to remove CPR artifacts (Gong *et al.*, 2016). This study introduces an improved adaptive filtering technique designed to mitigate CPR artifacts. Compared with the conventional adaptive filter, the proposed method has achieved a 1.7 dB enhancement in the signal-to-noise ratio (SNR) and a 5.6-point increase in accuracy. These findings demonstrate the efficacy of our approach in effectively attenuating artifacts associated with chest compressions and enhancing the precision of rhythm analysis during continuous CPR.

Before extracting features, authors have decomposed ECG signals into segments or beats, referred to as window sizes, typically ranging from 2 to 10 seconds.

1.3. Contribution of the paper. This study aims to contribute to the expanding knowledge on the early detection of shockable arrhythmias by examining real-time ECG signals. Our contributions to this field can be summarized as follows:

- An overview of shockable arrhythmias, their waveforms, and the immediate lifesaving technologies used to treat them is provided.
- The shockable arrhythmia detection model is discussed using ECG signal analysis. We present detailed literature on ECG analysis work for detecting shockable arrhythmias, ranging from traditional signal processing to advanced ML and DL techniques, including an overview of HPO.
- ECG datasets used in the state-of-the-art methods to detect shockable arrhythmias are discussed and summarized.
- Techniques for denoising the ECG signal to improve classification and eliminate false alarms are provided.
- A detailed review of traditional signal processing and machine learning feature extraction-based ECG classification algorithms is provided and their performance metrics are summarized. Moreover, we provide the pros and cons of the ML and DL methods and future directions.
- An overview of HPO techniques and their advantages is presented and some of the MA used in the ML

and DL algorithms to detect lethal arrhythmias are discussed.

- The limitations, challenges, and future scope of this field of study are discussed, and a comparative summary graph is provided.

This study reviews the literature on shockable arrhythmia classification methods and highlights the key approaches developed to create these automatic systems. The most prominent databases and performance measures used for shockable arrhythmia classification are also included. This study mainly focuses on shockable arrhythmia classification techniques. The issues, advantages, and future trends concerning the assessment of modern ML and DL methodologies reported in the literature are also examined. In addition, an overview of HPO techniques is also discussed. Although there are just a few review articles (Hammad *et al*., 2021; Dahal and Ali, 2022) in the literature on this subject, they only address some of these aspects. To enable readers to quickly find the desired information without having to search through various articles, this work provides an overview of all shockable arrhythmia classification techniques as a single resource that reviews all the aspects of ECG-based ventricular arrhythmia classification.

1.4. Paper organization. This paper is organized as follows. Section 2 discusses standard ECG signals as well as shockable arrhythmia signals and their representation. Sections 3–6 cover the databases, feature extraction, and classification of shockable ECG signals using traditional signal processing methods, ML methods, and performance metrics, respectively. Additionally, Sections 7 and 8 delve into DL methods and the use of HPO methods, respectively. Finally, Sections 9, 10, and 11 comprise the paper's discussion, limitations, conclusion, and future scope.

2. Difference between a normal ECG and a shockable arrhythmia

In general, the recorded electrical activity of the heart is visualized on a graph sheet, allowing doctors to easily observe all ECG episodes. Over a century ago, Dutch scientist Willem Einthoven developed electrocardiography. We have different types of lead systems to record the ECG signal from patients, such as single lead, three lead, and 12-lead, etc. Traditionally, the 12-lead system is more efficient for acquiring the ECG signal (Rangayyan, 2015). ECG signals are classified into two types based on the recording duration, i.e., resting and ambulatory. The duration of a resting ECG is around 5–10 minutes, whereas it is 24 to 48 hours for ambulatory ECG records. Ambulatory records are helpful in detecting long-term cardiac disorders during the patient's daily activities.

Most ambulatory ECG records are recorded using a Holter monitor. The shape of the ECG signal and the heart rate both indicate the functioning status of the heart (Dinakarrao *et al*., 2020), and distinct regions of the heart produce various segments of the ECG signal. A normal cycle of the ECG wave, non-shockable rhythm, ventricular fibrillation (VF), and ventricular tachycardia (VT) are visualized in Fig. 2, sourced from the PhysioNet publicly available databases. P, Q, R, S, and T are the five primary fiducial components (Rangayyan, 2015) of a standard ECG signal in healthy individuals; the R component can readily be distinguished from the others due to its high amplitude. Ventricular fibrillation is presented with non-uniform characteristics in OHCA, and variations in ventricular fibrillation amplitude specific to populations may influence survival outcomes. International guidelines advise against the initial defibrillation of rhythms assessed by AEDs with low amplitudes ($\geq$ 0.2 mV) (Nehme *et al*., 2021).

ECG analysis and classification activities can be used in various applications, such as disease categorization (Shadmand and Mashoufi, 2016a), heartbeat type detection (Dutta *et al*., 2011), biometric identification (Tantawi *et al*., 2015), and emotion recognition (Long *et al*., 2010). The detailed differences between shockable, non-shockable, and normal rhythms are depicted in Table 1. The duration and number of beats of ECG signal experimentation are mentioned in Table 2.

3. Databases

In cardiology, shockable arrhythmias are extremely dangerous heart rhythm disturbances that require immediate electrical intervention (defibrillation) for survival. Two of the most critical shockable arrhythmias include VF, characterized by a chaotic, uncoordinated quivering of the heart's ventricles, leading to effectively stopped blood pumping—a primary cause of sudden cardiac arrest. Another is VT, an abnormally rapid heart rhythm originating in the ventricles. VT can be sustained (lasting over a few seconds) or non-sustained. Sustained VT often deteriorates into VF if untreated. PhysioNet (`https://physionet.org`) is an invaluable resource for researchers studying cardiovascular diseases and developing life-saving algorithms. It offers precious databases for shockable arrhythmia research.

- MIT-BIH Arrhythmia Database: A classic, this database contains diverse ECG recordings, including examples of shockable arrhythmias.

- MIT-BIH Malignant Ventricular Ectopy Database (MVED): its focuses specifically on ventricular

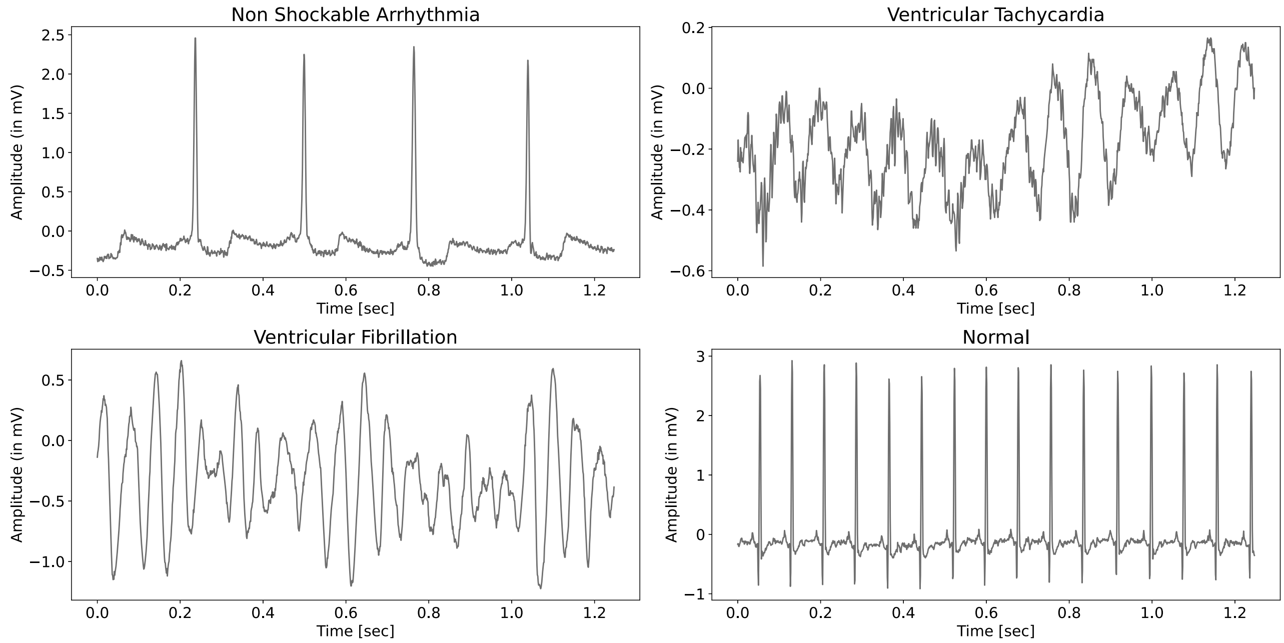

Fig. 2. Illustration of ECG signals from publicly available Physionet databases (CU ventricular tachycardia): non-shockable arrhythmia (a), ventricular tachycardia (b), ventricular fibrillation (c), normal sinus rhythm (d).

arrhythmias with a high risk of leading to sudden cardiac arrest.

