

# Identification of Classification Method for Sudden Cardiac Death : A Review

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**Abstract**—*Even in this new millenium, SCD still remains one of leading and unresolved problems in clinical cardiology. One of the most important factors in determining heart conditions is ECG paramaters because ECG signals are the most common technique for doctors in analyzing SCD. For detecting and prediciting SCD, there are many methods various classification have been proposed to expose. Remainder of this paper to list out methods classification for SCD used Sytematic Literature Review (SLR). SLR was carried out and reported based on the preferred reporting items for systematic reviews. 13 papers we retrieved by manual serach in four databases. 6 primary studies were finally included to indentification and analyzed. The Classification method for SCD from primary studies is -Nearest Neighbour (kNN), Decision Tree (DT), Support Vektor Machine (SVM), Probabilistic Neural Network (PNN), Naive Bayes, Multilayer Perceptron (MLP) Neural Network, and Long Short Term Memory (LSTM) Recurrent Neural Network (RNN). The review provides researchers with some guidelines for future research on this topic*

**Keywords**—*SCD, classification Method, SLR*

## I. INTRODUCTION

Sudden Cardiac Death (SCD) is a leading cause of mortality and although data from many regions to the world is limited, SCD remains a major public health burden worldwide [1], accounting 50% of deaths form cardiovascular disease and approximately 350.000 anual deaths in the United States [2] [3]. In [1] suggest that men have a three to four-fold higher risk for Scd compared woman. SCD Risk Factors is (1) age, sex, and ethnicity, (2) clinical risk factors, (3) coronary heart disease, (4) other structural heart disease, (5) Inherited arrhythmic disorder, and (6) electrocardiogram (ECG) paramaters [1].

One of the most important factors in determining heart conditions is ECG paramaters because ECG signals are the most common technique for doctors in analyzing SCD. ECG is simply a recording of the electronical activity generated by the heart.[4] [5]. An ECG represents a series of events,

such as the results of polarization and depolarization of cardiac tissue. These events, called waves are named by letters, the most important are P,Q,R,S, and T. [6] [7].

ECG signals have unique features, making researches conduct research in the field of SCD to get results automatically and accurately in classifying and indentifying disease form patterns of heart rhythm features.

Many papers published in online research to predict and develop new algorithms to encourage further reserach. For detecting and prediciting SCD, there are many methods various classification have been proposed to expose, such as k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Naive Bayes, Multilayer Perceptron (MLP) Neural Network, and Long Short Term Memory (LSTM) Recurrent Neural Network (RNN)

Remainder of this paper would list out methods for SCD detection and prediction based ECG signals with ECG and HRV parameters, and for literature review method uses Sytematic Literature Review (SLR).

## II. SYTEMATIC LITERATURE REVIEW (SLR)

This paper uses SRL guidelines, which is a form of secondary study that uses a well-defined methodolgy [8]. The SRL aims to be as fair as possibble by being auditable and reatable. According [8] the purpose of a SLR is to provide a compelete of possibble list of all studies that are related to certain subject area. Meanwhile, traditional reviews attempt to summarize resutls fo a number of studies.

Some researchers used the SLR method claim that this method is very appropriate for the literature review. In [9] indentified 103 eligible studies which summarized with respect to 5 research categories and inticated the problem studies and have a future research. In other studies [10] the authors provide a critical discussion on the limitations of existing methods.

SLR has steps : (1) research questions, (2) data sources & search procedures, (3) extraction data (inclusion and exclusion criteria).

#### A. Research Questions

This paper intended to identification of classification method for SCD with ECG dan HRV paramters. The SLR Research (RQ) that we intend to answer in this paper is as follows.

“What are the classification method for SCD and performance of each classification method by considering aspects : parameters, feature extraction, database and classification ?”

#### B. Data Sources and Search Procedures

The following search keywords are used to find relevant studies in paper’s tittle, keywords an abstract : “Elektrokardiogram”; “ECG” and “SCD”, and “Classification”; “Database”; “QRS”; “Feature Extraction”;

This paper has selected four databases to perform the SLR search process as follows : (1) ScienceDirect, (2)Springer,(3) IEEE eXplore, and (3) Google Scholar.

