IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 1, March 2024, pp. 984~993
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i1.pp984-993

1-dimensional convolutional neural networks for predicting sudden cardiac

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Article Info

Article history:

Received Jul 31, 2023
Revised Sep 29, 2023
Accepted Nov 7, 2023

Keywords:

Arrhythmic risk markers
Electrocardiogram
Machine learning
Sudden cardiac death
Sudden cardiac death prediction

ABSTRACT

Sudden cardiac arrest (SCA) is a serious heart problem that occurs without symptoms or warning. SCA causes high mortality. Therefore, it is important to estimate the incidence of SCA. Current methods for predicting ventricular fibrillation (VF) episodes require monitoring patients over time, resulting in no complications. New technologies, especially machine learning, are gaining popularity due to the benefits they provide. However, most existing systems rely on manual processes, which can lead to inefficiencies in disseminating patient information. On the other hand, existing deep learning methods rely on large data sets that are not publicly available. In this study, we propose a deep learning method based on one-dimensional convolutional neural networks to learn to use discrete fourier transform (DFT) features in raw electrocardiogram (ECG) signals. The results showed that our method was able to accurately predict the onset of SCA with an accuracy of 96% approximately 90 minutes before it occurred. Predictions can save many lives. That is, optimized deep learning models can outperform manual models in analyzing long-term signals.

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1. INTRODUCTION

Since the early 21 century, electrocardiogram (ECG) has been the basis for the diagnosis of cardiovascular pathology [1]. ECG signals shows the electrical activity of the heart, thus providing evidence of different heart diseases or abnormality such as arrhythmias [2]. Detection of any irregularity requires a long-time monitoring which could potentially results in sudden cardiac death (SCD). Moreover, due to the recent pandemic of Covid-19 outbreak, the mortality rate caused by sudden cardiac arrest (SCA) has substantially increased [3]–[5] and, estimated that nearly 3 million people will be affected by SCD worldwide without any apparent symptoms [6]. Despite of unknown reason, ventricular fibrillation (VF) has been underlined to account for 20% of the SCD cases [7]. SCD occurs due to onset of SCA which is mainly a failure of the heart to efficiently supply blood to the body organs. This results in a dramatic decrease in body oxygen and substantially lead to loss of consciousness within few minutes [8]. Also, due to the shorter time frame between SCA and SCD, it is very important to restore blood circulation within this period to prevent death. The recent public access defibrillation (PAD) procedures have drawn much attention as a way to rescuing patients from SCD after collapsing. Although PAD have been widely promoted, a better approach would be to detect and prevent the onset of SCD which could help providing urgent aid before the collapse. Developing such a warning system can help experts detect the onset minutes or even hours before so that

necessary precaution can be taken [9]. The technological advancement has enabled new ways to improve both, monitoring and data acquisition through digital devices [10].

Recent SCD detection and prediction studies use ECG signals to generate good features for training machine learning models [11]–[16]. These models include support vector machines (SVM) [17], [18], linear discriminant analysis (LDA), deep neural networks (DNN) [19] and rotated forests (RF) [20]. These features are often data dependent and often fail when presented with signals outside the distribution. With the use of machine learning in the diagnosis of heart diseases in recent years, it is necessary to create a strong model that can accommodate the differences.

The use of machine learning is increasing in almost every field. This technique relies on creating new signatures based on patients' electrocardiogram or heart rate variability (HRV) signals to accurately predict minutes before the occurrence of SCD. ECG signals have become the de facto standard in determining key features for diagnosing heart disease. These techniques have become indispensable in-patient care to improve patient survival. For example, Yadav et al. proposed early detection for SCA using random forest classifier (RF) [9]. The study was conducted using the MIMIC-III data report, which includes many patient characteristics such as blood pressure, body ion levels (calcium, potassium), as well as other characteristics of the observation room intensive care unit (ICU). Using RF, the study optimized the hyperparameters of the model using grid search and genetic algorithms, achieving an area under the operator curve (AUC) of 0.9787.

