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# Ventricular Fibrillation Prediction and Detection: A Comprehensive Review of Modern Techniques

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**Abstract:** This review offers a detailed examination of modern ECG signal processing techniques employed in the prediction and detection of ventricular fibrillation (VF). It contains a thorough analysis of recent advancements in the field, exploring the strengths, limitations, and real-world applications of these techniques. By evaluating the current state of research, the review seeks to identify the most effective approaches and highlight key areas where further investigation is needed, ultimately guiding future research efforts toward improving VF prediction and detection. Overall, AI has shown significant potential in a range of VF-related tasks. However, real-world implementation encounters several challenges, including difficulties in accurately interpreting ECG signals, the variability in individual physiological responses, and the infrequency of ventricular fibrillation events. Additionally, there are issues related to the critical timing required for detecting VF, the presence of similar arrhythmias, the need for adaptation to new ECG devices, energy consumption concerns, and the complex process of obtaining regulatory and legislative approvals for integrating software components into medical equipment. We consider that the present work might be useful in approaching the above challenges.

**Keywords:** ventricular fibrillation; features extraction; ensemble classifiers; machine learning; detection; prediction

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## 1. Introduction

The electrocardiogram (ECG) is one of the most widespread non-invasive methods of monitoring the electrical activity of the heart. It is essential in the diagnosis and management of a wide range of cardiac conditions. Ventricular fibrillation (VF) is a severe and potentially fatal arrhythmia that requires immediate medical intervention, usually in the form of defibrillation. VF is characterized by chaotic and rapid electrical activity of the ventricles, resulting in the inability of the heart to pump blood efficiently. If not treated immediately, VF can lead to sudden cardiac death. VF is caused by multiple foci of excitation in the ventricles, which generate unsynchronized electrical impulses. These foci disrupt the coordinated contraction of the ventricles, leading to inefficient mechanical activity.

According to statistics, sudden cardiac death accounts for approximately 50% of all cardiovascular deaths and 15–20% of all natural deaths in the United States [1]. Each year in the United States, an estimated 325,000 people suffer an out-of-hospital cardiac arrest [2]. Of these, ventricular fibrillation is one of the major causes, being involved in approximately 75% of sudden cardiac arrest cases at the onset of the event [3].

The human heart is an electrically active organ that functions based on electrical impulses generated by the sinoatrial (SA) node, also known as the heart's natural pacemaker. These impulses propagate through the tissues of the heart, causing the heart muscle to

contract and relax, which results in blood being pumped throughout the body. The ECG signal is recorded by placing electrodes on the surface of the skin, which detects the electrical potential differences generated by the electrical activity of the heart.

Early and accurate detection of VF is essential to increase the patient's chances of survival. Studies show that for every minute of delay in defibrillation, the chances of survival decrease by about 10% [4]. In this context, the development and implementation of advanced ECG signal processing methods for rapid and accurate detection of VF are of critical importance.

Recent technological advances in the field of signal processing have allowed the development of sophisticated algorithms for the detection and analysis of cardiac arrhythmias. These advances include the use of machine learning, deep learning neural networks, and advanced mathematical transformations to improve the accuracy and speed of VF detection. A 2020 study demonstrated that using convolutional neural networks (CNNs) to detect ventricular fibrillation from ECG signals achieved over 95% accuracy [5]. Also, the use of discrete wavelet transform (DWT) to preprocess ECG signals before applying machine learning algorithms led to significant improvements in arrhythmia detection accuracy, with sensitivities and specificities above 90% [1].

Machine learning has become a powerful tool in ECG data analysis. Machine learning and deep learning algorithms can be trained to recognize complex patterns in ECG signals that are associated with arrhythmias, including ventricular fibrillation. Convolutional neural networks (CNNs) have demonstrated outstanding performance in the classification and detection of ECG signals. CNNs are able to extract relevant features from ECG signals by means of convolutional layers, thereby reducing the need for manual data preprocessing. In [1], the authors used a CNN for arrhythmia detection applied to tachycardia ECG segments. The model achieved over 95% accuracy, demonstrating the potential of these networks in automatic VF detection. In [2], a custom CNN was developed for real-time detection of arrhythmias, achieving similar accuracy.

Deep learning, especially recurrent neural networks (RNNs), has also been explored for analyzing ECG signals. RNNs are effective in modeling temporal sequences and can capture the temporal dynamics of ECG signals. A notable example is the use of RNNs for VF detection [3] based on an LSTM (Long Short-Term Memory) model, a variant of RNN, to detect episodes of ventricular fibrillation with high sensitivity and specificity.

Advanced mathematical transforms, such as wavelet transform and Fourier transform, play a crucial role in preprocessing ECG signals and extracting relevant features. Discrete wavelet transform (DWT) is frequently used for multiresolution analysis of ECG signals. DWT can decompose the ECG signal into its frequency components, thereby facilitating the identification of specific features associated with VF. In [4], DWT was used to extract features from ECG signals and subsequently apply a machine learning algorithm to classify arrhythmias. The results showed a significant improvement in detection accuracy compared to traditional methods.

Fast Fourier Transform (FFT) is another technique used for spectral analysis of ECG signals. The FFT algorithm allows the signal to be transformed from the time domain to the frequency domain, thus facilitating the detection of frequency changes associated with arrhythmias. In [6], the use of FFT for the detection of ventricular fibrillation was demonstrated with an accuracy of approximately 94%. Although this method is effective, its combination with other techniques, such as DWT and machine learning algorithms, can lead to even better results.

Combining different ECG signal processing techniques and integrating them into a coherent system has led to the development of hybrid models that provide superior performance. For example, combining wavelet transforms with CNNs and RNNs has allowed improved arrhythmia detection and classification. An example of this hybrid approach is the study [7], which integrated DWT and CNN for arrhythmia detection in ECG signals collected from wearable devices. The model achieved high accuracy and demonstrated the viability of using these techniques in continuous patient monitoring. Recent advances in

ECG signal processing, fueled by machine learning and advanced mathematical transformations, have led to significant improvements in the detection of ventricular fibrillation. These techniques offer high accuracy and efficiency, with the potential to transform clinical practice and save lives through rapid and accurate interventions.

Despite these advances, there are still many challenges in the field of ventricular fibrillation detection. The variability of ECG signals between different patients, the presence of noise and artifacts in the recorded signals, and the need to develop robust models that work efficiently in real time are just some of the challenges that require innovative solutions. The identification and development of ECG signal processing methods that are both accurate and computationally efficient is essential for practical implementation in wearable monitoring devices and telemedicine systems. These systems could play a crucial role in the continuous monitoring of patients and early detection of episodes of ventricular fibrillation, thereby contributing to the reduction of mortality associated with this condition.

ECG signals vary considerably between different patients due to individual differences in the anatomy and physiology of the heart, as well as the presence of various cardiac conditions. This variability makes it difficult to develop universal models that work accurately for all patients. The study [8] showed that inter-patient variability can affect the performance of VF detection algorithms. Algorithms must be able to adapt to these differences to ensure reliable detection. Customized solutions, which involve training models on patient-specific data, could significantly improve detection accuracy.

ECG signals are often contaminated with noise and artifacts caused by patient movements, electromagnetic interference, and other external sources. These noises can adversely affect the accuracy of VF detection algorithms. In [9], the importance of effective noise filtering techniques to improve the quality of ECG signals was highlighted. The development of advanced preprocessing methods, which remove noise and artifacts without affecting the useful signals, is crucial for accurate VF detection.

Practical implementation of VF detection algorithms in continuous monitoring and telemedicine systems is another challenge. These systems require reliable solutions that can monitor patients long-term and transmit real-time data to medical monitoring centers. The study [10] showed the potential of telemedicine systems in the continuous monitoring of cardiac patients but also highlighted the need for VF detection algorithms that are robust and reliable in the long term. Integrating these technologies into healthcare systems can significantly improve patient management and reduce VF-related mortality.

This paper aims to provide a comprehensive review of modern ECG signal processing methods used for ventricular fibrillation detection. The main aim is to present and analyze recent techniques in the field, highlighting their advantages, limitations, and practical applications. This analysis aims to identify the most promising approaches and future research directions. The work is structured as follows: Section 1 is an introduction to the problem of detection and prediction of ventricular fibrillation with the presentation of the importance of detection and the main technological challenges encountered in the addressed field. Section 2 presents modern ECG signal analysis techniques, including machine learning algorithms, adaptive filtering Methods, wavelet transform techniques, and hardware implementations. In Section 3, the most relevant recent reference works on the topic of ventricular fibrillation detection and prediction are briefly presented with an analysis of the methods used and the performances obtained. Section 4 is dedicated to discussions regarding the possibility of detecting ventricular fibrillation with signal processing methods combined with neural networks with deep learning, as well as to the presentation of the main problems specific to their use in applications or methods of detecting or predicting ventricular fibrillation.

## 2. Modern ECG Signal Processing Techniques for Detection and Prediction of Ventricular Fibrillation

In the current technological era, modern ECG signal processing techniques are becoming essential for the detection and prediction of ventricular fibrillation. By using advanced data analysis algorithms and artificial intelligence, these techniques enable more accurate and faster interpretation of the complexity of cardiac signals. This not only improves early diagnosis but also optimizes clinical interventions, providing unprecedented opportunities to prevent critical episodes and save lives. In this chapter, we briefly present the most used signal-processing techniques and training algorithms for automatic classification. We exemplify works that use these techniques and discuss some hardware implementation methods.

The electrocardiogram (ECG) is a non-invasive and essential method in cardiology used to record the electrical activity of the heart. This is done by placing electrodes on the surface of the skin, which detect and record the electrical impulses generated by the myocardium during heart contractions. Normally, the ECG shows distinct waves (P, QRS, and T), each reflecting a specific phase of the cardiac cycle.

In ventricular fibrillation (VF), a severe and potentially lethal arrhythmia, these normal ECG features are profoundly altered. Figure 1 shows an example of normal rhythm and ventricular fibrillation. Ventricular fibrillation is characterized by chaotic and rapid electrical activity of the ventricles, which causes disordered and ineffective contractions of the heart. This prevents blood from pumping efficiently to the body, requiring emergency medical intervention.