- Creighton University Ventricular Tachyarrhythmia Database (CUDB): Another database specializing in VT recordings.

4. Feature extraction and shockable arrhythmia classification using traditional signal processing methods

4.1. Time domain methodologies. Amplitude analysis details the signal's instantaneous amplitude across time, and the corresponding graph represents the propagation of the signal. Time domain representation provides details about the momentary amplitude of the signal across time, and the corresponding graph also represents the signal's propagation. This time-domain analysis describes the temporal features of the ECG. Digital information collection has made measuring the VF signal amplitude easy, simplifying and expanding the analysis.

Time-domain methods involve analyzing signals in the time dimension, focusing on characteristics and patterns that occur over time in the ECG signal without considering frequency information. ECG characteristic points, such as the P wave, QRS complex, and T wave, are crucial landmarks in the ECG waveform that represent specific events in the cardiac cycle. Several algorithms are commonly used for the detection of ECG signal characteristics in time-domain analysis. These algorithms are designed to identify key features such as the P wave, QRS complex, and T wave, which are essential for diagnosing various cardiac conditions (Christov *et al.*, 2006). Some widely employed algorithms for ECG characteristic point detection in time-domain analysis include the Pan–Tompkin algorithm, which mainly focuses on QRS complex detection, a real-time QRS detection algorithm employing a bandpass filter, derivative, squaring, moving window integration, and adaptive thresholding to identify the QRS complex. Hamilton–Tompkin's algorithm mainly focuses on P and T wave detection. Adaptive threshold techniques, template matching methods, and wavelet transform-based methods are used for QRS complex detection. Table 3 lists the techniques with performance metrics employed by the researchers to extract the time domain features.

In the regression on the ACF (Chen *et al.*, 1987), peaks are randomly distributed for VF, whereas they are linearly distributed for normal arrhythmia and VT. Ripley *et al.* (1992), introduced three approaches to analyzing the ECG's amplitude distribution, irregularity, and rate. Thakor *et al.* (1990) developed sequential hypothesis testing, which calculates the period that crosses a threshold between consecutive pulses. The authors used a 20% threshold voltage of each one-second segment's highest absolute values. Similar to the TCI parameter, Arafat *et al.* (2011) developed the TCSC as an improved method of the reported work by Thakor *et al.* (1990) through limited modifications, including the

Table 1. Detailed differences between shockable, non-shockable and normal ECG signals.

S. no.	Feature	Shockable rhythm	Non-shockable rhythm	Normal ECG
1	QRS complexes	Irregular	Regular	Regularly spaced, upright
2	Heart rate	Increased (often >100 bpm)	Slow (often <60 bpm) or absent (asystole)	60–100 bpm
3	QRS amplitude	May be large	May be low	Moderate amplitude
4	P wave	Often absent	May be present and normal	Upright and precedes QRS complex
5	PR interval	Variable	May be normal	Constant and within a specific range
6	ST segment	May be elevated or depressed	May be slightly elevated or depressed	Isoelectric (flat)
7	T wave	Often absent or distorted	May be present and normal	Upright and follows QRS complex

Table 2. Details about the input and duration of the fragment from the state-of-the-art techniques.

S. no.	Literature	Database	Input	Duration [s]
1	Acharya *et al.* (2018)	CUDB, MITDB, and VFDB	Fragment	2
2	Sinha and Das (2021)	CUDB, MITDB, and VFDB	Fragment	2, 5, and 8
3	Tipathy *et al.* (2016)	CUDB, MITDB, and VFDB	Fragment	5 and 8
4	Rahul and Sharma (2022)	CUDB, VFDB, and AFDB	Fragment	5
5	Mathunjwa *et al.* (2021)	AFDB, CUDB, VFDB, and MITDB	Fragment	2
6	Nguyen *et al.* (2018a)	CUDB, VFDB	Fragment	8
7	Shen *et al.* (2023)	Real-time and publicly available	Fragment	7

usage of a three-second wide window size rather than a one-second wide window size as well as positive side and negative side thresholds rather than considering positive threshold values. Amann *et al*. (2007) developed a PST method for detecting VFs, which performed well on all databases, but the proposed method was sensitive to noise and artifacts. Overall, the amplitude analysis is sensitive to the morphology and dynamics of the ECG. During amplitude analysis, the waveform's temporal information is disregarded by Chen *et al*. (1987). Moreover, the VF amplitude is affected by the patient's size and shape. This makes it a limited estimator of the VF duration and a poor predictor of defibrillation outcomes. To address these problems, researchers have explored other characteristics of VF waveforms, using transformation techniques to interpret them.

4.2. Frequency domain methodologies. The Fourier transform (FT) is the foundation for frequency domain analysis. It decomposes the ECG signal into its constituent sinusoidal components, revealing the amplitude and phase information for each frequency. The FT helps identify dominant frequencies associated with normal heart rhythm (P waves, QRS complex and T waves) and potential arrhythmias.

A short-time Fourier transform divides the ECG signal into smaller windows, performs FT on each window, and provides a spectrogram that shows how the frequencies change over time. This is useful for analyzing transient events like arrhythmias. Features like heart rate variability (HRV) can be extracted by analysing the power within specific frequency bands. HRV reflects the fluctuations between heartbeats and is a marker of cardiac health.

Techniques like the Hilbert transform can be used to analyze the instantaneous frequency of the ECG signal, aiding in QRS complex detection and morphology analysis, which is crucial for arrhythmia classification. Frequency domain methodologies provide valuable tools for ECG feature extraction beyond what time domain analysis alone can offer. By understanding the frequency components of the ECG signal, healthcare professionals and researchers can gain deeper insights into heart function and identify potential cardiac abnormalities.

Table 3. Time domain methodologies used for detecting shockable ECG rhythms.

Author	Approach	Database	R	W [s]	Performance (%)		
					ACC	SEN	SPE
Chen *et al.* (1987)	ACF, regression analysis	Sample data	31	1.5	NA	86	100
Thakor *et al.* (1990)	Sequential hypothesis testing or TCI	Sample data	180	7	100	NA	NA
Chen *et al.* (1996)	Sequential hypothesis testing with blanking variability	VFDB	22	10	95	NA	NA
Zhang *et al.* (1999)	CPLX	Sample data, MITDB	204	8	100	100	100
Amann *et al.* (2007)	PSR	MITDB, CUDB, AHA	128	8	96.2	83.8	97.8
Amann *et al.* (2005b)	SCA, MEA, STE	MITDB, CUDB, AHA	128	8	96.2	98.5	71.2
Arafat *et al.* (2011)	TCSC	MIT-BIH, CUDB	83	3	98.14	80.97	98.51
Lee and Yoon (2016)	Adaptive threshold	MIT-BIH, CUDB	NA	4	NA	95.77	NA

The total amplitude of the signal is calculated with time domain approach directly using the time samples. In the frequency domain, mathematical functions or signals are analyzed with attention to frequency rather than time. Spectral analysis explains the distribution of signal energy in a range of frequencies. Table 4 employs frequency or spectral analysis methodologies to extract or choose features and detect shockable arrhythmias.

Myers *et al*. (1986) developed a vital tool for predicting VF, a power spectral method of heart rate variability applied to 24-hour ambulatory ECG signals. Clayton *et al*. (1993) discussed VF filter leakage, a narrow band-stop filter response, and VF leak, which determines the ECG segment's mean frequency area. Using Fourier analysis, the spectral technique calculates the content of energy and power over a range of frequencies. Prony modelling (Chen, 2000) provides a higher frequency resolution than FFT approaches. Compared with standard FFT or threshold crossing methods, the higher resolution capabilities may result in more precise rate estimates and better detection/discrimination for rhythmic (VT, VF, SVT) anomalies.