Electrocardiogram and irregular heartbeat are features used in the literature for early SCA. Among these, Murugappan *et al.* [11] reported several parameters obtained from ECG signals to predict SCA 5 min before the onset of VF. These features include Hurst index, entropy, and maximum Lyapunov index, which are then used to train three different methods including SVM, neuro-fuzzy classifier, and subtractive fuzzy clustering. Using the SVM classifier, the study achieved 100% accuracy using the MIT-Bosten Beth Israel Hospital (MIT-BIH) dataset. On the other hand, Lai *et al.* [21] suggested the use of different arrhythmia markers to predict the early detection of SCD. These include repolarization signals such as JTp/JTe, TpTe/QT calculated directly from the QRS wave and ECG characters, and conduction-based repolarization such as TpTe/QRS and TpTe/(QT c QRS) which were directly computed from the QRS waves and ECG signals.

Using a dataset of 18 normal patient and 28 SCD patients, the proposed method achieved an average accuracy of 99.49% with RF by identification of SCD 30 minutes before its occurrence. Using an echo state network (ESN) as a classifier, Alfaras *et al.* [10] proposed an arrhythmia prediction system by using ECG lead. Different preprocessing steps were applied including ECG re-sampling, filtering, heartbeat detection and feature normalization which resulted in a total of 63 features. Using the MIT-BIH dataset, the study reported a sensitivity of 95.7% with a positive predictive value of 75.1% using ensemble of ESNs. Using data from 18 normal patients and 28 SCD patients, the proposed method achieved an accuracy of 99.49% using RF by identifying SCD 30 minutes before it occurs. Using Echo State Network (ESN) as a classifier, Alfaras *et al.* [10] proposed an arrhythmia predictor using ECG processing. Different pre-processing techniques were used, including ECG resampling, filtering, heartbeat detection, and feature normalization, resulting in a total of 63 features. The study reported 95.7% sensitivity using the MIT-BIH dataset and 75.1% positive predictive value using the ESN cohort.

Ebrahimzadeh *et al.* [22] proposed a new method of local time subset feature selection technique as an optimized method to predict SCD 12 minutes before onset. The study also improved electronic equipment using various statistical analyzes to determine 83% effective received stimulus when training program consensus of features using multi-layer perceptron (MLP) classifier. Continuing their previous work, Ebrahimzadeh *et al.* proposed to accurately predict SCD by making a consensus selection strategy from the pool proposed in [7]. Using the body selection process in the body region proposed in their previous work, this work proposes to select a group of features to train a set of K-nearest neighbors (KNN), SVM, and MLP. The plan was evaluated in the MIT-BIH repository and achieved an accuracy rate of 82.85% in analysis 31 minutes before SCD onset.

Khazaei *et al.* [23] proposed a new method for early detection of SCD based on non-monotonic patterns of heart rate variability. In their work, features based on recursive quantile analysis and incremental entropy were subsequently extracted by variational analysis method for dimensionality reduction. Using a decision tree classifier, the proposed method can detect SCD with an accuracy of 95% six minutes before onset. Similarly, Sanchez *et al.* [24] proposed a set of features based on wavelet transform of ECG signals. Their research used methods such as homogeneity index, wavelet packet transform (WPT), and other nonlinear measurements to demonstrate the connectivity of the neural network. This study uses the MIT-BIH dataset to evaluate their system that can detect SCD with 95.8% accuracy 20 minutes before SCD. Additionally, Acharya *et al.* [25] proposed a new feature to predict SCD by extracting non-monotonic features from non-monotonic transform (DWT) of ECG signals. These properties include fractal dimension (FD), trendless fluctuation analysis (DFA), Hurst exponent, approximate entropy, and correlation dimension. Based on the extracted results, the superlist method was used to create a sudden cardiac death index (SCDI) that could predict SCD with 92.11% accuracy four minutes before using the SVM classifier.

Unlike other studies that mainly focus on ECG signals, Fujita *et al.* [26] proposed several nonlinear methods for the analysis of four-minute HRV signals. These properties include Tsallis entropy (TEnt), Renyi entropy (REnt), Hjorth parameters (activity, mobility, and complexity), and energy properties of the wavelet ransform (DWT). Using an SVM classifier, the proposed method achieves 94.7% accuracy in predicting SCD four minutes before it occurs.