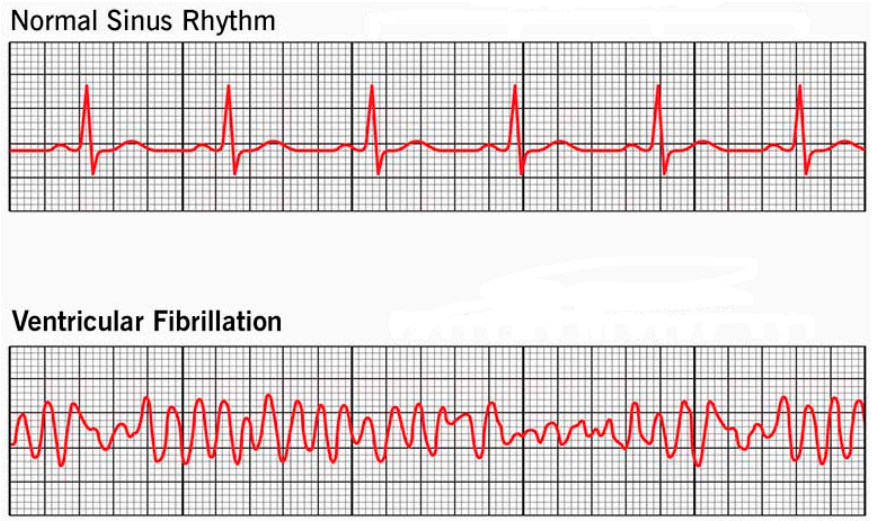


**Figure 1.** Example of Normal Sinus Rhythm and Ventricular Fibrillation.

Features of the ECG in ventricular fibrillation include the following:

1. Absence of P waves and normal QRS complexes: Chaotic electrical activity causes normal ECG waves to disappear. Instead, the ECG shows a disorganized pattern without the distinct structure of P waves, QRS complexes, or T waves.
2. Fast and irregular waves: In ventricular fibrillation, the ECG shows fast and irregular waves that vary in shape and amplitude. These waves are commonly referred to as "fibrillar waves" and reflect the unsynchronized electrical activity of the ventricular myocardium.
3. Extreme variability: The amplitude of fibrillar waves can vary considerably, some being very small (fine) and barely detectable and others larger (coarse). This variability depends on the duration and severity of episodes of ventricular fibrillation.
4. Very high rate: The heart rate in VF can be extremely fast, often exceeding 300 beats per minute. This reflects the rapid and chaotic nature of ventricular electrical activity.

Diagnosis of ventricular fibrillation based on ECG is crucial for immediate intervention, such as defibrillation, which can restore normal heart rhythm and save the patient's life.

Modern ECG signal processing techniques, through advanced algorithms and artificial intelligence, play a vital role in the prompt and accurate detection of these peculiarities, facilitating quick and effective interventions in cardiac emergencies.

### 2.1. Machine Learning Algorithms

Machine learning algorithms are essential in ECG signal analysis due to their ability to model and recognize complex patterns in high-dimensional data.

#### 2.1.1. Supervised Methods

Supervised methods involve training algorithms on a labeled dataset, where each training example is associated with a label indicating the correct class. in the context of the ECG signal, these labels indicate the presence or absence of ventricular fibrillation. We will explore some of the most commonly used supervised algorithms:

- Support Vector Machines (SVM): Support vector machines are machine learning algorithms that work by finding an optimal hyperplane that separates the data into two distinct classes. In the case of the ECG signal, SVM can be used to distinguish between normal and abnormal beats associated with ventricular fibrillation. SVM uses kernel functions to transform the data into a higher dimensional space where a linear hyperplane can more easily separate the classes. The Gaussian Kernel (RBF) is commonly used in ECG signal processing due to its ability to handle nonlinear data. SVM optimizes the edge, the distance between the data points of the two classes, and the separating hyperplane. This minimizes the risk of overfitting and improves the generalizability of the model. Examples of works that use SVM in the detection of ventricular fibrillation are [11–13].

A robust ventricular fibrillation prediction algorithm using only time-domain and nonlinear features while maintaining a one-minute prediction resolution was proposed in [14]. The authors used nine time-domain features and seven nonlinear features. SVMs with different kernels were used as classifiers. The authors obtained a high accuracy of 94.7% and a sensitivity of 100% by using two HRV features and Gaussian kernel SVM without complicated preprocessing of HRV signals. The advantages of the method are high accuracy and low computational burden, beneficial aspects for the embedded system, and real-time applications, which could help alert people earlier and, thus, improve patient survival chances.

- Random Forest: Random forest is a classification algorithm that builds multiple decision trees during training and improves accuracy by aggregating their predictions. The bagging (bootstrap aggregating) technique is used to generate training datasets by sampling with replacement, which leads to a reduction in model variance. Random forest provides feature importance measures, allowing the identification of the most relevant features of the ECG signal for ventricular fibrillation detection. Examples of works with random forest are [13,15,16].
- k-Nearest Neighbors (k-NN): The k-NN algorithm is a classification method that assigns classes based on the majority class among the k-nearest neighbors of an unknown point. The algorithm uses distance measures, such as Euclidean distance, Hamming distance, Chebyshev distance, and other types of distances, to determine nearest neighbors. We note that the selection of the k value influences the performance of the algorithm; values that are too low can lead to overfitting, while values that are too high can lead to underfitting. Examples of works with KNN are [13,17]

In the paper [18], the authors carried out a detailed study on the possibilities of detection and prediction of ventricular fibrillations using features extracted in the time domain, frequency and complexity measures using neural networks and supervised classifiers available in the Matlab 2019 environment in the machine learning toolbox.

#### 2.1.2. Unsupervised Methods

Do Not Require Training Labels and Are Used to Discover Hidden Structures in ECG Data

- K-means Clustering: K-means is a clustering algorithm that partitions the data into k clusters, with each cluster being represented by its center (centroid). The algorithm alternates between assigning each data point to its closest centroid and recomputing the centroids based on the average of the data points assigned to each cluster. The algorithm continues until convergence, where the data points stop changing clusters. An example of application in VF detection is reported in [19].
- Principal Component Analysis (PCA): PCA is a dimensionality reduction method that transforms the data into a new coordinate system, where the largest variations are captured by the first principal components. PCA calculates the eigenvalues and eigenvectors of the covariance matrix of the data, using these components to project the data into a low-dimensional space. The first principal components capture most of the variance in the data, allowing dimensionality reduction without significant loss of information. Examples of works in the field of VF are [20,21].

Several evaluation measures are used to evaluate the performance of these algorithms, including accuracy, sensitivity, specificity, and F1 score. In general, public and private datasets of ECG signals are used, and cross-validation techniques are applied to ensure the robustness of the results.

In [13], the performances of SVM, random forest, and KNN in the detection of ventricular fibrillation using an ECG dataset were compared. The results showed that SVM achieved an accuracy of 96%, sensitivity of 95%, and specificity of 97%. Random forest achieved similar values, and KNN had a slightly lower accuracy of around 94%.

The study [22] aimed to develop and evaluate machine learning models to predict the occurrence of arrhythmia after an acute myocardial infarction (AMI). Three ML models were used to predict the occurrence of tachyarrhythmias after AMI. After variable selection, the artificial neural network (ANN) model achieved the highest accuracy rate, outperforming the model built using the Grace variable set.

### *2.2. Neural Networks and Deep Learning Algorithms*

Neural networks are an advanced class of machine learning algorithms inspired by the structure and function of the human brain. They provide a flexible and robust approach to ECG signal processing capable of modeling complex relationships and identifying subtle patterns in the data. In the context of ventricular fibrillation (VF) detection and prediction, neural networks are particularly useful due to their ability to extract and learn relevant features from ECG signals.

We will discuss two main types of neural networks used very often in ECG signal analysis, namely convolutional neural networks (CNNs) and recurrent neural networks (RNNs), with an emphasis on specific architectures, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

In [23], the authors classify and compare deep learning (DL) architectures used in ECG arrhythmia detection in the period 2017–2023, architectures that showed superior performance. Thus, in [23], different DL models, such as convolutional neural networks (CNNs), multilayer perceptrons (MLPs), transformers, and recurrent neural networks (RNNs), are analyzed, and a summary of their effectiveness is provided. In [24], the authors provide a comprehensive overview of recent advances in prediction models and the implementation of AI and ML in the prediction and management of sudden cardiac arrest.

Current risk stratification for ventricular arrhythmias relies on static measurements that fail to adequately capture the dynamic interactions between arrhythmic substrate and triggers over time. To address this, in [25], a dynamic machine learning (ML) model and neural network were employed, which extracted features from longitudinally collected electrocardiograms (ECGs). These features were then used to predict the risk of malignant ventricular arrhythmias.

#### 2.2.1. Convolutional Neural Networks (CNNs)

Convolutional neural networks are designed to process data that have a spatial or temporal relationship, such as images and 1D signals, such as ECG. They are effective in extracting local features from the ECG signal and are often used in heartbeat classification and detection of ventricular fibrillation episodes. At the structural level, CNNs are composed of convolutional layers, pooling layers, and fully connected layers. Each convolutional layer applies a set of filters (kernels) to the input signal to extract local features. Convolutional layers perform convolution operations between low-dimensional filters and segments of the ECG signal. The filters are learned during training and enable the network to identify important features, such as P, QRS, and T waves in the ECG signal, that are essential for detecting episodes of ventricular fibrillation. Pooling layers perform subsampling operations such as max-pooling or average-pooling, reducing the size of representations and preserving important features. Pooling helps reduce data dimensionality.

To evaluate the performance of applied neural networks in ventricular fibrillation (VF) detection and prediction, some already mentioned evaluation measures, such as accuracy, sensitivity, specificity, and F1 score, are used. These measures are essential to determine the efficiency and reliability of the model.

CNNs are highly robust to noise, having the ability to filter out unwanted disturbances and preserve essential features. They excel at detecting subtle and local patterns in the ECG signal, which makes them particularly effective at identifying small but important details. In addition, CNNs are scalable and can be adapted to different resolutions of the ECG signal, thus ensuring flexibility in their application to various types of ECG data.

In [26], a CNN model was proposed for the automatic detection of ventricular fibrillation using ECG data. The goal of the study was to develop an automated system that could accurately classify ECG signals to identify ventricular fibrillation, a condition that can be fatal if not treated promptly. The CNN model developed in this paper was trained and tested on a dataset of ECG signals. The CNN was composed of several convolutional layers and pooling layers, followed by fully connected layers. The results of the study showed high accuracy in the detection of ventricular fibrillation, surpassing traditional methods of analyzing ECG signals.

Paper [7] presents a CNN model for the automatic detection of cardiac arrhythmias, including ventricular fibrillation, using an extensive electrocardiogram (ECG) dataset collected from wearable devices. The model was trained on over 91,232 recordings from 53,877 patients and demonstrated classification performance comparable to that of expert cardiologists with high sensitivity and specificity. This work is recent and highly cited, highlighting the advanced use of CNNs in the field of cardiac arrhythmia detection.