#### C. Extraction Data (Inclusion and Exluion)

Based on the review plan that has been prepared, the next step is to execute. Execution of search strings on all four web pages used as data sources resulted in 13 papers which were primary studies. Table 1 indicates the number study in selected from four databases platform.

TABLE I. SEARCH EXECUTION RESULTS

Publisher	Number of Articles found	Ref
Science Direct	3	[12] [13] [14]
Springer	5	[15] [16] [17] [18]
IEEE eXplore	3	[19] [20] [21] [22]
Google Scholar	2	[23] [24]
Jumlah	13	

1) *Inclusion and Exclusion* : Then the inclusion and exclusion criteria are applied by reading the title and the abstraction section of all primary study. Inclusion criteria based on topics related to research are published articles that discuss more about topics related to the SCD classification method, while selecting exclusions that are not related to the topic and looking for articles that are trusted. Results from the analysis through SLR revealed 6 studies for further consideration. All the selected studies have been gone through but only articles that able to answer the RQ of this SLR. Fig 1 shows the number of studies after each defined process.

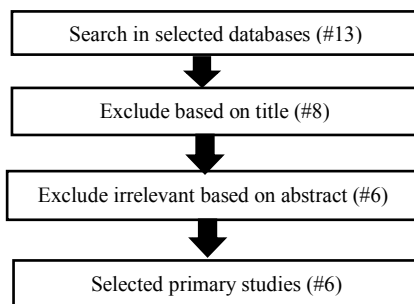


Fig 1. Finding Primary studies procedure

Table 2 depicts the number of primary studies addressing the identified classification method for SCD with aspects parameters, feature extraction, Database and Classification.

TABLE II. DEPICTS THE NUMBER OF PRIMARY STUDIES

Aspects	Ref
parameters, feature extraction, Database and Classification	[12][14][16] [21][22] 24]

### III. RESULTS AND DISCUSSION

This section provides discussions about this SLR, the discussion is about the research question, Identification of classification method for SCD are as follows :

#### A. Parameters

ECG characterized by several typical ECG paramater, such as P, R, and T-Wave, level of ST Segment, and RR and QT Intervals. RR and QT Interval are most important paramaters for diagnosis of SCD [25]. Researches in [24] using ECG segmentation method with ECG sampel four categories : P-Wave, QRS-Wave, T-Wave, and neutral (others), and then in [14] using the end of the T-Wave.

Heart Rate Variability is defined evaluation of beat to beat variability of the RR Interval [25]. Several of HRV parameters in time-domain (mean NN, SDNN, SDD, RMSSD, pNN50) and frequency-domain (LF, nLF, HF, nHF, LF.HF) and nonliner measure. HRV can be assessed form short (2-3 minutes) and long (24-Hours) ECG Signals, in [12] [16] [22] [21], they are predicted SCD by analyzing length of the signal HRV using nonlinear features,

#### B. Feature Extraction

The literature, various feature extraction techniques have been proposed to expose the distinctive information form ECG signals for different purpose to classification or predection. Those features can be used individually or in combination with other features.

In [24] ECG segmentation using simple local features instead fo compicated features, such as wavelet encoding. The extraction of features for HRV signal uses non-linear features, such as in [14] using Discrete Cosine Transform (DCT) is used for reducing the dimension of data, because in this paper the authors combined two method MLP ans SVM. In [22], the Researches using five feature extraction : Renyi Entropy (REnt), Fuzzy Entropy (FE), Hjort’s paramaters, Tsallis Entropy (TEnt), and Discrete Wavelet Transform (DWT). In [16] using 5 to decomposed ECG signal like Fractal Dimension (FD), Hurst’s exponent (H), Detrended Fluctuation Analysis (DFA), Approximate Entropy (ApproxEnt), Sample Entropy (SamEnt), and Correlation Dimension (CD). In [12] For feature extraction in this work to investigated nonlinear algorithms including Recurrence Qualification Analysis (RQA) and the increment entropy (IncEn). Researches in [21] to predict the SCD with length of signal four minutes using RAQ and Kolmogorov Complexity.