Deep learning has revealed many improvements in handcrafted features. For example, Kwon et al. developed an in-depth study to predict heart attack in the hospital using only four vital signs, namely body temperature, respiratory rate, systolic blood pressure, and heart rate [27]. The proposed model is based on recurrent neural network (RNN) and has been validated by two clinical datasets. The area under the receiver operating characteristic curve (AUROC) of the proposed system is 0.85, which outperforms other RF and logistic regressions based on machine learning model. On the other hand, Elola et al. developed a deep learning model to detect cardiac arrest in outpatients [28]. The authors analyzed two different models based on convolutional neural network (CNN) and RNN (PR) to determine whether the rhythm was a non-pulse-generating rhythm (PEA) or a non-pulse-generating rhythm (PR) using a 5-second electrocardiogram sequence. The two models achieve an accuracy of 93.5%, with a specificity of 95.5% for the RNN and 94.1% for the CNN model. Similarly, Nguyen *et al.* [29] proposed a shock adjustment system (SAA) that combines CNN model with support for early detection of SCA with electrocardiogram, shockable rhythm (SH), and non-shockable rhythm. The proposed method uses CNN to extract features from the signal and use them as input for optimization. The authors validated their test using a grid search algorithm with 5-fold cross-validation and reported 99.26% accuracy, 99.44% specificity, and 97.07% sensitivity. Tone Carboni *et al.* [30] proposed the combination of CNN + long-term shot memory (LSTM) to predict cardiac arrest in ICU patients using different physical parameters, including heart rate, respiratory rate, pulse rate, oxygen saturation, arterial blood pressure, and standard deviation of the R-R interval. Use CNN to extract high-level information from the body and combine it with LSTM recursion to capture time-dependent current in the signal. The proposed method achieves F1 scores ranging from 0.61 to 0.83 on variable physical symptoms where heart rate is the primary factor.

To reduce false positives that are often encountered when using machine learning models such as RF, a deep learning model that learns using four main parameters, including body temperature (BT), respiratory rate (RR), full form of heart rate (HR), and measured systolic blood pressure, for the 8 listed individuals [31]. The accuracy of the proposed method in predicting SCA within 24 hours is better than other RF and LR based models with an AUROC of 0.911. Similarly, Kim *et al.* [32] developed an artificial intelligence system that can predict SCA and respiratory failure based on patient data in the intensive care unit; these include medical history, recent surgeries, current health status, and vital signs. The proposed model consists of a 128-unit LSTM layer followed by a 0.5 probability output method. The model has an AUC-ROC of 0.886 for predicting cardiac arrest within 1 hour and 0.869 for predicting respiratory failure within 6 hours.

From the existing literature most studies using hand-crafted are based on higher-order linear and non-linear time-frequency features of the ECG signal to predict cardiac arrest. The features include statistical functions of time-domain features like heart rate variability and frequency-domain features like spectral distribution. Furthermore, these studies have relatively focused on onset of SCD prediction for shorter period of time. This is likely due to the complex feature extraction process that does not scale well when increasing the time duration before prediction. On the other hand, deep learning approaches have showed significant improvements but are trained on a large amount of data. Furthermore, these studies have relatively focused on out-of-hospital patients and used other features such as body temperature, Oxygen saturation levels and other physiological features. To alleviate the current shortcomings of the previous works, our study automates the feature discovering process by using deep learning techniques with only raw ECG signals. This is achieved by training a 1D convolutional neural network with discrete Fourier transform of the ECG signals. Using discrete fourier transform (DFT) features for training CNN network make our approach data efficient while maintaining higher performance. As shown in the results section, our method achieves state-of-art performance while accurately predicting up to 90 minutes before the onset of SCD.

In this study, we propose a novel approach based on deep learning techniques to develop a robust SCD detection model. For efficient training of our model, we first preprocess the ECG signals by converting the time-frequency features into a 1-D discrete Fourier transform and used as input features to train a convolutional neural network (CNN) model. Unlike other approaches, we use the recent state of the art Bayesian optimization algorithm to search for the best CNN architecture. As demonstrated in the result section, our approach is better than most of the recent state-of-the-art approaches while accurately predicting up to 90 mins before the onset of SCD. In summary, the contribution of our work is as follows:

a. We propose a deep learning approach based on 1D convolutional neural network that is data efficient through training of DFT of signals as opposed to raw ECG signals.

b. Our approach can predict up to 90 minutes before onset of SCD which is at par or better than existing state-of-art.
c. We have compiled the latest existing literature review of studies related to SCA detection based on both, handcrafted features, and deep learning approaches.

The rest of the paper is organized as follows. Section 2 gives brief details about various techniques and machine learning algorithms used for predicting the SCD. Methodology: collection of datasets, processing the signals and interval calculations, 1-D neural network algorithm and experimental set-up are explained in sections 3 and 4. Section 5 presents the results and comparative analysis of the proposed work. Finally, section 6 concludes the paper.