In [27], the authors implemented a deep CNN using the Keras framework with a TensorFlow (Google, Mountain View, CA, USA) and Python (Python Software Foundation, Beaverton, OR, USA) backend to predict ventricular fibrillation. The raw ECG signal consisting of a $12 \times 5000$ matrix was fed into the CNN, which is composed of two convolution layers with a kernel size of $3 \times 3$, a data distribution normalization layer, and a unit activation function rectified linear unit (ReLU) to provide nonlinearity to the model. These two-dimensional convolutions were intended to be effective for analyzing information between leads, such as V1-V2-V3. The output was then fed into two dense layers using a batch normalization intermediate layer with ReLU activation. The final output layer was enabled using the softmax function, which generated the probability of an input belonging to a specific class. The training dataset was fed into the network, and the network weights were updated using the RMSprop optimizer with binary cross-entropy as the loss function. After each epoch, the network was tested using an internal validation dataset. The network hyperparameters, batch, and step size were also tuned during this process, and the network with the lowest loss value was selected once the loss value in the validation set stopped decreasing for the next 12 epochs.

In [28], the authors use machine learning and deep learning models to automate diagnostics by capturing unseen patterns in datasets. Thus, the proposed method focuses

on data augmentation using the augmentation technique that increases the size of the dataset by generating different images. The system proposed by the authors is a novel CNN model tuned with hyperparameters to obtain an optimal combination of parameters that minimizes the loss function and produces a better result. The results reported in [28] show that the hyper-adjusted model outperforms other machine learning models and the basic CNN model for the accurate classification of normal and five other different types of arrhythmias.

The paper [29] presents a feature learning strategy that uses the improved variational mode decomposition technique to detect ventricular cardiac arrhythmias on ECG signals. A deep learning neural network and bat-rider optimization algorithm (BROA) as an optimized classifier are used to extract the features. To test the proposed algorithm, the ECG signals with arrhythmias from the MIT-BIH database are used.

#### 2.2.2. Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are specifically designed to process and model sequential data, which makes them ideal for analyzing ECG signals, which are sequential in nature. RNNs have an internal memory that allows them to retain information from previous states of the sequence, thus facilitating the capture of temporal dependencies.

At the structural level, RNNs consist of nodes or neurons that not only receive inputs from the current data but also from the previous states of the neurons in the network. This allows them to maintain a temporal context, which is essential for analyzing data sequences. Typically, a recurrent neural network is described by the following components: (i) Recursive Unit: Nodes in the RNN have recurrent connections that allow information to be preserved and propagated along the sequence; and (ii) Output Layer: The last layer of the network produces a prediction or classification based on accumulated information.

One of the main challenges of traditional RNNs is the vanishing gradient problem. During training, as the error signal is backpropagated through the network (backpropagation through time—BPTT), the gradient can become extremely small, making it difficult to adjust the weights and, thus, learn long-term dependencies.

- Long Short-Term Memory (LSTM)

LSTMs are an improved version of RNNs designed to overcome the evanescent gradient problem. They use a mechanism of memory cells and control gates that regulate the flow of information, allowing the network to learn and maintain long-term dependencies.

In the LSTM architecture, the memory cell stores the relevant information for long periods of time, while the input gate controls the amount of new information that is stored in the memory cell. The forget gate decides what information in the memory cell is forgotten, and the output gate determines how much of the memory cell's information is used to calculate the current state.

LSTMs have two major advantages, namely the following: (i) Long-term dependencies: The ability to capture long-term temporal dependencies that are essential for predictions based on long sequences of ECG signals; (ii) Information flow control: Gate mechanisms allow the network to adjust efficiently flow information and retain the most relevant features.

Yildirim in [3] used Long Short-Term Memory (LSTM) networks to predict ventricular fibrillation episodes. The model was trained on long sequences of ECG data, capturing the temporal dependencies essential for prediction. The LSTM model achieved an accuracy of 94.3%, with a sensitivity of 92.5% and a specificity of 95.8%. The model's ability to learn long-term temporal relationships was critical to its high performance.

- Gated Recurrent Unit (GRU)

GRUs are another variant of RNNs, similar to LSTMs, but with a simplified architecture. GRUs combine the forget gate and input gate into a single update gate, which reduces computational complexity and the number of parameters.

In the GRU architecture, the update gate controls how much of the previous state is maintained in the new state, while the reset gate decides how much of the previous information is forgotten.

GRUs stand out for their computational efficiency, having fewer parameters and a simpler architecture compared to LSTMs, making them faster and more computationally efficient. In many applications, GRUs provide performance comparable to that of LSTMs but at a lower computational cost.

RNNs, including LSTMs and GRUs, are extremely useful in ECG signal analysis for ventricular fibrillation detection and prediction due to their ability to process sequential data and learn complex temporal dependencies.

Implementation of GRU for Real-Time Monitoring of ECG. A recent example of the implementation of GRU networks for real-time monitoring of ECG signals and detection of ventricular fibrillation can be found in [30]. The researchers developed and evaluated a model based on GRU networks for the continuous analysis of ECG signals collected from patients with various heart conditions. The GRU model demonstrated outstanding performance in ventricular arrhythmia detection with significant accuracy and adaptability for implementation in portable, continuous medical monitoring devices. This paper [30] exemplifies the application of recurrent neural networks for real-time ECG monitoring and evaluates their performance in detecting cardiac arrhythmias, being a well-cited and relevant source in the field of medical research.

The paper [31] presents an algorithm for classifying electrocardiogram (ECG) beats using a combination of bidirectional recurrent neural network (BiRNN) and convolutional neural network (CNN) called BiRCNN. The end-to-end model was used, and the morphological features specific to the EXG signal were automatically extracted using a CNN and then processed using a recurrent bidirectional network. For the MIT-BIH arrhythmia database (MITDB), the authors obtained a sensitivity of 98.7% and a positive predictive value of 96.4% on average for the EBV class. For the SVEB class, the sensitivity was 92.8%, with a few percentages below the results reported at that time with other methods.

#### 2.2.3. Convolutional–Recurrent Neural Networks (CRNNs)

Convolutional–recurrent neural networks (CRNNs) combine the advantages of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), making them highly efficient for tasks involving both spatial and temporal features. In the context of ventricular fibrillation (VF) detection and prediction, CRNNs provide a robust and accurate approach to analyzing ECG signals.

CRNNs combine the convolutional layers of CNNs, which are excellent at capturing local and spatial features in ECG signals, with the recurrent layers of RNNs, which are ideal for modeling temporal dependencies in sequential data. The typical structure of a CRNN for ECG analysis may include convolutional layers, pooling layers, recurrent layers, and fully connected layers.

Convolutional Layers: These apply convolutional filters to ECG signals to extract local features, such as P, QRS, and T waves, essential for identifying abnormalities associated with VF. Convolutional layers help reduce noise and highlight relevant patterns.

Pooling Layers: These layers are used to reduce the dimensionality of the data while preserving the essential features. Pooling helps to reduce computational complexity and prevent overlearning.

Recurrent Layers (LSTM/GRU): After extracting the spatial features, the data are passed through recurrent layers, such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU). These layers are able to capture temporal dependencies and maintain relevant information over long periods of time, which is crucial for VF prediction.

Fully Connected Layers: Finally, the processed data are passed through one or more fully connected layers, which complete the processing and produce the final output, such as a PV probability.

Convolutional–recurrent neural networks (CRNNs) offer numerous advantages in the detection and prediction of ventricular fibrillation (VF). One of the main benefits is their ability to capture complex features. By combining the advantages of convolutional neural networks (CNNs), which excel at detecting local patterns, with those of recurrent neural networks (RNNs), which specialize in modeling temporal sequences, CRNNs can learn and identify intricate patterns that may indicate VF. CRNNs are also robust to noise. Convolutional layers can filter noise from ECG signals, ensuring that only relevant features are used for prediction, which prevents false alarms and improves the accuracy of VF detection. Another advantage of CRNNs is their ability to perform real-time detection and prediction, which is crucial for emergency medical interventions. These networks are able to process ECG data in real time, enabling rapid detection of VF episodes. The scalability and flexibility of CRNNs is also a significant advantage. These networks can be adjusted to accommodate various datasets and resolutions of ECG signals, making them versatile and applicable in different clinical scenarios. Thus, CRNNs provide a robust and accurate approach to the analysis of ECG signals, helping to improve the diagnosis and treatment of patients with ventricular fibrillation.

In [31], Xie proposed a model that combines the advantages of CNNs with a bidirectional recursive neural network to classify heartbeats from the MIT-BIH Arrhythmia Database (MITDB). Thus, with a CNN-type network, the morphological features of each ECG beat are extracted, and then, with a bidirectional recursive neural network (BiRNN), these features are analyzed to classify the heartbeats. For the MITDB database used for testing, the authors obtained a sensitivity of 98.7% for VEB heartbeats and a sensitivity of 92.8% for SVEB heartbeats [31].

In [32], the authors propose a method based on deep convolutional neural networks and sequence-to-sequence models to classify heartbeats and use a strongly unbalanced database as a class distribution to demonstrate the robustness of the proposed method. Thus, the authors use a sequence-to-sequence RNN model together with a convolutional neural network (CNN) to perform a heartbeat detection task.

In [33], the authors propose a recording-level, not heartbeat-level, ECG classification method by combining a 1D deep convolutional neural network (CNN) and a long-term memory network (LSTM). The proposed method [33] uses CNN to automatically extract features of ECG patches without complex data preprocessing or artificial feature schemes and then uses two LSTM layers to model the underlying temporal correlation relationship between ECG patches. For the vanishing gradient problem and to improve feature representation power, the authors construct a residual attention module by combining residual connectivity and attention mechanisms.

#### 2.2.4. Auto-Encoders and Generative Adversarial Networks (GANs)

Auto-encoders are a special category of neural networks used to learn relevant features from input data through an encoding–decoding process. They are composed of two main parts: the encoder and the decoder. The encoder transforms the input data into a small representation (called a code), and the decoder reconstructs the original data from this code. In the context of ECG signal analysis, auto-encoders can be used as follows:

- Preprocessing and Dimensionality Reduction: Auto-encoders can compress complex ECG signals into a more compact form, thereby reducing data size without losing essential information. This dimensionality reduction facilitates data analysis and further processing.
- Noise Removal: Auto-encoders can learn to distinguish the useful signal from background noise. After training, these can be used to filter noise from ECG signals, producing cleaner and easier-to-analyze versions.
- Anomaly Detection: By learning a compact representation of normal ECG signals, auto-encoders can identify anomalies or deviations from regular patterns. This is essential for detecting episodes of ventricular fibrillation, which are significant deviations from the normal heart rhythm.

Generative Adversarial Networks (GANs) represent an advanced technology in the field of deep learning, consisting of two competing neural networks: the generator and the discriminator. The generator creates fake (synthetic) data, and the discriminator tries to distinguish between real and generated data. Through this adversarial process, GANs learn to generate highly realistic synthetic data.