Jekova and Krasteva (2004) developed an algorithm that combines a slope variability analyzer with a bandpass digital filter for AEDs. It addresses the Hilbert transform's restriction, and the results have shown that it is sensitive to ECG amplitude regularity; moreover, it could be made more robust using an extensive database. Requena-Carrión *et al.* (2013) introduced a new method based on four spectral indices—the dominant frequency, peak frequency, median frequency, and organization index. According to the authors, unlike other spectral indices, the lead configuration does not affect the dominant frequency. Overall, the challenges associated with amplitude analysis are addressed by employing frequency analysis to evaluate the VF waveform. The method is reliable and less vulnerable to external factors. However, FFT analysis encounters fundamental limitations. Frequency domain analysis is effective only for stationary signals with constant waveforms. Additionally, the Fourier spectrum can only provide globally averaged information over the examined ECG trace segment, implying that any location-specific data present in the waveform is lost.

4.3. Time-frequency methodologies. Owing to the problem of losing location-specific information, wavelet processing has supplanted Fourier analysis as the preferred method. Due to its ability to clarify local spectral and temporal information inside a signal, it has increased in value and was first formed in the early 1980s. Wavelet approaches have solved engineering, medicine, science, and finance issues. EEGs, EMGs, and 12-lead ECGs are all used in the medical field. The last of those has experienced a surge in popularity in recent years, and it is currently being utilized to examine sinus rhythm and its constituent parts, VT and VF. The time-frequency methodologies are listed in Table 4. Due to its ability to clarify local spectral and temporal information within a signal, wavelet processing has increased in value since its inception in the early 1980s.

Wavelet approaches have addressed engineering, medical, scientific, and financial challenges. To evaluate the time-frequency distributions (TFD) of sinus rhythm, VT, and VF, Tompkins (1995) examined STFT, SPWVD, and CKD. The findings revealed that

SPWVD and CKD exhibited beneficial characteristics, but more discriminative features were needed for better categorization. Similarly, Balasundaram *et al.* (2013) analyzed the time series of VF by comparing linear and nonlinear analysis of the ECG during human VF. For linear analysis, the authors used the magnitude of the smoothed Wigner distribution, while for non-linear analysis, they employed a recurrence plot and correlation dimension for the time series, which describe the complexity and existence of nonlinear dynamics of VF. With the provided technique, the authors found that both linear and nonlinear signal processing methodologies demonstrate order in the ECG during human VF. Additionally, recurrence plot analysis has proven reliable for the time series analysis of ventricular arrhythmias.

A new technique described by Balasundaram *et al.* (2013) is a local and global pattern classification approach for identifying recurrent ECG signal patterns during ventricular arrhythmias. A wavelet-based approach was developed to automate the pattern detection process using ECGs. This suggested approach may be utilized to evaluate the proposed patterns on a broader database and conduct subgroup classifications to link clinical data with signal patterns.

Okai *et al.* (2018) proposed a method for fatal arrhythmias that extracts meaningful and effective spectrum characteristics of the ECG using the Gabor wavelet transform (GWT). The newly extracted parameters are essential for increasing recognition performance and decreasing calculation time. However, the wavelet methodology is more computationally efficient due to its excellent localization properties. Nevertheless, the challenge with this methodology lies in selecting the mother wavelet and determining the level of decomposition.

4.4. Empirical mode decomposition (EMD). Any non-stationary time series is adaptively and locally decomposed into a composition of intrinsic mode functions (IMFs) with zero-mean amplitude and frequency-modulated features. The original signal is recreated without losing information or distortion by superimposing each recovered IMF with the residual component. Table 5 represents the EMD methods for detecting shockable arrhythmias. Orthogonality is characteristic of identifying VF from NSR, and vice versa (Arafat *et al.*, 2009). The lower-order IMFs of NSR are not-orthogonal compared with the IMFs of VF. Anas *et al.* (2011) used the angle between the signal and its IMFs as a performance metric. Overall, in conventional signal processing, manual analysis of the morphological alterations related to various fatal arrhythmias is sensitive, qualitative, and prone to errors. The classification of VF and VT from other arrhythmias could be instantaneous and accurate. A CAD (Mandal *et al.*, 2021) is used in AEDs to accurately classify shockable rhythms.

5. Machine learning methodologies for shockable arrhythmia classification

The researchers have integrated the collected ECG features of conventional signal processing with ML algorithms such as decision trees, random forests, SVMs, and KNN classifiers to categorize shockable arrhythmias. A crucial part of ML is the feature extraction stage. There are four types of features extracted in the literature: (i) temporal or morphological feature methods (as explained in Section 4.1), (ii) spectral feature methods (as explained in Section 4.2), (iii) time-frequency features (as explained in Section 4.3), and (iv) nonlinear features or complexity features. The most common complexity features are entropy-based ones such as Shannon entropy (Oh *et al.*, 2017), fuzzy entropy (Oh *et al.*, 2017), Renyi entropy (Panigrahy *et al.*, 2021), sample entropy (Rajesh and Dhuli, 2017), approximate entropy (Sinha and Das, 2021), permutation entropy (Wang *et al.*, 2001), modified multiscale entropy (Wang *et al.*, 2001), higher-order spectra (Mendel, 1991), and energy (Oh *et al.*, 2017).

5.1. Feature selection. The feature selection stage in a machine learning algorithm is significant for improved model performance. Reducing the number of features can prevent overfitting, especially when dealing with high-dimensional datasets. It helps the model generalize better to new, unseen data, leading to improved performance. Selecting relevant features also reduces the computational cost of training a model. The training process becomes faster with fewer features, making it more scalable, especially for large datasets. Models with fewer features are often more interpretable and easier to understand. Feature selection allows focusing on the most relevant variables, facilitating the interpretation of the model's predictions. Additionally, feature selection helps identify and remove redundant or highly correlated features. Redundant features do not contribute additional information, and their inclusion may lead to computational inefficiency and potential model instability. The number of data points needed to obtain reliable estimates grows exponentially in high-dimensional spaces.

Feature selection helps mitigate the curse of dimensionality by focusing on the most informative features, making the learning task more manageable. The feature selection process reduces the number of redundant and uninformative features, thereby lowering the computational load and improving the system's overall performance. The following feature selection methods are used in the literature: (i) filters, (ii) wrappers (deterministic and randomized), and (iii) embedded methods. The techniques involved in filter-type feature

Table 4. Frequency and time-frequency domain methodologies used for detecting shockable ECG rhythms.

Author	Approach	Database	R	W [s]	Performance [%]		
					ACC	SEN	SPE
Myers *et al.* (1986)	Power spectral analysis	Sample data	18	120	NA	83.00	100
Clayton *et al.* (1993)	VF-filter	Sample data	70	4	NA	93.00	60.00
Chen *et al.* (2000)	Total least squares-based Prony modelling	MIT-BIH, CUDB	91	10	95.71	NA	NA
Krasteva and Jekova (2005)	Bandpass digital filter Peak detection algorithm	AHA, VFDB, CUDB	NA	10	93	98.00	NA
Requena-Carrión *et al.* (2013)	Slope variability Hilbert transform	CUDB	35	10	NA	94.20	96.60
Amann *et al.* (2005a)	Hilbert transform	MITDB, CUDB, AHA	123	8	NA	83.10	96.20
Millet-Roig *et al.* (1999)	CWD and CKD	MITDB, sample data	91	8	88.4	86.44	91.13
Jekova and Krasteva (2004)	Band-pass digital filtration Auxiliary count	AHA, MITDB	99	10	94.7	95.93	94.38
Sun *et al.* (2005)	Wavelet transform–Hurst	CUDB	NA	5	NA	83.00	84.00
Khadra *et al.* (1997)	Raised cosine wavelet transform	MITDB, sample data	45	2	NA	91.70	83.30
Junganf Tompkins (2003)	Daubechies wavelet	MITDB, CUDB	78	10	NA	92.30	NA
Selvakumar *et al.* (2007)	Daubechies 4 Cubic spline wavelets	MITD B,CUDB	74	10	NA	93.24	NA
Ilankumaran and Thamaraiselvi (2011)	Wavelet decomposition with adaptive threshold	MITDB, CUDB	NA	5	NA	100	100
Li *et al.* (2012)	Continuous wavelet transform morphology consistency	MITDB, CUDB	NA	10	87	85.00	91.00

Table 5. Empirical mode decomposition methodologies used for detecting shockable ECG rhythms.