2. METHODOLOGY

As opposed to existing approaches discussed in the previous section, our proposed approach is built on the recent deep learning techniques based on the convolution neural networks. The advantage of using our approach is twofold: i) Compared to the handcrafted features, our approach provides an end-to-end training by inherently learning the underlying pattern in predicting the onset of SCD; and ii) As shown in the results section, our approach was still accurate on predicting the onset of SCD up to 90 minutes earlier. Figure 1 shows the schematic diagram of the proposed approach.

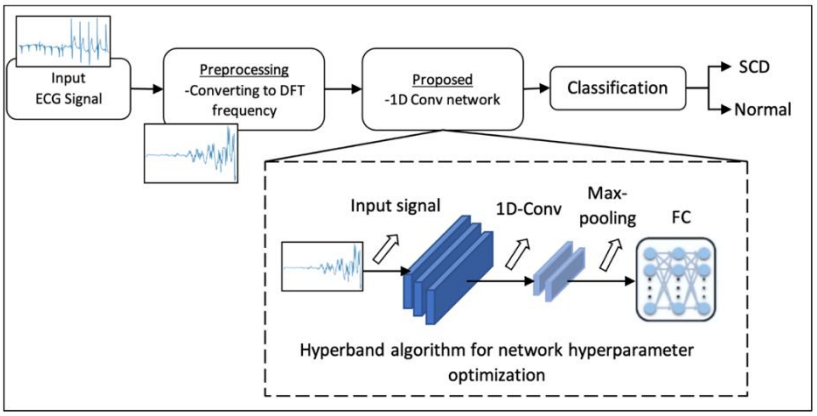

Figure 1. A schematic diagram of the proposed method

2.1. Dataset

The proposed method was evaluated using the popular MIT-BIH arrhythmia database [33], (sudden cardiac death holter database). The dataset consists of two channels 48 half-hour ambulatory ECG signals collected from 47 subjects at BIH arrhythmia laboratory. Out of 4,000 sets, a random subset of 23 recordings with 24-hour ambulatory ECG was sampled representing both inpatient and outpatient. On the other hand, the remaining 25 recording were carefully selected to represent significant arrhythmias which were less common. These recording were manually annotated by two independent cardiologists resulting in a digitized recording at a rate of 360 samples per second and channel with 11-bit resolution over a 10-mV range.

2.2. ECG signal preprocessing and interval calculation

The discrete Fourier transform represents the precise information about the frequency components in the ECG signal. The DFT is suitable for SCD prediction as it clearly captures the fluctuations regarding the anomalies in the heart rate. Moreover, the 1-minute segmented samples of the ECG signal inherently discard the long-term temporal changes. The ECG signals for all the patients are segmented into one-minute chunks for training as well as testing of the classifier. These one-minute chunks are transformed to corresponding DFT representations for the classifier input. For a time-domain discrete ECG chunk S(t) having T samples, the corresponding DFT can be represented by F(w) such that F(w) is the magnitude of the 'w' frequency component for the signal and is given by (1).

$$F(w) = \sum_{t=0}^{T-1} S(t) e^{-j2\pi \frac{w}{T}} \quad (1)$$

Preprocessing of ECG to DFT of a normal patient as shown in Figures 2(a) to 2(f). Figures 2(a) and 2(d) shows an example of ECG signal of both normal patient and SCD patient, respectively. Figures 2(b) and 2(e) displays a 10-second ECG sample fragments of normal and SCD patients, respectively. Finally,

Figures 2(c) and 2(f) illustrate the preprocessed DFT signals for training a classifier, which captures the irregularities in the heart rate and their variations vividly.