In the context of analyzing ECG signals for the detection and prediction of ventricular fibrillation, GANs can be used for:

- Synthetic Data Generation: GANs can create artificial ECG signals that mimic real signals. This is particularly useful in situations where there is a limited amount of real data for training. By generating synthetic data, GANs can augment datasets, thereby improving the performance of deep learning algorithms.
- Improving Training: Synthetic data generated by GANs can be used to diversify training datasets, exposing deep learning models to a wider variety of patterns and conditions. This contributes to increasing the robustness and generalization of the models in the detection of ventricular fibrillation.
- Anomaly Detection: GANs can be used to learn the typical distribution of normal ECG signals. Any significant deviation from this distribution, identified by the GAN discriminator, may indicate the presence of an abnormality, such as an episode of ventricular fibrillation.

The use of auto-encoders and GANs in the analysis of ECG signals brings multiple advantages in the detection and prediction of ventricular fibrillation. By reducing dimensionality and removing noise, auto-encoders facilitate more accurate analysis of ECG signals. At the same time, GANs help improve datasets by generating synthetic data, allowing deep learning models to learn more efficiently and become more robust.

The integration of these advanced technologies into medical diagnostic systems has the potential to increase the accuracy and efficiency of ventricular fibrillation detection, leading to faster and more accurate medical interventions. Finally, the use of auto-encoders and GANs can significantly improve the prognosis of patients with ventricular fibrillation, contributing to saving lives and increasing the quality of medical care.

In [34], the authors propose an anomaly detection model for ECG signals based on a CRNN and use a GAN composed of several 1D CNNs to perform data augmentation because the classes in the database used for testing are strongly unbalanced as a distribution of the data. Their model achieved excellent performance for class-imbalanced datasets.

Another example of using GANs for medical applications in the field of cardiology is the one presented in [35], where the authors use a custom GAN to perform ECG classification, where data labeling is broken. Thus, a GAN was optimized using a specialized loss function and trained to generate customized synthetic ECG signals for different arrhythmias.

#### 2.2.5. Techniques Used in the Training Stage

- Data Normalization: Data normalization is crucial in signal processing techniques because it ensures consistency and comparability between datasets, thereby reducing noise and improving the accuracy of analyses; common normalization techniques include scaling to a specific range (e.g., between 0 and 1), standardization (adjusting to zero mean and unit standard deviation), and min–max normalization.
- Data Augmentation: Since ECG data are often limited, data augmentation techniques such as adding Gaussian noise and time and frequency transformations can increase the size of the training dataset and improve the generalization of the model.
- Dropout: Dropout [36] is a regularization technique that reduces overlearning by randomly deactivating a proportion of neurons during training at a certain step and then reactivating them at the next step. Basically, neurons stopped at one step do not contribute to the calculation of the output of that layer and do not participate in the calculation of the gradient during the backward pass. This forces the network to be more robust and not rely too much on certain features. This technique, introduced by Hinton in [36], quickly became one of the most popular regularization methods.

#### 2.2.6. Validation Techniques

- Cross-Validation: The use of k-fold cross-validation allows the evaluation of model performance on multiple subsets of the dataset, ensuring robust performance estimation.
- Independent Test Dataset: Keeping an independent test dataset that is not used during training is essential for the final evaluation of the model and to ensure that the observed performance is representative of new data.

Neural networks, especially CNNs and RNNs, have been intensively studied for VF detection due to their ability to learn complex features from ECG data. In [1], the performance of CNN and LSTM in the detection of ventricular fibrillation was compared. CNN achieved an accuracy of 98.7%, sensitivity of 98%, and specificity of 99.2%. LSTM showed comparable performance, with an accuracy of 98.3%, sensitivity of 97.5%, and specificity of 99%. These results demonstrate that both networks are very efficient, with CNN having a slight superiority in terms of specificity.

Neural networks, especially CNNs and RNNs, provide powerful and efficient methods for the detection and prediction of ventricular fibrillation from ECG signals. Integrating these techniques into portable medical devices and remote monitoring systems is an important step toward improving the diagnosis and treatment of cardiac arrhythmias. Future research could explore the use of generative neural networks for data augmentation and the development of hybrid models that combine the advantages of CNNs and RNNs for even better performance.

### *2.3. Adaptive Filtering Methods*

Removing noise and artifacts from the ECG signal is crucial for its correct and accurate analysis, especially in the context of ventricular fibrillation (VF) detection and prediction. Adaptive filtering methods, such as the Kalman filter and the RLS filter, provide effective solutions for removing noise and artifacts from the ECG signal. These techniques allow for improved signal quality, essential for accurate detection and prediction of ventricular fibrillation. Studies in the literature demonstrate the effectiveness of these methods, highlighting their potential in clinical applications and real-time monitoring. An example of the use of adaptive filtering in this area can be found in the paper [37], which uses an adaptive filter in combination with a support vector machine (SVM)-based recognition system to detect abnormal heartbeats associated with ventricular fibrillation.

#### 2.3.1. Kalman Filter

The Kalman filter is a recursive algorithm used to estimate the state of a system from a series of noisy measurements. It is particularly useful in the real-time processing of ECG signals due to its ability to follow the dynamics of the signal and improve its quality by removing noise. A relevant example of the use of the Kalman filter is presented in paper [38], which proposes an algorithm for discriminating ventricular fibrillation (VF) signals from ventricular tachycardia (VT) signals through the adaptive filtering technique. This algorithm first adopts the VF and VT signals as the primary input of the adaptive filter, and the reference signals can be conveniently obtained by a suitable delay. The energy of the error signal (EE) acts as an eigenvalue, and the decision thresholds are determined by the learning period. To test the proposed method, sequential testing is used, which identifies with an accuracy of 97.4% VF and 100% VT after three tests.

The paper [39] presents an innovative method of using the adaptive Kalman filter to enhance ECG signals. In this paper, a sequential averaging filter is developed that, in essence, adaptively varies the number of complexes included in the averaging based on the characteristics of the ECG signal. Using a Bayesian framework, this paper develops a sequential averaging filter that adaptively adjusts the number of complexes included in the averaging based on the characteristics of the ECG signal. The filter is designed as an adaptive Kalman filter. Adaptive estimation of process and measurement noise covariances is achieved by maximizing the Bayesian evidence function of the sequential ECG estimation and by exploiting the spatial correlation between multiple simultaneously recorded ECG

signals. These noise covariance estimates allow the filter to give more importance to newly arrived data when it exhibits morphological variability and to reduce this importance when there is no morphological variability. The filter is evaluated by applying it to a variety of ECG signals.

The Kalman filter can be applied to enhance the real-time ECG signal by removing background noise and artifacts. In [40], the use of the Kalman filter for the separation of ECG components and the removal of background noise was demonstrated. The filter was able to improve the ECG signal, allowing more accurate detection of episodes of ventricular fibrillation.

#### 2.3.2. Recursive Least Squares (RLS) Filter

The Recursive Least Squares (RLS) filter is an adaptive method that adjusts the filter coefficients in real time to minimize the error between the target and the acquired signal. This technique provides excellent adaptive performance, being particularly useful in dynamic environments where signal characteristics can vary rapidly. The RLS filter minimizes a weighted root mean square error function recursively using an iterative estimation technique.

The RLS filter can be used to remove noise and artifacts from the ECG signal while maintaining real-time adaptive performance. A notable example from the literature is [41], who showed that the RLS filter can be used to filter muscle noise and other interference from ECG signals, improving the signal for accurate detection of arrhythmias, including ventricular fibrillation.

### *2.4. Wavelet Transform Techniques*

Wavelet transform is a powerful approach for multiresolution analysis of the ECG signal, allowing its decomposition into different frequency components. This technique is essential for identifying and isolating meaningful features in the signal, being particularly useful in the context of ventricular fibrillation (VF) detection and prediction.

#### 2.4.1. Discrete Wavelet Transform (DWT)

Discrete wavelet transform (DWT) is used to decompose the ECG signal into different levels of resolution, allowing detailed analysis of its characteristics. This involves using low-pass and high-pass filters to separate the signal into approximation and detail components at different scales. DWT uses a set of mother wavelets and daughter wavelets to analyze the signal at different scales. The decomposition process involves the following steps:

Applying Filters: The ECG signal is passed through a low-pass filter and a high-pass filter, generating two sets of coefficients: approximation coefficients (low frequency) and detail coefficients (high frequency).

Subsampling: The resulting coefficients are then subsampled, reducing the size of the data and allowing analysis at a lower scale.

Repeating the Process: The process is repeated on the approximation coefficients to obtain several levels of decomposition.

$$X[n] = \sum_{k} A_{j-1}[k]\psi_{j,k}[n] + \sum_{k} D_{j-1}[k]\varnothing_{j,k}[n]$$

where $A_j[k]$ and $D_j[k]$ are the approximation and detail coefficients at level $j$, and $\psi_{j,k}[n]$ and $\phi_{j,k}[n]$ are the corresponding wavelet functions.

DWT is used to extract relevant features from the ECG signal, such as P waves, QRS complexes, and T waves, which are essential for detecting episodes of ventricular fibrillation.

#### 2.4.2. Continuous Wavelet Transform (CWT)

The continuous wavelet transform (CWT) provides a time–frequency analysis of the ECG signal useful for non-stationary signals. *CWT* decomposes the signal into scales and translation, allowing a continuous representation of the signal in the time–frequency

domain. The *CWT* is defined as the integral of the convolution of the ECG signal with a continuously scaled and translated wavelet function:

$$CWT_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt$$

where $a$ is the scaling factor, $b$ is the translation factor, $x(t)$ is the ECG signal, and $\psi$ is the mother wavelet.

CWT allows detailed analysis of non-stationary ECG signals, facilitating the detection of dynamic changes associated with ventricular fibrillation.

In conclusion, wavelet transform techniques, such as DWT and CWT, provide powerful methods for multiresolution analysis of the ECG signal, essential for the detection and prediction of ventricular fibrillation. The literature studies demonstrate the ability of these methods to extract relevant features and provide detailed representations of the ECG signal, helping to improve the accuracy and reliability of cardiac monitoring systems [42]. Future research could explore the integration of wavelet transforms with other machine learning techniques to develop hybrid models that combine the advantages of multiple signal analysis methods for optimal performance.

### *2.5. Hardware Implementations*

The experimental results demonstrate the effectiveness and practical applicability of various machine learning techniques and neural networks in the detection and prediction of ventricular fibrillation. Benchmarking shows that advanced algorithms, such as CNN and LSTM, provide superior performance in terms of accuracy, sensitivity, and specificity. Practical implementations in software (MATLAB and Python) and hardware (FPGA and wearable devices) highlight the potential of these technologies to be integrated into real-time patient monitoring systems, thus improving the diagnosis and treatment of cardiac arrhythmias. Future research could explore the development of hybrid solutions that combine the advantages of multiple techniques to achieve optimal performance in varied clinical settings.

Hardware implementations such as Field-Programmable Gate Array (FPGA) are essential for real-time ECG signal processing due to high computational requirements and low latency. The integration of VF detection algorithms in portable ECG monitoring devices is a growing field, with multiple proposals presented in the works in the field in recent years.