Author	Approach	Database	R	W [s]	Performance (%)		
					ACC	SEN	SPE
Arafat *et al.* (2009)	EMD, Bayes decision theory	MITDB	48	7	NA	99.50	99
Anas *et al.* (2011)	EMD	MITDB, CUDB, VFDB	105	2	98.62	99.02	82.89
Anas *et al.* (2010)	EMD function and mean signal	MITDB, VFDB, CUDB	48	8	99.21	91.09	99.42
Kaur and Singh (2013)	EMD and approximate entropy	VFDB, CUDB	57	NA	90.98	91.34	90.54

selection include chi-square (Cai *et al.*, 2021), analysis of variance (Desai *et al.*, 2016), fuzzy clustering (Alonso-Atienza *et al.*, 2014), information gain-based selection (Rahman *et al.*, 2015), and Fisher score (Desai *et al.*, 2016). The relevant set of features is also chosen using statistical analysis in this procedure. The deterministic wrapper technique uses common methods include the sequential feature selection method (Mar *et al.*, 2011) and forward selection (Marcano-Cedeño *et al.*, 2010; Nguyen *et al.*, 2017). The genetic algorithm (Li *et al.*, 2014) is the preferred method for randomized wrappers. The standard approach for the embedded method is regularization (Sharma *et al.*, 2017). After feature selection, the dimensionality of the chosen features is reduced through feature reduction. The best examples of this process are principal component analysis (Ebrahimzadeh and Pooyan, 2011) and linear discriminant analysis (Wang *et al.*, 2013).

6. Classification

After selecting the significant features, classification becomes the final step in categorizing the incoming ECG data. Leveraging existing data to classify fatal arrhythmias can yield predefined results. Hence, most authors in the literature use supervised ML algorithms, including the ANN, SVM, KNN, DT, and RF. Moreover, regression (Pulluri and Kumar, 2022) is also employed in the supervised ML approach. All the advantages, disadvantages, and future directions of ML methods are presented in Table 6.

6.0.1. SVM classifier. The SVM is known as a linear classifier, as it separates classes by creating a hyperplane in high-dimensional space. Additionally, it can function as a nonlinear classifier using kernel functions such as sigmoid and Gaussian radial basis functions. The SVM has been widely utilized in shockable arrhythmia classification studies (Zhang *et al.*, 2011; Hou and Zhang, 2014; Alonso-Atienza *et al.*, 2012a; 2012b; Kavya and Karuna, 2023).

6.0.2. KNN classifier. KNN classifies feature vectors in the feature space based on the labels of neighboring training data. Using Euclidean distance, it calculates the distances between an unknown feature vector and each other vector in the training set. The class that the nearest k samples mostly correspond to is then assigned to the unidentified feature vector, resulting in a scenario of majority voting. The positive integer k has a well-known influence on classification accuracy and must be a positive value. KNN is commonly employed in shockable arrhythmia classification studies (Kinoshita, 2006; Ibaida and Khalil, 2013; Ebrahimzadeh and Pooyan, 2011; Mjahad *et al.*, 2022; Sidharth *et al.*, 2023; Picon *et al.*, 2019; Kwok *et al.*, 2022).

6.0.3. Decision tree classifier. The goal of DT learning, as outlined by Mohanty *et al.* (2019), is to establish connections between observations and interpretations. These interpretations can either be a desired value or a desired class label, resulting in structures known as classification trees or regression trees, depending on the type of conclusion. In classification trees, the leaves display class labels, while in regression trees, they represent continuous values.

6.0.4. Random forest classifier. A random forest (Desai *et al.*, 2016) utilizes averaging as a meta-estimator to fit multiple decision tree classifiers on different subsets of the dataset, thereby enhancing prediction accuracy and reducing overfitting. One of the ensemble classifiers employing multiple decision trees is the RF tree. By training various decision trees using diverse subsets of training data, this method determines the output class label based on the percentage of votes cast across all trees.

6.0.5. Artificial neural network (ANN). An ANN (Noruzi *et al.*, 2017) is a mathematical model based on the functioning principles of biological neural networks. It is one of the most popular pattern classifiers, utilizing interconnected artificial neurons with trainable weights. The network typically consists of input, output, and hidden layers. With a variety of network architectures and learning techniques, ANNs can effectively address problems involving both linear and nonlinear classification.

6.1. Performance metrics. The performance of the machine and deep learning classifiers are validated using the following metrics: accuracy, positive predictivity, sensitivity, specificity and F1-score. These are calculated with the help of a confusion matrix. The fundamental confusion matrix is shown in Fig. 3. The table is divided into four quadrants there. Each one represents a combination of a data point's actual class (positive or negative) and the prediction made by a classification model. A detailed explanation of the contents is explained as follows:

- True positive (TP): This quadrant (upper left) represents the number of cases where the model correctly predicted a positive class.
- False positive (FP): This quadrant (upper right) represents the number of cases where the model incorrectly predicted a positive class while the data point actually belonged to the negative class (Type I error).
- True negative (TN): This quadrant (lower left) represents the number of cases where the model correctly predicted a negative class.
- False negative (FN): This quadrant (lower right) represents the number of cases where the model incorrectly predicted a negative class while the data point actually belonged to the positive class (Type II error).

By analyzing the distribution of values across these four quadrants, we can gain valuable insight into the performance of a classification model, helping us assess how well the model identifies both positive and negative cases. Classification metrics are often used to compare and track performance in production. These metrics may be applied in a wide range of situations. The following are some measures used to evaluate an ECG classification task.

Accuracy (ACC). The accuracy of a classifier is simply the number of times it predicts accurately. Mathematically, it the number of correct predictions divided by the total number of forecasts,

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{1}$$

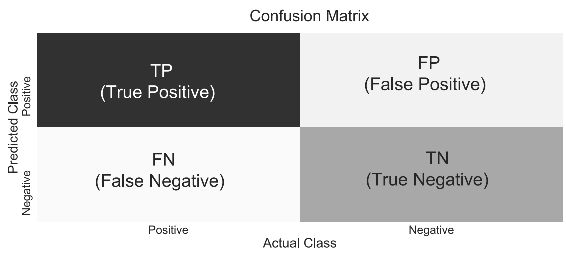

Fig. 3. Basic representation of the confusion matrix.

Precision or positive predictivity (PP). The number of correctly predicted situations that turned out to be positive is explained by precision. Precision is beneficial when the risk of a false positive is greater than that of a false negative. It is given by

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{2}$$

Recall or sensitivity. The term recall refers to how many of the actual positive cases the model was able to accurately anticipate. It is a good statistic to utilize when a false negative is more problematic than a false positive. It is given by

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{3}$$

Specificity. It is the percentage of negative cases predicted as negative. It is also known as the true negative rate. It is computed as

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \tag{4}$$

F1-score. It is the harmonic mean of precision and recall:

$$F1\text{-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{5}$$

Table 6 illustrates how proper selection of robust features influences the performance of machine learning algorithms (Mohanty *et al.*, 2019; Mohanty, 2018; Sinha and Das, 2020), which can be obtained using non-linear signal processing methods. Therefore, it relies on the practitioner's ability to make optimal choices. Notably, the SVM classifier is preferred by many authors due to its exceptional binary classification performance, although it has demonstrated poor accuracies when applied to short segments of the ECG signal. Most approaches perform well with smaller datasets, but prediction accuracy tends to gradually decline as the dataset size increases. To overcome these limitations, employing, testing, and deploying appropriate DL models is essential for achieving good prediction accuracy.