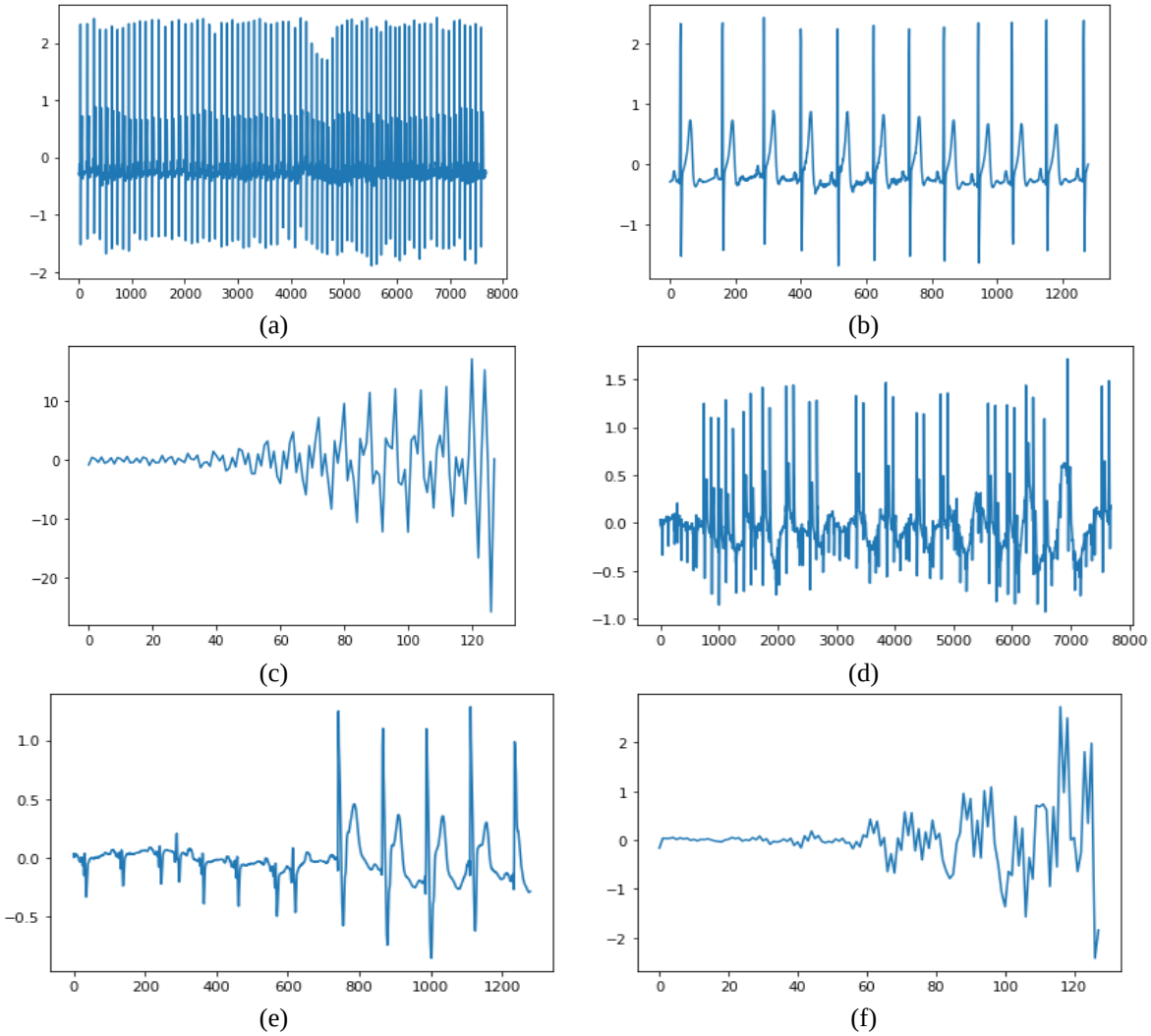

Figure 2. Preprocessing of ECG to DFT of a normal patient (a) 1-minute ECG sample of a normal patient, (b) 10-seconds ECG sample of a normal patient, (c) DFT 1-minute segment of a normal patient, (d) 1-minute ECG sample of a SCD patient, (e) 10-seconds ECG sample of a SCD patient, and (f) DFT 1-minute segment of a SCD patient

2.3. 1D–convolutional neural network

The proposed classifier is based on a 1D convolutional neural network with convolution being performed across the frequency bins in the discrete Fourier transform for each one-minute ECG segment. The convolutional network is suited for predicting anomalies in the ECG representations because of being invariant to positions in the input signal. Moreover, the shared parameters for convolutional filters sliding across the signal make the training efficient for low footprint devices. Given the DFT representation *F(w)*, a convolution operation is then applied as a sliding window across the frequency axis, i.e., the *w* components. Output for the convolution layer applied across the frequency axis is represented by O(n) (as seen in (2) such that O(n) is the ***n*** index of output vector resulting from the convolution with a kernel filter K(i) of length *I*.

$$O(n) = \sum_i^I K(i) F\left(i - n + \frac{I}{2}\right) \quad (2)$$

The output of convolution layers is then fed to fully connected dense layers for classification. The architecture of the neural network model has been finalized using hyper parameter tuning. The convolution is equivalent to sliding a small window of the size *I* across the frequency axis of the DFT and the output vector

contains the weighted means of the sliding windows such that the weights are shared across all the windows. The output representation O(n) from the convolution layers is flattened and used as input for a feed-forward classifier that predicts the likelihood for SCD.