#### C. Databases

Various database are publicly available to evaluate the methods proposed in studies that target the analysis ECG signals. The following database used for difference purpose in ECG signal analysis : The MIT-BIH SCD Holter open access database and the normal Sinus Rhythm database were used to obtain the SCD and normal signal. The database

consisted of 41 ECG signals taken from 23 patients (age : 18-89 years) with SCD and 18 (age : 20-50 years) normal subject. The sampling rate of SCD and normal SCD signals 256Hz and 128 Hz. The SCD Holter Database is used to predict SCD using HRV parameters. For the ECG parameter using the QT Database was produced by Physionet, it consist of short segment (15 minute) extracted from 105 Holter recording with frequency of 250 Hz.

#### D. Classification

##### 1) ECG Parameters

In [14] both, MLP Neural Networks and Fixed-size Least-squares SVM used as regression algorithms to determine the end of the T-wave. FS-LSSVM approaches are more suitable as regression algorithm than MLP NN. Despite the small Training set used, that FS-LSSVM methods outperformed the state-of-the-art techniques

In [24] introduces a newly-proposed LSTM RNN architecture to segment ECG intervals : Deep Bidirectional LSTM (DBLSTM) is a RNN that uses LSTM cells and computes both forward and backward hidden sequences, by stacking up these type of layers and a new deep network. Deep Learning Methods outperform a traditional Markov Model (MM) in terms of accuracy and using simple local features instead of complicated. T-Wave segmentation can achieve an accuracy of 90%, compared to that of 74.2% using Markov Models.

##### 2) HRV Parameters

In [12] used classifier of DT, kNN, Naive Bayes, and SVM with 10-fold cross validation method for evaluate the classifiers performance. Using the decision tree classifiers the authors achieved SCD detection six minutes before its onset with accuracy, specificity and sensitivity of 95%

In [16] classifiers of DT, kNN, SVM they are used to differentiate between ECG of normal subjects and those of subjects at risk of developing SCD. In this work, ten-fold cross validation method is used to build and evaluate features. Their proposed technique achieved an accuracy of 92.11% (kNN), 98.68% (SVM), 93.42% (kNN) and 92.11% (SVM) for one, two, three and four minutes before SCD onset.

In [21] to classify normal and SCD using kNN, DT, SVM, and PNN. The ten times ten-fold cross validation is used to test the performance of all classifiers. The researches are able to predict the SCD four minutes before its onset with an average used kNN an accuracy of 86.8%, sensitivity of 80%, and specificity of 94.4% and for PNN accuracy of 86.8%, sensitivity of 85%, and specificity of 88.8%.

In [22] use three different classifiers kNN, DT and SVM to explore with the goal of determining the best classifier. Their proposed automated SCD onset prediction method for four minutes earlier show accuracy of 94%, sensitivity 95%, and specificity of 94.4%.

Table 3 shows summary of studies published in prediction of SCD using ECG Parameters and HRV Parameters. The best performance for the classification method is SVM used 6 features extraction (FD, H, DFA, ApproxEnt, SamEnt, and CD) an accuracy of 98.68%. In [12] [21] used the same feature extraction but the researches in [12] get the best performance an accuracy, specificity sensitivity of 95% than in [21] get a value of <95%. In [24] introduces newly-proposed LSTM RNN architecture used 15 minutes duration, and get performance an accuracy of 90%. There is not a DL-based method for ECG signal segmentation yet [24].

TABLE III. SUMMARY OF STUDIES.