6.2. Impact of supervised and unsupervised learning techniques on classification performance. Supervised learning techniques include SVMs, KNN, DTs, naive Bayes, and random forests. These methods require labelled data where examples are already categorized (e.g., shockable vs. non-shockable arrhythmia). This allows the model to learn the relationship between features and class labels, achieving high accuracy for classification tasks. For instance, Choi *et al.* (2024) used a linear kernel SVM classifier to achieve an accuracy of 99.28% in classifying shockable arrhythmias. Similarly, Nguyen *et al.* (2018b) employed SVMs, KNNs, and RFs to detect sudden cardiac arrest, with all classifiers exceeding 99% accuracy. On the other hand, unsupervised learning techniques like K-means clustering, fuzzy c-means clustering, hierarchical clustering, and Gaussian mixture models do not require labeled data. These methods are valuable for data exploration, feature engineering (creating new informative features from existing data), and data augmentation (increasing the size and diversity of datasets). Ultimately, unsupervised learning can aid supervised learning models in achieving better classification performance by providing insights into the data structure and facilitating the creation of more effective features.

7. Deep learning methodologies for shockable arrhythmia detection

A neural network is an artificial intelligence tool that teaches machines to analyze information like the human brain does. A specific type of ML technology called deep learning uses interlinked nodes in a layered pattern to imitate the human brain. Deep neural networks are established using more than two fully connected multilayer perceptrons. DL networks are classified as convolutional, fully connected, and belief networks depending on the architecture. The major advantage of the DL network is that it does not need handcrafted features, since it forms them automatically. In the literature, researchers have mostly used the CNN model. The basic CNN architecture is illustrated in Fig. 4. The CNN has a signal input layer to hold the raw signal samples and a convolution layer that performs the feature extraction and selection process. Moreover, filters are learned in the CONV layer. The input is convolved with each filter, and the dot product between the weights of the filters and the input signal is computed. Next, pooling is used to reduce the size of the parameters and the computational complexity.

However, it also reduces overfitting problems. In a fully connected layer, all activations in the preceding layer are entirely connected (Li *et al.*, 2016). Thus, matrix multiplication can be used to identify their activations. The advantages, disadvantages, and future directions of DL methods for shockable arrhythmias are listed in Table 8. Acharya *et al.* (2018) used an 11-layer CNN, and this approach obtained the highest accuracy in detecting shockable arrhythmias against non-shockable rhythms but it obtained less accuracy on short segments of ECG signals. To boost the performance of CNNs, Sakr *et al.* (2023) and to reduce noise, researchers have converted 1D signals to 2D signals. The optimized 2D CNN model Lai *et al.* (2021) showed better results in short ECG segments (3 s). Hammad *et al.* (2022), to avoid overfitting problems in DL, converted the 1D signal to a 2D image and used a hybrid model (combining two learning models) for classification. The hybrid model combines the feature extraction of the CNN with the feature memorization of the convolutional long-short term memory (LSTM) network.

Picon *et al.* (2019) proposed a novel deep learning architecture that integrates 1D-CNN blocks with an LSTM network, leveraging data from the OHCA database. This innovative approach significantly enhances efficacy compared with certain prior deep learning methods, some of which being tailored for the detection of life-threatening ventricular arrhythmias. Meanwhile, to reduce the training time and obtain better results, Tripathi *et al.* (2022) used pre-trained CNN architectures such as Alexnet, DenseNet201, and GoogLeNet, and converted the 1D signal to 2D images using the superlet transform. Mathunjwa *et al.* (2022) converted the 2 s segment 1D signal to a 2D image using a recurrence plot. In this approach, VF is classified at the first stage classification using ResNet-18, which supports more convolutional layers in the CNN.

Effective management of the resuscitation protocol during OHCA is crucial during CPR. Jekova and Krasteva (2021) used an optimized end-to-end convolutional neural network (CNN) without pre-filtering or additional sensors. Isasi Liñero *et al.* (2020) developed a CNN algorithm to generate dependable decisions regarding shock or no-shock scenarios during CPR. Chest compression artifacts were eliminated by applying a recursive least squares filter. The resulting filtered ECG data was then inputted into a CNN classifier comprising three convolutional blocks and two fully connected layers for shock or no-shock classification. Shen *et al.* (2023) devised and authenticated the effectiveness of a convolutional neural network (CNN) for diagnosing shockable arrhythmias within a groundbreaking, compact AED. Krasteva *et al.* (2023) employed three convolutional neural networks (CNNs) with raw ECG input (lasting five, 10, and 15 s) to make shock advisory decisions during CPR, with 26 consecutive analyses conducted at one-second intervals.

The integration of the CNN with a recurrent neural network (RNN), as opposed to utilizing the CNN in isolation, markedly improved sensitivity values Andersen

Table 6. Machine learning methodologies used for detecting shockable ECG rhythms.

Author	Database	Classifier	Advantage	Remarks	Performance metrics
Li *et al.* (2009)	MITDB, CUDB	SVM along with PSR, Hurst index features	1. Fastest algorithm 2. Obtained good results with fewer features	Poor performance on 3 s window length	ACC: 90.5 SEN: 90.2 SPE: 90.7
Mohanty (2018)	VFDB, CUDB	SVM along with DWT, VMD features	1. Effective features were extracted	Time-consuming to find weights and ranks	ACC: 99.13 SEN: 90.2 SPE: NA
Nguyen *et al.* (2018a)	VFDB, CUDB	SVM with a combination of features	1. No overfitting 2. Less complexity	1. Less accuracy 2. Used public database without a clinical environment	ACC: 95.7 SEN: 90.8 SPE: 96.9
Sharma *et al.* (2019)	MITDB, VFDB	SVM along with Wavelet decomposition, entropy-based features	1. Obtained better results on short window length 2. No need for preprocessing	Small dataset used for the implementation	ACC: 98.9 SEN: 99.66 SPE: 98.35
Mohanty *et al.* (2018)	VFDB, CUDB	Cubic SVM and C4.5	1. Less complexity 2. C4.5 got good results	More effective features are needed	ACC: 97.02 SEN: 97.86 SPE: 90.97
Mohanty *et al.* (2019)	MITDB, CUDB, VFDB	Decision tree, C4.5, SVM along with DWT	1. High accuracy 2. Easy to implement	Time-consuming	ACC: 99.23 SEN: 98.0 SPE: 99.32
Ibtehaz *et al.* (2019)	VFDB, CUDB	SVM along with EMD, DFT features	1. Overfitting eliminated 2. Classified both classes accurately	Small datasets used for developing the method	ACC: 99.19 SPE: 99.98 SEN: 98.40
Sinha and Das (2020)	MITDB, CUDB	SVM along with DWT features	1. Various ECG arrhythmias are extracted	1. Complex 2. More feature combinations are needed	ACC: 98.82 SPE: NA SEN: NA
Sharma (2020)	MITDB, CUDB, VFDB	SVM along with orthogonal wavelet features	1. No need for preprocessing 2. Obtained better results on short window length	Used much less data	ACC: 98.10 SPE: 97.32 SEN: 98.25
Hammad *et al.* (2021)	MITDB, CUDB, VFDB	SVM along with nonlinear features	1. No need for finding large peaks 2. More robust	Required more time	ACC: 90.14 SEN: NA SPE: NA
Panigrahy *et al.* (2021)	CUDB, VFDB, MITDB	SVM along with adaptive boosting algorithm	1. With fewer features obtained better results 2. Needs less memory for real-time implementation	Worse performance on short WL	ACC: 98.25 SEN: 98.18 SPE: 98.20
Tripathy *et al.* (2016)	CUDB, MITDB, VFDB	Random forest along with VMD	1. Capture the clinical parameters of ECG from various modes 2. Each mode provides distinct features	Smaller dataset used	ACC: 97.23 SEN: 96.54 SPE: 97.97
Oh *et al.* (2017)	CUDB, MITDB, VFDB	K-NN along with nonlinear feature extraction	1. Cost effective 2. Exceptionally good at capturing shocking rhythms	Complex	ACC: 98.32 SEN: 95.16 SPE: 99.20
Chen *et al.* (2022)	CUDB, PTBDB	Fuzzy c-means clustering	Robust, and classification is possible before the occurrence of an event	Only four features extracted	ACC: 98.4 SEN: 97.5 SPE: 99.1

Table 7. Effects of machine learning algorithms on classification performance.