The authors of the paper [43] focus on the development and implementation of specialized on-chip signal processors for real-time detection of cardiac abnormalities based on the ECG (electrocardiographic) signal. These abnormalities include ventricular fibrillation (VF), ventricular tachycardia (VT), and premature ventricular complexes (PVCs). The architecture is realized on the FPGA platform to demonstrate the detection of abnormal ECG signals in real time.

The paper [44] presents a long-term wearable single-lead ECG processor for the early detection of cardiac arrhythmias. To ensure proper functional verification, the proposed system is implemented on FPGA and tested using the ECG arrhythmia database.

In [45], an accurate classification of ECG beats in real time was pursued with the help of algorithms that are executed on a TSK3000A embedded processor core (IP cores used) and implemented in hardware targeting FPGA (Xilinx Spartan 3AN).

In [46], an integrated simulated environment was developed using IAR Embedded Workbench software to construct an embedded system with an MSP430-f2274 microcontroller and Visual Studio (Visual C# 2008) tool for software build. Real-time experiments were conducted to evaluate five lightweight ventricular fibrillation (VF) detection algorithms and investigate factors affecting their performance, including sensitivity, specificity, positive-predictivity, accuracy, and computational time. The findings were validated using a prototype of a wearable electrocardiogram (ECG) system developed in the study. Key

conclusions include the following: (1) The choice of detection algorithm, data filtering, and window size significantly impacts real-time VF detection performance, with the detection algorithm exerting the greatest influence and requiring careful selection; (2) Optimal threshold selection is crucial for balancing performance metrics. Among the algorithms evaluated, the Time Delay (TD) algorithm consistently outperformed others across different window sizes and filtering methods, prioritizing detection accuracy and robustness over efficiency.

In paper [47], a method for identifying patients with cardiac dysfunction based on artificial intelligence and a smartwatch equipped with advanced sensors was presented. The smartwatches used were able to monitor the heart rate, its variations, and other relevant metrics, and on the part of the algorithms, specific AI methods were used to analyze the collected data and detect signs of left ventricular dysfunction. The results showed that smartwatches, together with advanced AI algorithms, can be used as an effective screening tool for LVD, enabling early interventions and continuous monitoring.

## 3. Recent Reference Works on the Topic of Ventricular Fibrillation Detection and Prediction

In this chapter, we present and review recent reference work on the detection and prediction of ventricular fibrillation. We analyze the methods, results, and significant contributions of this research in advancing understanding and practice in the diagnosis and management of this critical cardiac arrhythmia.

We also present, in more detail, the most significant (from the point of view of citations) works in the field of arrhythmia detection and/or prediction, ventricular fibrillation being essentially a cardiac arrhythmia.

**Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., and Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine, 25(1), 65-69. https://doi.org/10.1038/s41591-018-0268-3**

The aim of this paper [7] was the development and validation of a deep neural network (DNN) algorithm capable of detecting and classifying cardiac arrhythmias, including ventricular fibrillation, at a level comparable to that of expert cardiologists, using electrocardiogram (ECG) outpatients. The study involved the use of an extensive dataset, including more than 91,000 ambulatory electrocardiogram (ECG) recordings from more than 53,000 patients. The developed algorithm reached a global accuracy of 95%, being validated by an evaluation method on an independent dataset. In terms of sensitivity, the algorithm reached values between 92% and 97% for different types of arrhythmias, while its specificity ranged between 94% and 98%. The performance of the algorithm was compared with that of cardiologists, and it was shown that it can identify and classify arrhythmias with similar accuracy, thus providing an extremely valuable tool for monitoring and diagnosing arrhythmias in everyday clinical practice. These results underscore the potential of deep learning algorithms to supplement clinical expertise and help improve the care of heart patients.

**Attia, Z. I., Noseworthy, P. A., Lopez-Jimenez, F., Asirvatham, S. J., Deshmukh, A. J., Gersh, B. J., . . ., and Friedman, P. A. (2019). An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. The Lancet, 394(10221), 861-867. https://doi.org/10.1016/S0140-6736(19)31721-0**

The aim of this paper [30] was to develop and validate an algorithm based on artificial intelligence (AI) for the identification of patients with atrial fibrillation (AF) during sinus rhythm, demonstrating the potential of using AI technology for the prediction of severe arrhythmias, including ventricular fibrillation. The main goal was to demonstrate the ability of this algorithm to predict AF events based on ECG recordings from asymptomatic patients. The retrospective study used a large set of data collected from more than 180,000 patients from various medical centers, which ensures a significant variability and representativeness of the studied population. The algorithm demonstrated a remarkable 97% accuracy in

correctly detecting atrial fibrillation, with performance validated by rigorous statistical analysis. The sensitivity of the algorithm, that is, the ability to correctly identify patients with atrial fibrillation, was 95%, while the specificity, the ability to correctly exclude patients without this condition, reached the value of 98%. These results highlight the considerable potential of the algorithm to serve as a valuable tool in improving the diagnosis and management of atrial fibrillation, providing physicians with an efficient and accurate means for risk assessment and patient monitoring in clinical practice.

**Ribeiro, A. H., Ribeiro, M. H., Paixão, G. M., Oliveira, D. M., Gomes, P. R., Canazart, J. A., . . ., and Ribeiro, A. L. (2020). Automatic diagnosis of the 12-lead ECG using a deep neural network. Nature Communications, 11(1), 1760. https://doi.org/10.1038/s41467-020-15432-4**

In this paper [48], the aim was the development and validation of a deep neural network (DNN) algorithm capable of automatically diagnosing various cardiac conditions based on 12-lead electrocardiograms (ECGs). To achieve this goal, the authors collected an extensive 12-lead ECG dataset from patients in various clinical settings. Data were preprocessed to remove noise and artifacts, and ECG recordings were segmented and labeled according to diagnosis by expert cardiologists. The DNN model developed by the team was trained to recognize and classify a wide range of heart conditions, including atrial fibrillation, ventricular tachycardia, and other arrhythmias, using these labeled data. The algorithm demonstrated an overall accuracy of 93% in correctly diagnosing various cardiac conditions, with performance validated by a rigorous evaluation method on an independent dataset. The sensitivity of the algorithm ranged between 90% and 96% for various cardiac conditions, while the specificity was between 92% and 97%. These results were compared with diagnoses made by experienced cardiologists, demonstrating that the algorithm can diagnose heart conditions with similar accuracy, thus providing a powerful tool for improving the diagnosis and management of heart disease in clinical practice. Implementation of this algorithm can lead to faster and more accurate diagnosis, helping to improve the quality of patient care and reduce medical errors.

**Luz, E. J. S., Schwartz, W. R., Cámara-Chávez, G., and Menotti, D. (2016). ECG-based heartbeat classification for arrhythmia detection: A survey. Computer Methods and Programs in Biomedicine, 127, 144-164. https://doi.org/10.1016/j.cmpb.2015.12.008**

This review article [49] provides a comprehensive review of ECG-based heartbeat classification methods for the detection of arrhythmias, including ventricular fibrillation, and discusses the advantages and disadvantages of various approaches. The paper addresses various methods and algorithms used in ECG signal processing and heartbeat classification, highlighting recent advances and current challenges. Data preprocessing steps to remove noise and artifacts are discussed, as are techniques for extracting relevant features from ECG signals that help discriminate heartbeat types. In addition, various machine learning and deep learning algorithms used for heartbeat classification, such as artificial neural networks, support vector machines, and decision tree-based methods, are reviewed. Algorithm performance evaluation is an essential part of the paper, with the metrics and methodologies used to evaluate their accuracy and efficiency being discussed. The paper emphasizes the importance of standardized databases for training and testing algorithms, as well as the need to address the challenges of inter-subject variability and robustness under real-world conditions. The results presented in the paper indicate that deep learning models, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), achieved the best performance, with average accuracy ranging between 92% and 98% in detecting arrhythmias. The sensitivity and specificity of these models were also remarkable, with mean values between 90% and 95% for different types of arrhythmias. Current trends and future research directions are also discussed, including integration with wearable devices and mobile technologies for continuous patient monitoring. In conclusion, the paper [49] provides a detailed overview of the field of ECG-based heartbeat classification for arrhythmia detection, highlighting both the current achievements and the challenges to be addressed to improve the diagnosis and monitoring of cardiac conditions.

**Al-Zaiti, S. S., Besomi, L., Carey, M. G., Lopes, R. D., Hoekstra, J. W., and Lindsell, C. J. (2020). Machine learning-based prediction of acute coronary syndrome using only the pre-hospital 12-lead electrocardiogram. Nature Communications, 11(1), 3966. Available online: https://www.nature.com/articles/s41467-020-17804-2 (accessed on 27 November 2024).**

The above paper [50] presented a machine learning-based algorithm designed to predict acute coronary syndrome using only the pre-hospital 12-lead electrocardiogram (ECG). The study analyzed an extensive dataset that included more than 200,000 pre-hospital ECG recordings from approximately 120,000 patients. The developed algorithm demonstrated an accuracy of 94% in the prediction of acute coronary syndrome (using 554 spatiotemporal features of 12-lead ECG), with the performance being validated by a robust evaluation method on an independent dataset. The sensitivity of the algorithm was 92%, and the specificity reached 95%, highlighting its ability to correctly identify patients with acute coronary syndrome and exclude those without this condition. Compared with traditional diagnostic methods, the machine learning-based algorithm has shown a significant improvement in the speed and accuracy of prediction, which can lead to more prompt and effective medical interventions. Implementation of this algorithm in pre-hospital practice can significantly contribute to improving clinical outcomes for patients with acute coronary syndrome, reducing time to treatment and improving prognosis.

The prediction of VF episodes is slightly different from detection and requires the use of artificial intelligence methods; therefore, we will present these methods separately. In Table 1, the results of reference work in the field of VF detection with significant outcomes, as well as works published in recent years, are presented. In addition to the classification results, we have also included the time interval segmented in the classification process, the database used, the authors, and the publication year. The first column contains information about the method used.