The single 1D convolutional layer consists of 16 filters each having a kernel size of 8 striding across the frequency bins with a step size of 8. The convolution layer also includes batch normalization and Relu activations followed by the subsampling layer based on Max pooling. The output from the subsampling layer is reshaped to a flat embedding which is followed by the fully connected dense layer having 40 units. Finally, the dense layer is connected to the output layer which consists of two SoftMax units representing the class like likelihoods for the target categories. Proposed algorithm for SCD prediction as shown in Algorithm 1.

Algorithm 1. Proposed algorithm for SCD prediction

Input: ECG-Signal (E)
Output: Per-minutes Class-labels (L)
1. Segment E in 1 minute time chunks S
2. Compute F for S by DFT: $F(w) = \sum_{t=0}^{T-1} S(t) e^{-j2\pi \frac{wt}{T}}$
3. Compute O for F by convolution: : $O(n) = \sum_{i}^{I} K(i) F\left(i\text{-}n + \frac{I}{2}\right)$
4. Compute class likelihoods K for O by feed-forward classifier
5. Compute class labels L = argmax(K)
6. Return L

3. EXPERIMENTAL SETUP

The ECG data for both normal and SCD patients consists of two-channel signals. For the experiments, only the first channels were considered for both types of patients. ECG for all the 18 normal patients are used whereas for the SCD patient's ECG for only 20 SCD patients is used as VF onset information for the remaining three patients is not available. The ECG signals for the normal patients in the data set are sampled at 128 samples per second signals while the ECG signals for the SCD patients are sampled at 250 samples per second. For unbiased comparison with the normal patients, the ECG signals for the SCD patients were down sampled to 128 samples per second. The classification model is trained over 10 minutes of ECG signals. The 10 minutes before VF onset are selected as the training set for SCD patients while random 10 minutes are selected for the normal patients.

The 10 training minutes are segmented into 1-minute segments as the training samples with corresponding labels indicating the type of patient being SCD or normal. Each 1-minute sample of the ECG signal is transformed into its Discrete Fourier Transform DFT with a resolution of 1024 frequency bins. The DFT representation for the 1-minute segments is used as the input features for the CNN-based classification model. The training and testing of the classification model are performed using ECG signals by a disjoint set of patients.

The classification model is based on CNN applied to the discrete Fourier transform of one-minute ECG segments with convolution running across the frequency bins as input features. Besides DFT, the discrete Wavelet transform DWT, time-frequency, spectrogram as well as the raw ECG signals have been tested as the input for the classification model, and the DFT has been found to give the best results. 18 patients have been used to train the CNN. 10 from SCD and 8 from normal patients' datasets whereas a total of 20 patients have been used for testing, 10 from each dataset.

Keeping the training set smaller than the test set also simulates the limited size of labeled ECG datasets representing the actual real-world problem. Training and testing cycles were repeated for 10 iterations sampling different patients for each iteration. The trained model was tested single minute segments for test patients such that the test minute was selected to be up to 90^{th} minute with 5-minute intervals before SCD for the SCD patients and was selected randomly sampled for the normal patients.

4. RESULTS AND DISCUSSION

Multiple input features and classification models have been analyzed for the prediction task and the results are summarized in this section. Figure 3 presents the prediction accuracy by the CNN model for 20 test patients using 1024 bins of DFT frequencies as the input. The prediction accuracy is averaged over 10 iterations of different training and test samples. The results display that the prediction accuracy stays above 94% till 90 minutes before the SCD. The model achieves the highest accuracy of 99.5% 15 minutes before the SCD. Prediction accuracies 5 and 10 minutes before the SCD are 98.5% and 97.5% respectively. Accuracies are higher for minutes close to SCD, specifically till 15-minutes earlier. The accuracy drops slowly for minutes earlier than 15. However, the accuracy values keep fluctuating without a linear trend in a range of 92.5% to 99.5% over the 90 minutes. The accuracies have been measured after 5 minutes intervals.