Learning approach	Data labeling	Applications	Benefits for classification
Supervised learning	Required (labelled)	Classification tasks (e.g., arrhythmia detection)	High accuracy
Unsupervised learning	Not required (unlabelled)	Data exploration, feature engineering, data augmentation	Improved feature representation

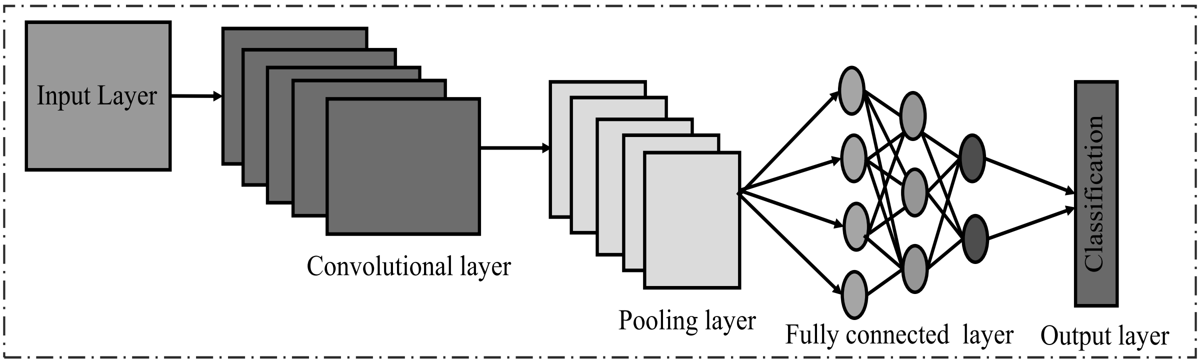

Fig. 4. Architecture of the basic convolutional neural network.

et al. (2019). DL algorithms surpass traditional ML algorithms in detecting shockable arrhythmias, yielding more robust and reliable results. The primary limitation of deep learning is the lack of extensive training data required to achieve high efficiency. Additionally, training the model is a time-consuming process.

8. Hyperparameter optimization methods

The performance of any model (ML and DL) depends on its HPO capability (Claesen and De Moor, 2015). In general, creating an effective model is a complex and time-consuming task, including selecting the best algorithm and fine-tuning the model's hyperparameters to achieve the best architecture. Fine-tuning hyperparameters is essential to creating a successful ML model, particularly for deep neural networks and tree-based ML models that include many hyperparameters. Due to the use of many types of hyperparameters in ML algorithms (for example, categorical, discrete, and continuous hyperparameters), the techniques for tuning them vary. DL models work based on the theory of ANNs. Since the fundamental neural network architecture is the same for all of these DL models, their hyperparameters are also similar. DL models gain more from HPO than other ML models since they frequently have an abundance of hyperparameters that need tuning.

Hyperparameters are required since they specify the model architecture and cannot be directly predicted from data learning. They must be defined before training an ML model (Yang and Shami, 2020). To find the best hyperparameter, the proper optimization method must be used. Since many HPO problems are non-convex and non-differentiable optimization problems, conventional optimization techniques may not be suitable for them and may instead produce a local rather than a global optimum. A traditional optimization gradient-based method can optimize the learning rate in a neural network.

Many additional optimization techniques, such as decision-theoretic techniques, Bayesian optimization algorithms, multi-fidelity optimization algorithms, and MAs, are more appropriate for HPO problems than standard optimization methods such as gradient descent (Decastro-Garcia *et al*., 2019). Decision-theoretic approaches are grid search (Bergstra *et al*., 2011; Nguyen *et al*., 2018a; Madan *et al*., 2022) and random search (Bergstra and Bengio, 2012; Krasteva *et al*., 2020) optimization methods. They are founded on creating a hyperparameter search space, finding the hyperparameter combinations inside the search space, and then choosing the hyperparameter combination that performs the best. Each hyperparameter configuration is addressed independently in the grid search and random search. Compared with the former, the best results were obtained using the latter in arrhythmia detection (Valarmathi and Sheela, 2021).

Contrary to GS and RS, the Bayesian optimization (Eggensperger *et al*., 2013; Elola *et al*., 2019) model chooses the next hyperparameter value based on the outcomes of the previous hyperparameter values, avoiding numerous unnecessary evaluations. As a result, Bayesian

Table 8. Deep learning methodologies used for detecting shockable ECG rhythms.

Author	Database	Classifier	Advantage	Remarks	Performance
Acharya *et al.* (2018)	MITDB, VFDB, CUDB	CNN	1. No need for handcrafted features	Need a large database and training time is longer	ACC: 93.18 SEN: 93.24 SPE: 96.24
Tseng and Tseng (2020)	CUDB, MITDB	Deep CNN	1. Low computation cost 2. Predict the VF before the onset	Multicentre collaboration is used for data collection	ACC: 97 SEN: NA SPE: NA
Panda *et al.* (2020)	CUDB, VFDB	CNN along with FFREWT decomposition	Possibility of multi-scale signal analysis	Less data used	ACC: 99.03 SEN: NA SPE: NA
Jaureguibeitia *et al.* (2020)	OHCA	CNN	Data segments of 1 s are used	1. Single device model is used for data collection 2. Noise was not eliminated	ACC: 98.6 SEN: NA SPE: NA
Mathhunjwa *et al.* (2021)	AFDB, CUDB, VFDB, MITDB	CNN	1. No need for noise elimination and feature extraction 2. Data augmentation was used	1. Complex 2. High computational cost and requires more memory	ACC: 98.41 SEN: NA SPE: NA
Lai *et al.* (2021)	MITDB, CUDB, VFDB, AHADB	Optimized 2D deep CNN	1. Obtained better results on the short segment 2. Robust	Time consumption and complexity	ACC: 98.82 SEN: 95.05 SPE: 99.43
Dahal and Ali (2023)	AHADB, VFDB, CUDB	Wasserstein conditional generative adversarial network, DNN	The proposed approach outperformed compared with hybrid models	The proposed method was implemented only on 4 s segments	ACC: 99.45 SEN: 99.18 SPE: 99.7
Rahul and Sharma (2022)	CUDB, VFDB, MITBIH	1D-CNN, Bi-LSTM	1. Comparated with 2D-CNN, the computational cost is lower than for 1D-CNN	The overfitting problem arose	ACC: 99.41 SEN: NA SPE: NA
Rajeshwari and Kavitha (2022)	AHADB, VFDB	DNN	1. Selected only related features 2. No overfitting problem in the training	1. Low performance on ventricular arrhythmia classification 2. Computational time is high and lower performance on lower data	ACC: 98.23 SEN: 92.71 SPE: 95.71
Nguyen *et al.* (2018a)	CUDB, VFDB	CNN	Detection improved	More complex and more time-consuming to train the classifiers	ACC: 99.26 SEN: 97.07 SPE: 99.44
Nasimi and Yazdchi (2022)	MITDB, VFDB, CUDB	CNN	1.Implemented the proposed model on the Raspberry Pi 2. No preprocessing stage	More complex	ACC: 99.1 SEN: 96.13 SPE: 99.64

optimization can identify the ideal hyperparameter combination in fewer iterations than grid search and random search. It is critical to parallelize Bayesian optimization models because they balance exploring unfamiliar areas with exploiting parts that have already been evaluated.

Researchers have adopted multi-fidelity optimization algorithms to handle problems with limited data. Hyperband (Li *et al.*, 2017; Han *et al.*, 2020) is an improved version of random search, and it eliminates ineffective hyperparameter configurations in each iteration to conserve resources and time. Another alternative solution for HPO is MAs, a class of techniques used to tackle complex, ample search space and nonconvex optimization problems. MAs are classified as single solution or trajectory method population-based algorithms. Single-solution MAs begin with a single starting solution and move away from it, describing a trajectory in the search space (Jaddi and Abdullah, 2020). Population-based metaheuristic algorithms consider a group (population) of solutions. However, the most commonly used algorithms in classifying shockable arrhythmias are population-based metaheuristic ones such as evolutionary computation (Cuevas *et al.*, 2017) and swarm intelligence (Chakraborty and Kar, 2017). Under evolutionary computation, the genetic algorithm (Mirjalili, 2019; Katoch *et al.*, 2021; Haupt and Haupt, 2004) is a part of the field, which is inspired by Darwinian evolution in biology and recombination. Mutation operators change a population of individuals. Swarm intelligence aims to generate computational intelligence through simple analogues of social interaction instead of purely individual cognitive abilities (Chakraborty and Kar, 2017).