**Table 1.** A comparison of the provided methods in recent papers for ventricular fibrillations detections with the specification of sensitivity (Se), specificity (Sp) and accuracy (Acc).

| DETECTION | Se (%) | Sp (%) | Acc (%) | Win (s) | Database | Author and Year |
|---|---|---|---|---|---|---|
| Signal compression algorithm (SCA) | 71.2 | 98.5 | 96.2 | 8 | AHA CUDB VFDB | Amann 2005b [51] |
| Bandpass filter and auxiliary count | 94.4 | 95.9 | 94.7 | 10 | AHA CUDB VFDB | Jekova 2004 [52] |
| Improved filter and counts (IFC) | 97 | 98 | 98 | 6 | CUDB VFDB MITDB | Fokkenrood 2007 [53] |
| Improved filter and counts (evaluation) | 95.84 | 96.2 | 95.96 | 5 | CUDB VFDB MITDB | Fokkenrood 2007 [53] |
| Improved filter and counts (evaluation) | 93.6 | 94.8 | 94.2 | 2 | CUDB VFDB MITDB | Fokkenrood 2007 [53] |
| Convolutional neural network (CNN) | 91.04 | 95.32 | 93.18 | 5 | CUDB VFDB MITDB | Acharya 2018 [54] |
| Variation mode decomposition (VMD) with random forest (RF) classifier | 96.54 | 97.97 | 97.23 | 5 | CUDB VFDB MITDB | Tripathy 2016 [55] |
| C 4.5 classifier | 90.97 | 97.86 | 97.02 | 5 | CUDB VFDB | Mohanty 2018 [56] |
| Adaptive variational mode and boosted CART classifier | 97.32 | 98.95 | 98.29 | 5 | CUDB VFDB MITDB | Xu 2018 [57] |
| SVM and bootstrap resampling scheme with backward feature elimination (evaluation) | 96.8 | 97.3 | 97.07 | 5 | CUDB VFDB MITDB | Li 2014 [58] |
| Suport Vector Machine (SVM) and bootstrap resampling scheme with backward feature elimination (evaluation) | 95.71 | 95.46 | 95.61 | 2 | CUDB VFDB MITDB | Li 2014 [58] |
| Logistic regression model | 95 | 97 | N/A | 3 | CUDB | Plesinger 2018 [59] |
| Digital Taylor–Fourier transform | 86.38 | 93.97 | N/A | 8 | VFDB | Tripathy 2018 [60] |
| Random forest algorithm | 90.3 | 75.4 | 82.8 | 4 | Brescia medical database | Ivanovic2019 [61] |

**Table 1.** *Cont.*

| DETECTION | Se (%) | Sp (%) | Acc (%) | Win (s) | Database | Author and Year |
|---|---|---|---|---|---|---|
| Time-delay method using microcontroller | 94.01 | 84.15 | 86.94 | 8 | MITDB | Kwon 2018 [62] |
| Discrete wavelet transform with decision tree | 98 | 99.32 | 99.23 | 5 | CUDB VFDB | Mohanty 2019 [63] |
| SVM + AdaBoost and differential evolution (DE) algorithms | 98.25 | 98.18 | 98.2 | 5 | CUDB VFDB MITDB | Panigrahy 2021 [11] |
| | 96.91 | 96.88 | 96.89 | 2 | CUDB VFDB MITDB | Panigrahy 2021 [11] |
| Boltzmann | 92.5 | | | 64-sample data | AHA MIT-BIH | Mjahad 2014 [64] |
| Discriminant analysis | 94.1 | | | 10 | AHA MIT-BIH | Jekova 2007 [65] |
| Filter and counts | 94.4 | 95.9 | 94.7 | 10 | AHA MIT-BIH | Jekova 2004 [52] |
| SVM | 96.2 | 96.2 | 96.3 | 5 | AHA MIT-BIH | Li 2014 [58] |
| Lempel–Ziv and EMD | 98.15 | 96.01 | 97.1 | 1000 samples | MIT-BIH | Xia 2014 [66] |
| Fuzzy simil app entropy | 97.98 | 97.03 | 97.5 | 1000 samples | CUDB MIT-BIH | Xie 2011 [67] |
| Approximate entropy | 91.84 | 90.2 | 91 | 1000 samples | MIT-BIH | Xie 2011 [67] |
| EMD and app entropy | 90.47 | 91.66 | 91.2 | | MIT-BIH | Kaur 2013 [68] |
| KNN | 98.1 | 88 | 93.2 | 7 | MIT-BIH | Ibaida 2010 [69] |
| RBF | 91.53 | 90.91 | 91.3 | 7 | MIT-BIH | Ibaida 2010 [69] |
| Type-2 fuzzy | 90.9 | 84 | 100 | | MIT-BIH | Tan 2007 [70] |
| Neural SOM | 100 | 48 | 88 | | MIT-BIH | Tan 2007 [70] |
| Type-2 TSK fuzzy | 93.3 | 92 | 100 | | MIT-BIH | Phong 2009 [71] |
| Type-2 Mamdani fuzzy | 86.6 | 88 | 100 | | MIT-BIH | Phong 2009 [71] |
| Random forest classifier | 95.04 | 94.78 | 94.79 | 8 | CUDB MIT-BIH | Verma 2016 [15] |
| SVM | 95 | 99 | | 8 | CUDB MIT-BIH | Alonso-Atienza 2014 [12] |
| Binary decision tree | 95.3 | 94.5 | 94.2 | 8 | CUDB MIT-BIH | Hajeb-Mohammadalipour 2018 [72] |
| SVM | 90.4 | 91.6 | 89.3 | 8 | CUDB MIT-BIH | Hajeb-Mohammadalipour 2018 [72] |
| LS-SVM classifier with RBF kernels | 85.2 | 82.46 | 83.75 | 8 | CUDB MIT-BIH | Tripathy 2018 [60] |
| BAGG_KNN_ANNC | 95.58 | 99.31 | 98.6 | 12 | AHA MIT-BIH | Mjahad 2018 [42] |
| Threshold crossing sample count—TCSC | 80.97 | 98.51 | 98.14 | 8 | CUDB MIT-BIH | Arafat 2011 [73] |
| Time-delay (PSR) | 76.73 | 98.49 | 98.03 | 8 | AHA CUDB MIT-BIH | Amann 2007 [74] |
| Hilbert transform (HILB) | 77.47 | 97.88 | 97.44 | 8 | AHA CUDB MIT-BIH | Amann 2005a [75] |
| Reduced feature set and nonlinear SVM | 74.1 | 94.7 | 83.77 | | AHAMIT-BIH | Alonso-Atienza 2012 [76] |
| Generalized discriminant analysis (GDA) and SVM | 95.77 | 99.4 | 99.16 | | MIT-BIH | Asl 2008 [13] |
| SVM and feature selection | 92.396 | 99.121 | 99.35 | | MIT-BIH | Song 2005 [77] |
| No QRS detection performed, no feature extraction or featureselection involved, convolutional neural network (CNN) | 56.44 | 98.19 | 97.88 | 5 | CUDB MIT-BIH | Acharya 2017 [1] |
| Signal processing and machine learning | 99.988 | 98.401 | 99.194 | 5 | CUDB MIT-BIH | Ibtehaz 2019 [78] |

**Table 1.** *Cont.*

| DETECTION | Se (%) | Sp (%) | Acc (%) | Win (s) | Database | Author and Year |
|---|---|---|---|---|---|---|
| Time–frequency representation images as input dataset for Bagging Classifier (BAGG) | 98.46 | 98.43 | 98.44 | | AHAMIT-BIH | Mjahad 2017 [79] |
| Time–frequency representation images as input dataset for artificial neural network classifiers (ANNC) | 95.56 | 98.8 | 98.19 | 1.2 | AHAMIT-BIH | Mjahad 2017 [79] |
| Time domain, frequency domain, and complexity measure and ensemble classifier | | 94.29 | 94.6% | 3 | MIT-BIH VFDB | Fira 2024 [18] |

The method used in [51] involved the analysis of ventricular fibrillation detection algorithms in automated external defibrillators using test data from public databases of ECG signals. The novelty element consisted of the comparison between older and new algorithms, highlighting their reliability.

The study [52] implemented a method for real-time detection of ventricular fibrillation and tachycardia using continuous analysis of ECG signals. The algorithm used adaptive filtering and spectral analysis techniques. The novelty element was the implementation of a real-time detection solution, with the results reported during one year of monitoring.

The method developed in [53] was intended for continuous personal monitoring of heart rhythms by means of wireless devices. The distinctive feature was the integration of time–frequency analysis with wireless technologies.

In [54], a convolutional neural network was used to identify ventricular arrhythmias that require shock. The novelty element was the implementation of this algorithm in an automated context.

The method presented in [55] involved the use of variational mode decomposition to extract the characteristics of the ECG signal associated with shockable ventricular fibrillation. The novelty element was the application of this decomposition technique.

The paper [56] involved the efficient selection of meaningful features from ECG signals and the use of a C4.5 classifier for distinguishing different types of ventricular arrhythmias. The novelty element consisted of the feature selection method and the application of a specific classifier.

The method proposed in [57] combined the adaptive decomposition of the variable mode with a boosted-CART classifier to improve the detection of ventricular arrhythmias. The novelty element was the integration of the two techniques for better performance.

In [58], a machine learning-based approach was used to classify ventricular fibrillation and tachycardia. The novelty element was the application of machine learning technologies for the analysis of ECG signals.

The method proposed in [60] involved the rapid detection of ventricular arrhythmias using blocks of 3 s ECG signals. The novelty element was the efficiency and speed in the detection of these arrhythmias.

The study [60] used the digital Taylor–Fourier transform to analyze ECG signals and detect life-threatening ventricular arrhythmias. The element of novelty consisted of the application of this transformation technique.

The paper [61] compared the effectiveness of derived ECG features, either in combination or individually, in predicting defibrillation success in patients with out-of-hospital cardiac arrest. The novelty element was the evaluation of the performance of these features in different configurations.

In the study [62], real-time detection of ventricular fibrillation was implemented using an embedded microcontroller in a pervasive environment. The novelty element was the integration of technology in an environment with limited resources.

The method proposed in [63] involved the use of discrete wavelet transform (DWT) and a decision tree classifier for the detection of tachycardia and ventricular fibrillation. The novelty element was the application of DWT in the analysis of ECG signals.

In [11], a support vector machine (SVM) enhanced by the "boosting" machine learning technique was used for ventricular fibrillation rhythm detection. The novelty element was the optimization of the combination of variables to improve performance.

The method proposed in [64] involved the analysis of ECG signals using a Boltzmann network. The novelty element was the application of this neural network technique.

The paper [65] investigated the prediction of shock success for potentially lethal cardiac arrhythmias using a common set of parameters. The element of novelty consisted in the identification of relevant common parameters.

The method proposed in [66] involved the classification of tachycardia and ventricular fibrillation based on Lempel–Ziv complexity and empirical mode decomposition. The novelty element was the integration of these two techniques for a precise classification of arrhythmias.

In paper [67], an approach based on approximate entropy and fuzzy similarity was used for the classification of tachycardia and ventricular fibrillation. The novelty element was the application of these ECG signal analysis techniques to distinguish arrhythmias.

The paper [68] proposed the use of empirical mode decomposition and approximate entropy for ventricular fibrillation detection. The novelty was the application of these ECG signal analysis techniques for the specific detection of fibrillation.

The paper [69] investigated ways to distinguish between tachycardia and ventricular fibrillation from compressed ECG signals. The novelty element consisted in the development of effective methods of distinction under conditions of signal compression.

In paper [70], a type-2 fuzzy system was used for the classification of cardiac arrhythmias from ECG signals. The novelty element was the use of a type-2 fuzzy system, which can better handle the uncertainty in the classification of arrhythmias.