Before finalizing the DFT as input, multiple features have been tested as input to the CNN model. The 60th minute before the SCD has been analyzed for testing all the features and Table 1 presents the average accuracies for 10 iterations with different patients. The DFT outperformed other features such as DWT, Raw, and spectrogram, by providing an accuracy of 94.5%.

Apart from the DFT features, the other features compared are raw ECG signal, discrete Wavelet transform DWT, discrete Fourier transform, and time-frequency spectrogram. Table 1 displays that the highest accuracy is achieved for DFT, whereas spectrogram also reports a relatively higher accuracy of 90%, as compared to the DWT and the raw ECG. For the DWT, DB4 has been used as the mother wavelet. After finalizing the DFT as input representation, empirical analysis has been carried out to select a suitable number of frequency bins for the DFT. The same CNN architecture has been used to predict the 60th-minute before SCD using different DFT frequency lengths. Moreover 'sensitivity' and 'specificity' were also computed 60 minutes before SCD in Table 2. 'Sensitivity' refers to accurate classification rate particularly for positive SCD prediction whereas 'specificity' refers to accurate classification rate for negative SCD prediction or normal prediction.

The model reports as sensitivity of 95.5% and specificity of 93.5% which implies that the model is slightly more accurate at predicting patients as susceptible to SCD as compared to predicting normal patients accurately. When analyzing the impact of frequency bin selection, the results reported in Figure 4 reveal interesting patterns. The results confirm that higher frequency resolution of the DFT increases the prediction accuracy monotonically up to 1024 frequency bins after which the accuracy reaches a somewhat steady-state level of 94.5% for the prior 60th model.

We also compare the performance of the proposed model against other architectures. Figure 5 shows the performance difference with other models. We can clearly see that our model performed reasonably well compared to all other models. This suggest that the DFT features used with the CNN model can accurately predict the SCD onset than other models.

4.2. Performance comparison with the state-of-the-art

We also compared our proposed methodology with the current state-of-the-art methods. The present study has been compared in various aspects of recent works such as dataset used, length of the signal, feature extraction method and number of features utilized, classifier, and performance measures (accuracy, sensitivity, and specificity). As it can be seen from Table 3, our proposed method performs better than most of the state-of-the-art methods while maintaining accuracy for additional 60 minutes before the onset of cortical spreading depolarization (CSD). The present study has been provided best accuracy of 97%, sensitivity of 97.5%, and specificity of 96.5% using DFT (1024) with the signal length of 50 minutes before severe combined immunodeficiency (SCID).