Ref	Data (ECG/HRV)	Year	Feature Extraction	Length of Signal	Classifier	Best Performance
[12]	HRV	2018	Recurrence Qualification Analysis (RQA), Increment Entropy (IncEn)	1-minutes episode (6 minutes before onset)	DT, kNN, Naive Bayes, and SVM	accuracy, specificity sensitivity 95%
[14]	ECG	2018	Discrete Cosine Transform (DCT)	N/A	MLP, SVM	N/A
[16]	HRV	2015	Fractal Dimension (FD), Hurst's exponent (H), Detrended Fluctuation Analysis (DFA), Approximate Entropy (ApproxEnt), Sample Entropy (SamEnt), Correlation Dimension (CD)	1-minutes episode (4 minutes before onset)	DT, kNN, SVM	accuracy : 92.11% (kNN), 98.68% (SVM), 93.42% (kNN), 92.11% (SVM)
[21]	HRV	2015	using RAQ, Kolmogorov Complexity	1-minutes episode (4 minutes before onset)	kNN, DT, SVM, and PNN	kNN (accuracy 86.8%, sensitivity 80%, specificity 94.4%) PNN (accuracy 86.8%, sensitivity 85%, and specificity 88.8%)
[22]	HRV	2016	(REnt), Fuzzy Entropy (FE), Hjort's parameters, Tsallis Entropy (TEnt), and Discrete Wavelet Transform (DWT)	1-minutes episode (4 minutes before onset)	kNN, DT and SVM	accuracy 94%, sensitivity 95%, specificity 94.4%
[24]	ECG	2018	Wavelet encoding	15 minutes duration	LSTM RNN	accuracy 90%

#### IV. CONCLUSION

The goal of this paper is to conduct a SLR on identification of classification method for SCD used ECG and HRV parameters. Our aims are to investigate and identify the performance of classification method from

aspects parameters, features extraction, databases, and classification.

To contributing research in cardiology to delineate ECG signals for SCD, our proposed is combining the vital information of waveforms with other methods Deep

Learning in recognizing symptoms, more accurate heart related diseases can be diagnosed.