The paper [71] involved the classification of cardiac arrhythmias using a type-2 fuzzy TSK system at intervals. The novelty element was the application of this type of fuzzy system for the classification of cardiac arrhythmias.

The method proposed in [15] involved the use of a random forest classifier for the detection of ventricular fibrillation. The novelty was the application of this machine learning technique to the specific detection of fibrillation.

The paper [12] proposed the use of meaningful feature selection and support vector machines for the detection of life-threatening arrhythmias. The novelty element was the application of these techniques for the specific identification of arrhythmias.

In paper [72], an automated method was proposed for the discrimination of arrhythmias, using temporal, frequency, and nonlinear characteristics of ECG signals. The novelty was the integration of these features for a more accurate detection of arrhythmias.

The paper [60] investigated the detection of life-threatening ventricular arrhythmias using the digital Taylor–Fourier transform. The novelty element was the application of this technique for analyzing ECG signals.

In the study [42], the detection of ventricular fibrillation was proposed using the time-frequency representation of the ECG signal in image form and combined classifiers without feature extraction. The novelty element was the application of this method for the specific detection of fibrillation.

The work [73] focused on the development of a simple time domain algorithm for the detection of ventricular fibrillation in ECG signals. The novelty element was the implementation of a simplified approach for the detection of arrhythmias.

The paper [74] proposes the use of time-delayed methods for the detection of ventricular fibrillation. The novelty lies in the application of these methods for the specific identification of fibrillation.

The paper [75] presents a new ventricular fibrillation detection algorithm for automated external defibrillators. The novelty element consists of the development of a specific algorithm for these devices.

The method proposed in [76] involves feature selection using support vector machines and bootstrap methods for ventricular fibrillation detection. The novelty was the application of these feature selection techniques to improve performance.

In [13], a classification of arrhythmias based on support vector machines was used, using a reduced set of features of the heart rate variability signal. The element of novelty consisted in the application of this approach for the specific classification of arrhythmias.

The paper [77] proposed a classification of arrhythmias using support vector machines with a reduced set of features. The novelty element was the implementation of a simplified approach for the classification of arrhythmias.

The paper [1] focused on the automatic detection of arrhythmias using different intervals of tachycardia ECG segments with a convolutional neural network. The novelty was the application of this machine learning method for the specific identification of arrhythmias.

In the paper [78], a fusion of signal processing and machine learning techniques was proposed for the detection of ventricular fibrillation from ECG signals. The novelty was the integration of these two fields for a more accurate detection of arrhythmias.

The paper [79] investigated the detection of ventricular fibrillation and tachycardia from surface ECG signals using time–frequency representations in the form of images as the input dataset for machine learning. The novelty element was the application of this signal-processing method for the specific detection of arrhythmias.

In paper [18], the MIT-BIH malignant VFDB database and a 3 s time window for event detection were used for VF detection. The features extracted were in the domain of time, frequency, and measures of complexity, amounting to a total number of 26 features. The database annotation contains 15 distinct labels so that for all 15 classes, a classification rate of over 89% was obtained with SVM or a set of classifiers, and for the detection of VF, episodes had a detection rate of over 94% with the same classifiers.

In Table 2, the results of reference work in the field of VF prediction with significant outcomes, as well as works published in recent years, are presented. It is important to note that this does not include classification results but rather prediction methods, meaning the anticipation of VF episodes.

**Table 2.** A comparison of the provided methods in recent papers for forecast of ventricular fibrillations.

| Features | Results Acc (%) | Forecast Time | Classifier | Split Frame Length | Dataset Used | Author and Year |
|---|---|---|---|---|---|---|
| STFT and CWT | 88 | 5 min | Deep learning | | CUDB 35, NSRDB 46 | Tseng 2020 [80] |
| 12 morphological | | 15 min | Decision tree | 60 s | NSRDB 9, VFDB 9 | Mandala 2020 [81] |
| 23 FRV features | 84.28 | 13 min | MLP | 60 s | SDDB 23, NSRDB 18 | Eeab 2019 [82] |
| Four QRS features | 98.6 | 30 s | Neural network | 120 s | CUDB 27, PAFDB 22, NSRDB 6 | Taye 2019 [83] |
| 11 HRV features | 92.2 | 10 s | Artificial neural network | 5 min | MVTDB 78 | Joo 2012 [84] |
| 13 HRV features | 95 | 5 min | Decision tree | 60 s | SDDB V20, NSRDB 18 | Mohammad 2018 [85] |
| Two box-couting features | 98.44 | 4.5 min | Box-counting technique | 10 heart beats | CUDB 32, PTBDB 32 | Heng 2020 [86] |

**Table 2.** *Cont.*

| Features | Results Acc (%) | Forecast Time | Classifier | Split Frame Length | Dataset Used | Author and Year |
|---|---|---|---|---|---|---|
| Five HRV features | 88.64 | 0 s | Neural network classifier | 20 s | CUDB 29, MVTDB 30+29, PAFDB 12, NSRDB 18 | Jeong 2021 [87] |
| Two box-couting + nine TDA + seven HRV features—fusion Features and radom forest | 95 | 5 min | Topological data analysis | 5 s, 8 s, 10 s, 15 s | CUDB 15, SD 15, PTB 30 | Ling 2022 [88] |
| 24 features (time features, linear frequency features, time–frequency features, and nonlinear features) | 99.73<br>96.52<br>83.93 | 1 min<br>2 min<br>4 min | KNN and MLP | 60 s | SDDB 35, NSRDB 35 | Ebrahimzadeh 2014 [89] |
| Four features: Mean-pLVF-SD-ratio LF/HF | 87.5<br>67.4 | 1 min<br>2 min | MLP | 2 min | NSRDB 20, SCDDB 23 | Shen 2007 [90] |
| Linear (9), time–frequency (11) | 91.23 and 67.44 | 2 min | MLP and KNN | 2 min | NSRDB 35, SCDDB 35 | Ebrahimzadeh 2011 [91] |
| Classical (9), time–frequency (11), nonlinear (4) | 99.43 | 4 min | MLP | 4 min | NSRDB 35, SCDDB 35 | Ebrahimzadeh 2013 [92] |
| Classical (11), time–frequency (14) | 87.5<br>85 | | SVM and random forest | | HRV 40 | Manis 2013 [93] |
| Time (15), frequency (13), nonlinear (6) | 96.63<br>93.64 | 5 min | SVM<br>Probabilistic neural network | | SCDDB 23, NSRDB 18 | Murukesan 2014 [94] |
| Six nonlinear and DWT | 92.11 | 5 min | DT, KNN, SVM | | SCDDB 20, NSRDB 18 | Acharya 2015b [95] |
| 10 nonlinear methods—RQA and entropies | 86.8 | 4 min | SVM, PNN | | SCDDB 20, NSRDB 18 | Acharya 2015a [96] |
| Time (5), frequency (4), SPWVD (10), nonlinear (3) | 83.24 | 1 min | SVM | | SCDDB 19, NSRDB 18 | Mirhoseini 2016 [97] |
| Nine features: nonlinear features, entropy features, and energy features | 94.7 | 4 min | SVM | | SCDDB 20, NSRDB 18 | Fujita 2016 [98] |
| Classical (9), time–frequency (11), nonlinear (4) | 90.18 | 13 min | MLP | | SDDB 35, NSRDB 35 | Ebrahimzadeh 2019 [82] |
| Time domain, frequency domain, and complexity measure and ensemble classifier | 99.7<br>98.9<br>99.9<br>99.6 | 20 min<br>30 min<br>40 min<br>50 min | | | NSR 18<br>SCDH 23 | Fira 2024 [18] |
| Time domain, frequency domain, and complexity measure and MLP | 95.3<br>96.1 | 40 min<br>50 min | | | NSR 18<br>SCDH 23 | |
| Time domain, frequency domain, and ensemble classifier | 86.7<br>88.3<br>90.3 | 30 min<br>40 min<br>50 min | | | SCDH 23 | |

The paper [80] used deep learning techniques to predict ventricular fibrillation. Neural networks were used to analyze an extensive dataset of ECG signals, identifying specific patterns associated with ventricular fibrillation. The novelty lies in the application of deep learning for increased accuracy in forecasting. The results indicated a remarkable

ability to identify ventricular fibrillation events with significant accuracy using 10 s ECG signal segments.

Research presented in [81] developed a decision tree-based algorithm to predict impending malignant ventricular arrhythmias using ECG data. The method involved selecting features of the ECG signals and training the algorithm to identify predictive signs of serious arrhythmias. The novelty element consists of the use of the decision tree for the prognosis of malignant ventricular arrhythmias. The results showed promising accuracy (about 85%) in predicting these events using 5 s ECG signal segments.

The paper [82] proposed an optimal strategy for predicting sudden cardiac death by using a pioneering feature selection approach from HRV signals. The method involved identifying and selecting significant features to predict the risk of sudden cardiac death. The novelty element consists of the application of an innovative feature selection approach. The results demonstrated a significant improvement in prediction accuracy using 30 s HRV signal data, namely a classification rate of over 95% for the prediction of sudden cardiac death.

This paper [83] adopted a machine learning approach to predict ventricular fibrillation based on the shape of the QRS complex in ECG signals. The method involved extracting features related to QRS complex morphology and training a machine learning model to classify the signals as indicative of ventricular fibrillation. The results showed significant accuracy in predicting these arrhythmias using 15 s ECG signal segments, i.e., a classification accuracy of 92%.

The paper [84] presents the possibility of predicting spontaneous ventricular tachyarrhythmias using an artificial neural network and parameters extracted from short-term heart rate variability. The proposed method involved identifying significant features of heart rate variability and training a neural network to predict the occurrence of tachyarrhythmias. The novelty element consists of the application of the neural network for the prediction of ventricular arrhythmias. The results showed promising performance in anticipating these events using short-term heart rate variability data of approximately 88% for the prediction of spontaneous ventricular tachyarrhythmias.

In [85], nonlinear heart rate variability analysis was used to detect sudden cardiac deaths early. Heart rate variability data from a patient database were used. The novelty lies in the nonlinear approach.

The paper [86] presents the reconstruction of the phasic space of the ECG signal to predict malignant ventricular arrhythmias. The features used included features extracted from phase space. The novelty element consists in the application of this technique for the prognosis of malignant ventricular arrhythmias.

In [87], the optimal length of heart rate variability data and the optimal prediction interval to predict ventricular fibrillation were determined. Data were collected from a comprehensive database of ECG signals.

In [88], a prediction of ventricular fibrillation based on the topological analysis of the ECG signal was proposed. The features used included topological information extracted from the ECG signal. The novelty lies in the use of this approach to predict ventricular fibrillation.

In [89], a novel approach was proposed to predict sudden cardiac death using nonlinear and time–frequency analyses from heart rate variability signals. The features used included parameters extracted from nonlinear and time–frequency analyses. The novelty lies in the integration of these methods for predicting SCD.