To detect shockable arrhythmias, Li *et al.* (2014) and Nguyen *et al.* (2017; 2018b) used a genetic algorithm for optimal feature selection purposes. The problem with the genetic algorithm is that it works efficiently for sequential execution but not for parallelization. Genetic algorithms may sometimes be inefficient due to their very low convergence speed (Haupt and Haupt, 2004). Another more popular type of evolutionary algorithm is differential evolution (Karaboğa and Ökdem, 2004). Panigrahy *et al.* (2021) used a differential evolution algorithm to select the best feature combination. Tashan *et al.* (2019) proposed an immune proportional-integral-derivative control system to regulate heart rate. In this study, the authors used a differential evolution algorithm to optimize the controller parameters. The limitations of these techniques are due to the stagnation of the population and slow convergence. The other class of MAs that has recently gained more popularity for optimal feature selection and optimizing hyperparameters in classifiers for the classification of ventricular arrhythmias covers swarm intelligence techniques. The foundation of swarm intelligence is the assertion that social interaction in a social environment is the source of intelligent human cognition. Numerous algorithms use this sociocognition and can be applied to various optimization challenges. The individual swarm members operate autonomously, each exhibiting stochastic behaviour in their perception of their natural neighbourhood. The collective group intelligence of swarms allows them to use their environment and resources efficiently. A swarm system's primary trait is self-organization, which aids in evolving global-level responses through local-level interactions. There are numerous optimization techniques presented, motivated by metaphors of swarming activity in nature, including particle swarm optimization (Shadmand and Mashoufi, 2016b; Kaliappan *et al.*, 2022), whale optimization (Rana *et al.*, 2020), grasshopper optimization (Rajeshwari and Kavitha, 2022; Sharma *et al.*, 2021), and grey wolf optimization (Nadimi-Shahraki *et al.*, 2021; Karthiga *et al.*, 2022), which are used in the classification of shockable arrhythmias. Moreover, ant colony optimization (Korürek and Nizam, 2010), migration-modified biogeography-based optimization (Kaliappan *et al.*, 2022), bacterial foraging optimization (Kora *et al.*, 2020), bee colony optimization (Karthiga *et al.*, 2022), artificial immune systems (Sengur, 2008), biogeography-based optimization (Kaliappan *et al.*, 2022), and cuckoo optimization (Sharma *et al.*, 2021), are used in other arrhythmia classifications of ECGs.

9. Discussion

SCA primarily arises from VAs, emphasizing the critical importance of timely intervention. AEDs play a critical role in identifying cardiac irregularities and delivering well-timed shocks to restore normal heart rhythms. Accurate discrimination of shockable and non-shockable arrhythmias is important within the short duration of ECG segments. The research rate on shockable arrhythmias is increasing exponentially, as shown in Fig. 5. From the literature, we can say that shockable arrhythmias are classified more accurately using deep learning techniques over traditional and machine learning techniques. Figure 6 shows the average classification accuracies obtained using all the discussed methods from the literature.

In time-domain methodologies, TCI and TCSC obtained high accuracies but considered only positive peaks and 1 s window analysis, which may not include the R peaks when the heart rate is too low (less than 60 bpm). In the TCSC method, the authors considered positive and negative peaks but did not consider the signal's shape. The frequency-domain methodologies, VF filter, and power spectral analysis are suitable for stationary signals where the waveform is not altered. In the

Table 9. Details of ECG databases used for shockable arrhythmias.

Author	Database	Records	Subjects	Duration [min]	Sampling frequency [Hz]	Digitization resolution [bit/sample]	Channels	Arrhythmia type
Moody and Mark (2001)	MIT-BIH	48	47	30	360	11	2	Normal, other arrhythmias
Goldberger *et al.* (2000)	CUDB	35	–	8	250	12	1	VT, VF, VFL
Greenwald (1986)	VFDB	22	16	30	250	12	2	VT, VF, VFL
Greenwald (1986)	AHADB	80	–	5	250	12	2	Ventricular arrhythmias
Greenwald (1986)	NSRDB	18	18	24 h	128	–	2	NSR
Greenwald (1986)	AFDB	25	25	10 h	250	12	2	AF

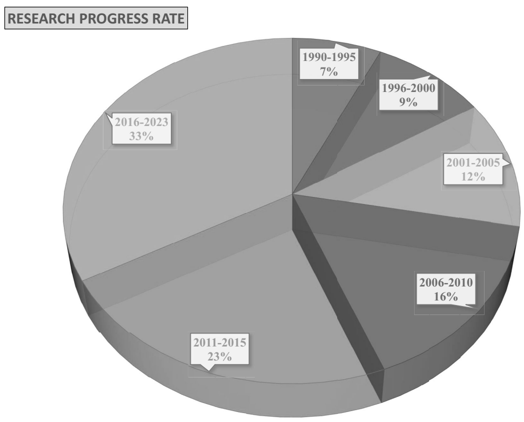

Fig. 5. Research rate progress in the area of shockable arrhythmia detection.

time-frequency domain, performance accuracy improved, but problems were faced in selecting the mother wavelet and decomposition level. The authors proposed signal-driven multiscale analysis methods such as EMD and VMD for signal decomposition. Multiscale analytic techniques show improved classification performance but have more computing complexity for detecting shockable arrhythmias. Later, authors proposed ML algorithms with a combination of traditional methodologies. Most authors used moving average, notch filters, and low-pass Butterworth filters in the preprocessing stage to remove artifacts. The performance metrics for the preprocessing stage are the root mean square and signal-to-noise ratio. Moreover, decomposition techniques have been used before feature extraction.

The feature extraction phase stands as a pivotal juncture in machine learning algorithms. Nevertheless, various factors, including the application relevance, classification technique, and computational efficiency, weigh significantly in determining the appropriate feature extraction approach. Some authors have extracted time, frequency, wavelet, and nonlinear features. Nonlinear features have shown better accuracies in the classification of shockable arrhythmias. If the extracted feature set has high dimensionality, it becomes a critical problem for the analysis of the ECG signal. Feature selection and dimensionality reduction methods have been used to overcome the problem of high dimensionality. The majority of classifiers used for ECG analysis are the SVM, KNN, DT, RF, and Bayesian classifiers in ML. In DL, the most commonly used classifier is the CNN for the detection of shockable arrhythmias. We recommend using CNN with other classifiers (hybrid model) to boost the model's efficiency. We also recommend the usage of large databases such as PTB-XL (Wagner *et al.*, 2020), real-time data, or constructing new large ECG datasets.

In addition, researchers have recently focused on HPO methods to enhance the performance of ML and DL models. Compared with grid, random, Bayesian, and hyperband algorithms, MAs have a more remarkable ability to solve nonconvex, non-smooth, and discontinuous problems. However, algorithms like genetic and particle swarm optimization methods have more complexity but eventually perform better for more complex optimization problems. These metaheuristic algorithms are recommended for all types of hyperparameters, and are especially suitable for large configuration spaces, as they can obtain near-optimal solutions even after very few iterations. They are restricted to HPO and used for feature selection purposes. Apart from particle swarm optimization, all other swarm intelligence algorithms, such as grasshopper, wolf, honey badger, and ant colony, are also used for HPO. In fact, these MA algorithms work very effectively when solving large-scale optimization problems.