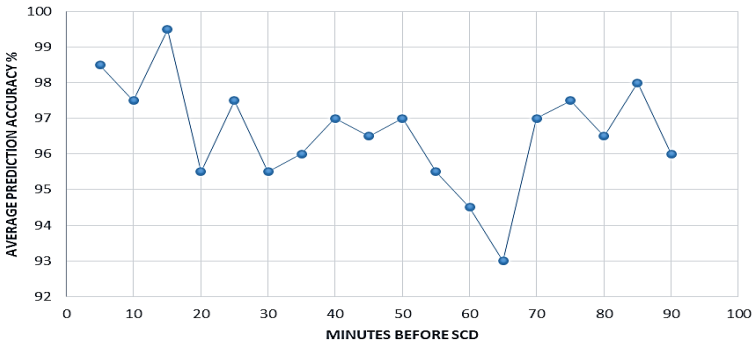

Figure 3. Prediction accuracy % for minutes before SCD

Table 1. Performance comparison of DFT with other features

Features	Average % accuracy
DWT	52.5
Raw	54.0
DFT	**94.5**
Spectrogram	90.0

Table 2. SCD prediction scores for DFT

Features	Accuracy %	Sensitivity %	Specificity %
DFT	94.5	95.5	93.5

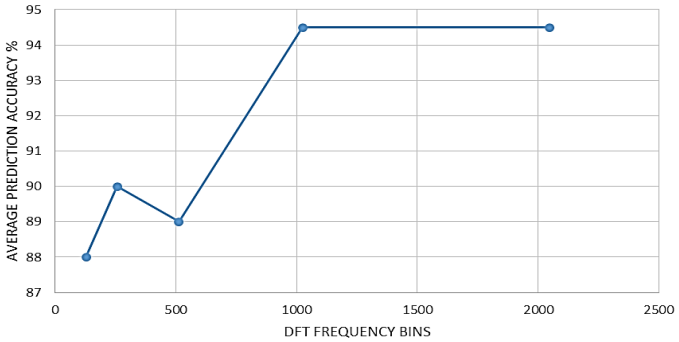

Figure 4. Performance comparison of using different bin-size frequencies

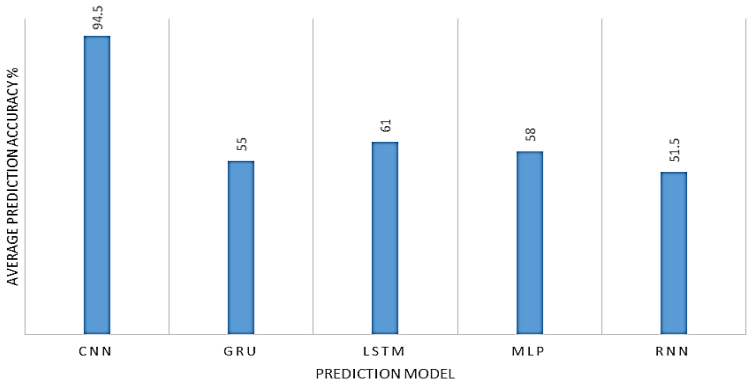

Figure 5. Performance comparison of CNN against other models

Table 1. The comparison of our algorithm and other recent methods for Predicting sudden cardiac death based on ECG parameters and HRV signal

Author (year)	Material			Methodology		Best performance		
	Data type	Dataset used	Length of signal(min)	Feature extraction (No of features)	Classifier	Acc (%)	Sen (%)	Spe (%)
Acharya *et al.* (2015) [25]	ECG	SDDB NSRDB	4 minutes before SCID	Nonlinear features (18) and SCDI	DT, SVM	92.11%	92.50%	91.67%
Fujita *et al.* (2016) [26]	HRV	SDDB NSRDB	4 minutes before SCID	Nonlinear features (4)	SVM, KNN	94.70%	95.00%	94.40%
Sanchez *et al.* (2018) [24]	ECG	SDDB NSRDB	20 minutes before SCID	Nonlinear heart rate variability analysis Nonlinear methods HI	EPNN	95.80%	unknown	unknown
Khazaei *et al.* (2018) [23]	HRV	SDDB NSRDB	6 minutes before SCID	Wave packet transform RQA (13) and increment entropy (2 out of 14)	DT, KNN, SVM, NB	95.00%	95.00%	95.00%
Ebrahimzadeh *et al.* (2018) [22]	HRV	SDDB NSRDB	12 minutes before SCID	Nonlinear method HRV features (23) Time local subset feature selection	MLP	88.29%	unknown	unknown
Ebrahimzadeh *et al.* (2019) [7]	HRV	SDDB NSRDB	13 minutes before SCID	HRV features (23) time local subset feature selection	MLP	90.18%	unknown	unknown
Lai *et al.* (2019) [21]	ECG	SDDB NSRDB AHADB	30 minutes before SCID	Arrhythmias risk markers (5) and SCDI	DT, KNN, SVM, NB, RF	99.49%	99.75%	99.04%
Present study	ECG	SDDB NSRDB	30 minutes before SCID	DFT (1024)	CNN	95.50%	97.00%	94.00%
Present study	ECG	SDDB NSRDB	50 minutes before SCID	DFT (1024)	CNN	97.00%	97.50%	96.50%
Present study	ECG	SDDB NSRDB	60 minutes before SCID	DFT (1024)	CNN	94.50%	95.50%	93.50%

5. CONCLUSION

In this study, the subject of predicting SCD was investigated using deep learning techniques. We showed that despite of the feature engineering currently employed in most of the recent works, efficient learning algorithm is required to accuracy predict for longer time duration. Therefore, we proposed deep learning techniques to automatically learn the underlying pattern of the DFT features extracted from ECG signals of the patients. Our method achieved the-state-of-art performance while accurately predicting for longer time duration with a small additional computation. We also compared our method with other deep learning models and found that our approach was significantly better than the other existing deep learning approaches such as LSTM, gated recurrent units (GRU), MLP, and RNN. As part of the future work, we intend to further apply dimensionality reduction techniques to mitigate the additional cost currently encountered by our approach. Additional pruning of network weights is another important research direction to ensure large models can be reduced while maintaining the model performance for low-end devices.

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