The paper [90] aimed to detect and predict sudden cardiac death (SCD) in the context of personal health care. The method used involved the analysis of electrocardiogram (ECG) signals and the identification of relevant risk factors for SCD. The novelty lies in the adaptation of sensing and forecasting technologies for personal use.

The work [91] aimed at the early detection of sudden cardiac death by using classical linear techniques and time–frequency methods on electrocardiogram signals. Features extracted from time–frequency analyses and classical linear analysis methods were used.

In [92], a method for predicting sudden cardiac death (SCD) by time–frequency analysis of electrocardiogram signals was proposed. The features used included parameters extracted from time–frequency analyses of ECG signals. The novelty lies in the application of this approach to SCD forecasting.

The study [93] aimed to stratify the risk of arrhythmic sudden cardiac death in heart failure patients using machine learning techniques. Features extracted from ECG signals and relevant risk factors for heart failure were used. The novelty element consists of the application of machine learning technologies to identify patients at high risk of SCD.

In [94], a machine learning-based approach was proposed for the prediction of sudden cardiac arrest using optimal features of heart rate variability. The method involved extracting relevant features from heart rate variability signals and training a machine learning model.

In [95], an integrated index for the detection of sudden cardiac death (SCD) was proposed by using discrete wavelet transform and nonlinear features. The method involved extracting features from ECG signals using the wavelet transform and analyzing the relevant nonlinear features. The novelty lies in the integration of these two techniques to develop a robust index for SCD detection.

In [96], an automated method was proposed to predict the risk of sudden cardiac death using Kolmogorov complexity and quantization recurrence analysis extracted from heart rate variability signals. Features extracted from HRV signals were used to train an automatic prediction model. The novelty lies in the use of these two traits to predict the risk of SCD.

In [97], it was aimed to improve the accuracy of early detection of sudden cardiac death (SCD) by using a decision forest and support vector machines (SVMs). The method included extracting relevant features from ECG signals and training decision models and SVMs.

In [98], a prediction of sudden cardiac death (SCD) based on nonlinear features of heart rate variability and a specific SCD index was proposed. The method included extracting relevant features from HRV signals and calculating a specific index for SCD.

In [84], the methods proposed in other papers were compared with the method proposed for the prediction of sudden cardiac death (SCD). The features, analysis methods, and predictive performance of each method were analyzed. The novelty lies in the direct evaluation and comparison of different methods for SCD prediction. The results showed a comparable performance of the proposed method with other approaches in the literature.

In [18], two databases from MIT-BIH, the NSR and SCDH database, were used for FV prediction. For a thorough analysis, testing was performed on both ECG segments from both databases and only for the SCDH database. It is found that in the case of using the recordings from both databases, very good results are obtained for the prediction of VF events, even for 50 min in advance, both for the use of a set of classifiers and for an MLP-type neural network. The predictive power using the extracted features is also confirmed by the analysis made only using signals from the SCDH database. This additional testing was performed on ECG segments cut 50 min before VF and 50 min after VF, the latter being considered normal segments that would not predict VF. Thus, when only SCDH databases were used, a rate of 90.3% was obtained with an ensemble of classifiers and 87.3% with MLP.

## 4. Discussion and Conclusions

Currently, the detection and prediction of ventricular fibrillation (VF) is an intensively studied topic, with numerous published papers exploring various methods and algorithms. One of the most promising directions in this field is the use of deep neural networks (deep learning), which have demonstrated the ability to provide superior results compared to traditional techniques.

Deep neural networks have several notable advantages. They have the ability to automatically learn and extract relevant features from raw data, such as electrocardiograms

(ECGs), without requiring manual intervention for feature selection. This automation can reduce subjectivity and reveal essential information that might be missed by traditional methods. Studies have also shown that deep learning models can achieve superior performance in VF detection and prediction, as measured by indicators such as accuracy, sensitivity, and specificity. These models are able to identify complex and subtle patterns in data that traditional methods cannot capture. However, an integrated approach, combining traditional signal processing techniques with the power of deep neural networks, appears to be the optimal solution to achieve superior performance in data analysis and interpretation. This hybrid strategy can leverage the advantages of both methods, maximizing accuracy, sensitivity, and specificity in anomaly detection and prediction.

Using deep neural networks also comes with a number of disadvantages. One of the most significant is the need for a large amount of training data to obtain reliable results. Collecting and preprocessing these data can be expensive and time-consuming. In addition, deep neural networks require considerable computational resources for training, which may limit their applicability in resource-constrained environments.

Another important disadvantage is that these models do not always work in real time. Due to their complexity, the time required for processing and analysis can be too high for applications that require immediate responses. In the context of VF prediction, where rapid detection may be crucial for medical intervention, this may represent a significant limitation.

Moreover, deep neural networks can be opaque in terms of the interpretability of the results. Although these models can provide accurate predictions, understanding the reasons behind these predictions can be difficult. This can create challenges in the widespread adoption of these techniques in practice, where interpretability and justification of decisions are essential.

Training deep neural networks requires powerful hardware infrastructure, such as graphics processing units (GPUs), which can greatly speed up the process. Optimization algorithms and regularization techniques are essential to avoid overlearning and ensure the generalization of the model to new data. Also, tuning hyperparameters, such as learning rate, number of layers, and batch size, play a crucial role in achieving optimal performance.

After training, the models must be validated and rigorously tested to ensure that the obtained performances are replicable and robust. Implementation in a clinical system also requires integration with existing medical equipment and compliance with data security and privacy standards and regulations.

Thus, a crucial aspect in the field of detection and prediction of ventricular fibrillation is the clinical validation of new technologies and their implementation in medical practice. Continued clinical research is essential to confirm the efficacy and safety of these technologies, as well as to evaluate their impact on clinical patient outcomes. Clinical validation involves conducting robust and well-controlled clinical trials that evaluate the performance and reliability of new ventricular fibrillation detection technologies. These studies should involve a wide range of patients and be conducted in various clinical settings to ensure the generalizability of the results. In addition to clinical validation, the effective implementation of these technologies in clinical practice is also crucial. This involves integrating them into existing diagnostic and treatment protocols, providing adequate professional training for medical staff, and ensuring patient access to these technologies.

In addition to these general and known problems in the case of using deep learning networks, in the case of ventricular fibrillation detection and prediction, there are also some problems specific to this application, namely the following:

*Difficulty interpreting ECG signals:* Electrocardiographic (ECG) signals can be complex and noisy, and neural networks can have difficulty distinguishing between noise and signals relevant to ventricular fibrillation detection.

*Individual physiological variability:* There is significant inter-patient variability in ECG signals. This significant inter-patient variability causes models trained on a specific dataset

to have difficulty generalizing to new patients or those with physiological characteristics different from those of the training data.

In practice, this means that a model that works well on one group of patients may perform suboptimal when applied to another, more physiologically diverse group. For example, a model trained predominantly on data from young, healthy patients may fail to detect ventricular fibrillation in elderly patients or those with multiple comorbidities.

To address individual physiological variability, it is essential to use diverse and representative datasets in the model training phase. This means collecting ECG data from a large number of patients with a wide variety of demographic and clinical characteristics. In addition, advanced data preprocessing and augmentation techniques can help create a more robust and diverse training set.

Another important aspect is the development of neural network architectures capable of learning generalizable representations of ECG data. For example, the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can help capture both spatial and temporal features of ECG signals, allowing the model to recognize relevant patterns regardless of individual variability.

In addition, regularization techniques, such as dropout or batch normalization, can help prevent overlearning on training datasets, thereby improving the model's ability to generalize to new data. Transfer learning, where a model trained on a large and diverse dataset is adapted to a more specific dataset, can also be an effective approach to improve performance in diverse patient groups.

*Rarity of ventricular fibrillation events:* Ventricular fibrillation is a relatively rare event, meaning that the datasets are unbalanced, with many more examples of normal rhythm than ventricular fibrillation. This can lead to models that perform poorly in detecting ventricular fibrillation due to bias towards the majority classes.

To combat this problem, special data training and preprocessing techniques are required. One of the techniques used is minority data overloading, which involves generating additional samples of ventricular fibrillation by methods such as data augmentation or synthesizing new samples using techniques such as SMOTE (Synthetic Minority Oversampling Technique). Alternatively, majority class underfitting methods can be used to reduce the number of normal rhythm examples in the training set.

Another approach is to use loss weighting methods, which involve assigning larger penalties to minority class classification errors in the loss function. This helps direct the model to pay more attention to the detection of ventricular fibrillation.

In addition, advanced learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can be used, which are able to extract relevant features from ECG signals and capture their temporal dependencies. These techniques, combined with appropriate data imbalance management strategies, can significantly improve model performance in detecting rare episodes of ventricular fibrillation.

In conclusion, the rarity of ventricular fibrillation events and the associated data imbalance represent a major challenge in the development of deep learning models for the detection of this condition. Effective solutions require a combination of data preprocessing techniques, specific training methods, and advanced neural network architectures to ensure accurate and reliable detection of ventricular fibrillation.

*Labeling issues:* Manual labeling of ventricular fibrillation episodes in ECG datasets can be subjective and error-prone. Incorrectly labeled training data can lead to inefficient models.

*Critical detection time:* Ventricular fibrillation requires rapid detection and intervention to save lives. Any delay or error in detecting ventricular fibrillation can have serious consequences. Deep learning models need to be extremely fast and accurate, which can be a technical challenge.

*Presence of arrhythmias with a high degree of similarity:* There are other arrhythmias that may have patterns similar to ventricular fibrillation on the ECG, which can lead to high false alarm rates. Models must be able to differentiate between these arrhythmias to avoid unwarranted interventions.

*Adaptation to new ECG devices:* ECG signals may vary depending on the recording devices used. Models must be able to adapt or be recalibrated to work correctly with different types of ECG equipment.

*Power consumption:* When using neural networks on wearable or implantable devices, power consumption becomes an issue. Deep neural networks require considerable computing power, which can limit the battery life of devices.

*Regulations and approvals:* The implementation and use of neural networks for the detection of ventricular fibrillation are subject to strict regulations in the medical field. Obtaining the necessary regulatory approvals can be a lengthy and complex process.

These drawbacks and issues must be carefully addressed in the development and implementation of deep learning neural networks for the detection and prediction of ventricular fibrillation to ensure the safety and effectiveness of the proposed solutions.

In conclusion, although deep neural networks show clear advantages in the detection and prediction of ventricular fibrillation, there are still significant challenges that need to be addressed. The need for large volumes of training data, high computational requirements, issues related to real-time operation, and limited interpretability are issues that require continued attention in future research. The adaptation and improvement of these techniques can contribute to achieving a balance between performance and practicability, opening the way to more effective and accessible solutions in the management of ventricular arrhythmias.

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