Hybrid optimization methods are among the most fascinating recent trends (Kavya and Karuna, 2024). Indeed, an increasing number of articles are being

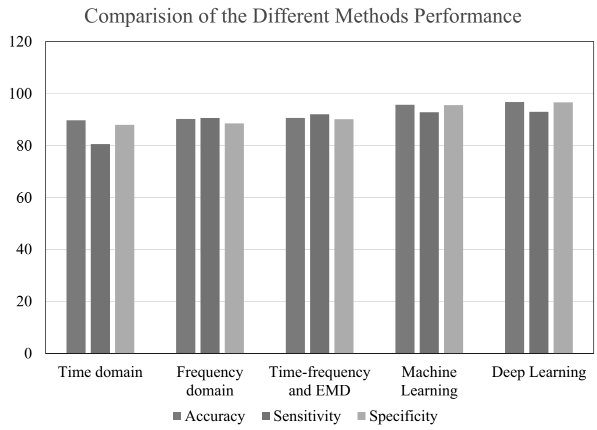

Fig. 6. Comparison of average performance metrics of all shockable arrhythmia methods (Hammad *et al.*, 2021).

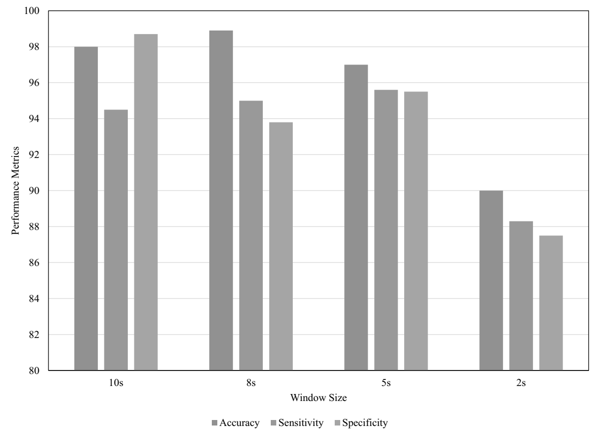

Fig. 7. Average accuracies of shockable arrhythmia detection of ECG signals on different window sizes (Sinha and Das, 2021).

published about combining metaheuristics with different optimization techniques. Different metaheuristics can be used, and hybrid algorithms can also integrate metaheuristics with local search or exact algorithms (Blum *et al.*, 2011). Furthermore, combining ideas from other metaheuristics and research fields might result in novel and intriguing approaches, such as the integration of fuzzy logic with several optimization techniques. These hybridizations can boost the algorithm's efficiency for better and more effective problem-solving by utilizing the advantages of each algorithm.

Accuracy, precision, sensitivity, specificity, F-measure, and area under the curve are all success measures for ECG analysis and classification. The most commonly used measures among all the metrics are accuracy, sensitivity, and specificity. However, researchers have used more than one metric to present the performance.

10. Limitations

After conducting a comprehensive review of a large body of existing studies in the field of shockable arrhythmia classification analysis, where several approaches have been compared and contrasted, one can observe that most authors have used the Physionet public database. Hence, the validity of all detection techniques is limited to the available public dataset only. Moreover, limited subjects have been used to develop the model. Denoising methods are crucial for successful detection of shockable arrhythmias, and good-quality ECG signals are very important. Therefore, the morphology of the ECG signal is affected by the position of ECG leads, power line interference, muscle noise, and other artifacts. Additionally, issues regarding the lack of globally consistent regulatory norms for the quantity of ECG leads, databases, ECG analysis technologies, unified evaluation metrics, and security mechanisms are also a concern.

For quick inference, a short segment length is always preferred. However, the foremost limitation is the poor accuracy of the ECG signal's short segments (window size 2 s or less than 2 s), as shown in Fig. 7. Furthermore, a more detailed feature set is crucial. A VF signal is nonlinear and nonstationary exhibiting chaotic behaviour. The literature shows that an exhaustive set of nonlinear features (entropy-based, Lyapunov exponents, detrended fluctuation analysis, etc.) provides good classification results. Traditional signal processing methods might not be as accurate as advanced deep and machine learning methods, although most researchers have used the same features of traditional signal processing methods. The limitation lies in the usage of a more informative set of features in ML and DL techniques, and in a few models, the same data have been used for training and testing the models. DL methods extract the features in the process itself, but they require a large dataset and more computational time, and have higher complexity. The complexity of the majority of DL models prevents their use in practical applications. Moreover, many ML models are unreliable in facing overfitting problems, making them unsuitable for practical applications.

The majority of earlier studies gathered ECG signals from small datasets, such as the MIT-BIH database, resulting in poor classification results, especially when employing DL approaches. Moreover, no generalized methodology for data collection and organisation makes it challenging to compare data across different databases. Most of the datasets used belong to imbalanced data. Despite the general popularity of metaheuristic algorithms, there will always be disputes about a particular metaheuristic's suitability for handling a variety of issues. Additional limitations in the context of this survey paper include the fact that only the classification of shockable arrhythmias has been evaluated despite the vast body of ECG arrhythmia-related investigations published in the literature.

11. Conclusion and future work

An ECG is a valuable and noninvasive method for diagnosing heart abnormalities. Ventricular arrhythmias are a critical cause of cardiac arrest. Early detection of lethal or shockable arrhythmias, followed by proper shock therapy using AEDs or ICDs, can save patients' lives. However, manually reading ECG signals in acute settings remains challenging. Therefore, automatic ML and DL detection methods could help doctors accurately screen and identify lethal arrhythmias.

This review paper comprehensively summarises methods ranging from traditional signal processing methodologies to advanced ML and DL models for classifying shockable arrhythmias against non-shockable rhythms. This enables readers to understand easily, progressing from time-domain techniques to advanced DL models due to the reported advantages, disadvantages, and future trends of ML and DL approaches. We provide detailed information on stages such as preprocessing, feature extraction, feature reduction, and classification. Additionally, we offered an overview of some existing proper hyperparameter optimization techniques (including metaheuristics), which reduces the burden of manual tuning. Furthermore, we summarize the databases and performance metrics used in the literature.

In summary, this review paper serves as a valuable resource for interested readers, providing the development and understanding of methodologies for shockable arrhythmia classification from a single source. Additionally, we hope it will contribute to a better understanding of the difficulties associated with the classification of shockable rhythms, motivating future research on hybrid DL and ML models with proper metaheuristic optimization techniques along with large datasets.

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Appendix

In this review paper, all the abbreviations utilized in the script are shown in Table A1.

Table A1. List of abbreviations utilized throughout this manuscript.

Abbreviation	Full form	Abbreviation	Full form
ACC	Accuracy	MEA	Modified exponential algorithm
ACF	Autocorrelation function	MIT-BIH	Massachusetts Institute of Technology–Beth Israel Hospital
AED	Automatic external device	MITDB	MIT-BIH arrhythmia database
AFDB	MIT-BIH atrial fibrillation database	ML	Machine learning
AHA-ADB	American Heart Arrhythmia Association database	PVC	Premature ventricular contractions
AI	Artificial intelligence	PSR	Phase space reconstruction
ANN	Artificial neural network	RF	Random-forest classifier
CAD	Computer-aided diagnosis system	R	Number of records used
CKD	Cone-shaped kernel	SCA	Signal compression algorithm
CNN	Convolutional neural network	SCA	Sudden cardiac arrest
CPLX	Complexity measure	SCD	Sudden cardiac death
CPR	Cardiopulmonary resuscitation	SEN	Sensitivity
CVD	Cardiovascular disease	SPE	Specificity
CWD	Choi William’s distribution	SPWVD	Smoothed pseudo Wigner–Ville distribution
CUDB	Creighton University ventricular tachyarrhythmia database	STE	Standard exponential algorithm
CV	Cross-validation	STFT	Short-time Fourier transform
DL	Deep learning	SVM	Support vector machine classifier
DNN	Deep neural network	TCI	Threshold crossing interval
DT	Decision tree classifier	TCSC	Threshold crossing sample count
EWT	Empirical wavelet transforms	TFD	Time-frequency distribution
EMD	Empirical mode decomposition	VF	Ventricular fibrillation
F	Number of features extracted	VFDB	MIT-BIH malignant ventricular arrhythmia database
FFREWT	Fixed frequency range empirical wavelet transform	VF-Filter	Signal content outside the mean frequency
HPO	Hyperparameter optimization	VMD	Variational mode decomposition
KNN	*k*-Nearest neighbour classifier	VT	Ventricular tachycardia
MA	Metaheuristic algorithms	W(s)	Window length in seconds

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