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#### REFERENCES

- [1] C. X. Wong *et al.*, "Epidemiology of Sudden Cardiac Death: Global and Regional Perspectives," *Hear. Lung Circ.*, vol. 28, no. 1, pp. 6–14, 2019.
- [2] E. J. Benjamin *et al.*, *Heart Disease and Stroke Statistics-2019 Update: A Report From the American Heart Association*, vol. 139, no. 10, 2019.
- [3] L. G. Tereshchenko, E. Z. Soliman, B. R. Davis, and S. Oparil, "Risk stratification of sudden cardiac death in hypertension," *J. Electrocardiol.*, vol. 50, no. 6, pp. 798–801, 2017.
- [4] S. Kaplan Berkaya, A. K. Uysal, E. Sora Gunal, S. Ergin, S. Gunal, and M. B. Gulmezoglu, "A survey on ECG analysis," *Biomed. Signal Process. Control*, vol. 43, pp. 216–235, 2018.
- [5] R. Singh and J. J. Murphy, "Electrocardiogram and arrhythmias," *Anaesth. Intensive Care Med.*, vol. 19, no. 6, pp. 322–325, 2018.
- [6] L. B. Marinho, N. de M. M. Nascimento, J. W. M. Souza, M. V. Gurgel, P. P. Rebouças Filho, and V. H. C. de Albuquerque, "A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification," *Futur. Gener. Comput. Syst.*, vol. 97, pp. 564–577, 2019.
- [7] S. Nurmaini, P. R. Umi, R. M. Naufal, and A. Gani, "Cardiac arrhythmias classification using Deep Neural Networks and principle component analysis algorithm," *Int. J. Adv. Soft Comput. its Appl.*, vol. 10, no. 2, pp. 14–32, 2018.
- [8] B. Kitchenham and S. Charters, "Source: " Guidelines for performing Systematic Literature Reviews in SE " ", Kitchenham et al Guidelines for performing Systematic Literature Reviews in Software Engineering Source: " Guidelines for performing Systematic Literature Reviews i," pp. 1–44, 2007.
- [9] J. Kaur, S. S. Sehra, and S. K. Sehra, "A Systematic Literature Review of Sentiment Analysis Techniques," no. 4, 2017.
- [10] M. Mirzaie, "State of the Art on the Quality of Big Data: A Systematic Literature Review and Classification Framework."
- [11] Z. Yin, L. M. Sulieman, and B. A. Malin, "Review A systematic literature review of machine learning in online personal health data," vol. 0, no. 0, pp. 1–16, 2019.
- [12] M. Khazaei, K. Raeisi, A. Goshvarpour, and M. Ahmadzadeh, "Early detection of sudden cardiac death using nonlinear analysis of heart rate variability," *Biocybern. Biomed. Eng.*, vol. 38, no. 4, pp. 931–940, 2018.
- [13] D. Magri *et al.*, "QT spatial dispersion and sudden cardiac death in hypertrophic cardiomyopathy: Time for reappraisal," *J. Cardiol.*, vol. 70, no. 4, pp. 310–315, 2017.
- [14] A. A. Suárez-león, C. Varon, R. Willems, S. Van Huffel, and C. R. Vázquez-seisdedos, "T-wave end detection using neural networks and Support Vector Machines," *Comput. Biol. Med.*, 2018.
- [15] J. Ram *et al.*, "T-Wave Morphology Restitution Predicts Sudden Cardiac Death in," pp. 1–12.
- [16] U. R. Acharya *et al.*, "An integrated index for detection of Sudden Cardiac Death using Discrete Wavelet Transform and nonlinear features," *Knowledge-Based Syst.*, vol. 83, no. 1, pp. 149–158, 2015.
- [17] J. P. Amezcuita-Sanchez, M. Valtierra-Rodriguez, H. Adeli, and C. A. Perez-Ramirez, "A Novel Wavelet Transform-Homogeneity Model for Sudden Cardiac Death Prediction Using ECG Signals," *J. Med. Syst.*, vol. 42, no. 10, 2018.
- [18] I. Mohapatra, P. Pattnaik, and M. N. Mohanty, *Cardiac Failure Detection Using Neural Network Model with Dual-Tree Complex Wavelet Transform*, vol. 846. Springer Singapore, 2019.
- [19] T. W. Shen, H. P. Shen, C. H. Lin, and Y. L. Ou, "Detection and prediction of Sudden Cardiac Death (SCD) for personal healthcare," *Annu. Int. Conf. IEEE Eng. Med. Biol. - Proc.*, pp. 2575–2578, 2007.
- [20] F. Lopez-Caracheo, A. B. Camacho, C. A. Perez-Ramirez, M. Valtierra-Rodriguez, A. Dominguez-Gonzalez, and J. P. Amezcuita-Sanchez, "Fractal dimension-based methodology for sudden cardiac death prediction," *2018 IEEE Int. Autumn Meet. Power, Electron. Comput. ROPEC 2018*, no. Ropec, pp. 1–6, 2019.
- [21] U. R. Acharya, H. Fujita, V. K. Sudarshan, D. N. Ghista, W. J. E. Lim, and J. E. Koh, "Automated Prediction of Sudden Cardiac Death Risk Using Kolmogorov Complexity and Recurrence Quantification Analysis Features Extracted from HRV Signals," *Proc. - 2015 IEEE Int. Conf. Syst. Man, Cybern. SMC 2015*, pp. 1110–1115, 2016.
- [22] H. Fujita *et al.*, "Sudden cardiac death (SCD) prediction based on nonlinear heart rate variability features and SCD index," *Appl. Soft Comput. J.*, vol. 43, pp. 510–519, 2016.
- [23] E. Ebrahimzadeh, M. Pooyan, and A. Bijar, "A Novel Approach to Predict Sudden Cardiac Death ( SCD ) Using Nonlinear and Time-Frequency Analyses from HRV Signals," vol. 9, no. 2, pp. 1–14, 2014.
- [24] H. Abrishami and M. Campbell, "Supervised ECG Interval Segmentation Using LSTM Neural Network," no. August, 2018.
- [25] S. Zulj, R. Magjarevic, D. Miklavcic, and T. Jarm, "Biomedical Signal Processing and Control Matlab-based tool for ECG and HRV analysis," *Biomed. Signal Process. Control*, vol. 10, pp. 108–116, 2014.