Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network

Article *in* Future Generation Computer Systems · August 2017

DOI: 10.1016/j.future.2017.08.039

8 authors, including:

U Rajendra Acharya
Ngee Ann, Singapore University of Social Science, Singapore; University of Malaya…

Shu Lih Oh
Ngee Ann Polytechnic

Raghavendra U
Manipal Academy of Higher Education

Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network

U Rajendra Acharya[1,2,3], Hamido Fujita[4*], Shu Lih Oh[1], U Raghavendra[5], Jen Hong Tan[1], Muhammad Adam[1], Arkadiusz Gertych[6], Yuki Hagiwara[1]

[1]Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore.

[2]Department of Biomedical Engineering, School of Science and Technology, Singapore University of Social Sciences, Singapore.

[3]Department of Biomedical Engineering, Faculty of Engineering, University of Malaya, Malaysia.

[4]Iwate Prefectural University (IPU), Faculty of Software and Information Science, Iwate 020-0693 Japan.

[5]Department of Instrumentation and Control Engineering, Manipal Institute of Technology, Manipal University, Manipal, India 576104.

[6]Department of Surgery, Department of Pathology and Laboratory Medicine, Cedars-Sinai Medical Center, Los Angeles, California, USA.

*Corresponding Author

Postal Address: [4]Iwate Prefectural University (IPU), Faculty of Software and Information Science, Iwate 020-0693 Japan

Telephone: +81-19-694-2578; Email Address: hfujita-799@acm.org

Abstract

Ventricular tachycardia (VT) and ventricular fibrillation (VFib) are the life-threatening shockable arrhythmias which require immediate attention. Cardiopulmonary resuscitation (CPR) and defibrillation are highly recommended means of immediate treatment of these shockable arrhythmias and to resume spontaneous circulation. However, to increase efficacy of defibrillation by an automated external defibrillator (AED), an accurate distinction of shockable ventricular arrhythmias from non-shockable ones needs to be provided upfront. Therefore, in this work, we have proposed a novel tool for an automated differentiation of shockable and non-shockable ventricular arrhythmias from 2 seconds electrocardiogram (ECG) segments. Segmented ECGs are processed by an eleven-layer convolutional neural network

(CNN) model. Our proposed system was 10-fold cross validated and achieved maximum accuracy, sensitivity and specificity of 93.18%, 95.32% and 91.04% respectively. Its high performance indicates that shockable life-threatening arrhythmia can be immediately detected and thus increase the chance of survival while CPR or AED -based support is performed. Our tool can also be seamlessly integrated with an ECG acquisition systems in the intensive care units (ICUs).

Keywords – Automated external defibrillator (AED); ECG signals; Non-shockable; Shockable; Ventricular Arrhythmias.

1. Introduction

Unforeseen interruption in heart beat is a condition known as cardiac arrest or sudden cardiac arrest (SCA) [1–3] . Ventricular arrhythmias (VAs) are the prime reasons for SCA due to which the rhythm and rate of the heart beat is tampered [4,5] . It is noticed that in VA, the heart beat is either too slow, a condition known as bradycardia or too fast, a condition known as tachycardia. Other irregular rhythms that are also seen are called fibrillation [6] . Sudden cardiac death (SCD) happens within minutes after unnoticed or untreated SCA. Also, SCA is a leading cause of mortality which constitutes to more than 350,000 deaths in the United States annually [7] . Time is pivotal during SCA. Thus, to stabilize irregularities of arrhythmias during SCA event, an automated external defibrillation (AED) is considered as best immediate treatment [8] . An AED sends an electric shock to the heart to restore the heart beat to a normal and rhythmic pace [9] . There are a few typical examples of VAs namely ventricular tachycardia (VT), ventricular fibrillation (VFib), ventricular tachycardia (VT), ventricular flutter (VFL), ventricular bigeminy (VB), ventricular ectopic beats (VEB), and ventricular escape rhythm (VER).

Figure 1 illustrates the generation of normal, VFib and VT ECG signals. The contractions in a normal heart is regular thus, produces a regular and rhythmic ECG signal. On the other hand, in VFib, the lower chambers of the heart quiver fast and erratically hence, producing an erratic and nonrhythmic ECG signals. Likewise, in VT, there are abnormal impulses in the lower chambers of the heart causing the heart to beat more rapidly, and therefore, producing ECG signals that are unsynchronized and chaotic [10] .

The deviation of a normal and rhythmic pattern is known as arrhythmia. VFib is a form of arrhythmia which happens when different parts of the heart muscles contract at different times causing an uncoordinated ventricular contraction [11]. The VFL is a type of arrhythmia which affects the ventricles [11]. It is regarded as a transition stage between VT and VFib. These conditions contribute to the poor perfusion of oxygen and blood flow to vital organs and can be life-threatening if not treated immediately [11]. Therefore, defibrillation is required in such conditions (VFib, VFL, and VT). However, not all ECG signals can be defibrillated [12,13]. The other VAs such as VB, VEB and VER also need immediate treatment, yet, using only CPR without the need of defibrillation (non-shockable) through AEDs [14].

The electrical mechanism or performance of the shockable and non-shockable VAs is reflected in the ECG, whose signal morphology and features can be evaluated to decide if the shock-advisable clinical intervention is required [14,15]. Generally, AEDs are furnished with an algorithm to assess the ECG signals. A shock can only be applied to the patient if the algorithm detects a shockable ECG signal [16].

Therefore, there is a need to develop a tool for an automated detection system to accurately identify shockable and non-shockable ECG signals at an instance. Literature research has shown that there are many different techniques that researchers have implemented in the development of an automated shockable and non-shockable diagnosis system (see Table 8). According to Table 8, most of the techniques are based on traditional machine learning approaches where the input ECG signals are subjected to a standardized workflow including: pre-processing, feature extraction, feature selection, and classification performed by independent algorithms. The approach proposed in this paper is different. The ECG signals are segmented into 2 seconds and pre-processed for noise removal. Then the 2 seconds segments are fed into an eleven-layer deep convolutional neural network (CNN) modelto automatically classify the input ECG segments into shockable or non-shockable ones. The CNN also learns different feature extractors and feature selection techniques.

The proposed CNN model has been successfully implemented in our previous works. An eleven-layer deep CNN was applied to 2 second and 5 second ECG segments for an automatic classification of arrhythmias [17] and coronary artery disease [18]. Also, an eleven-layer CNN was employed in the diagnosis of myocardial infarction with two different experiments (with and without noise removal) [19]. Since our previous works [17–19] have shown high classification accuracies of ECG segments, we thus we propose a CNN-based approach to identify life-threatening ventricular arrhythmias.

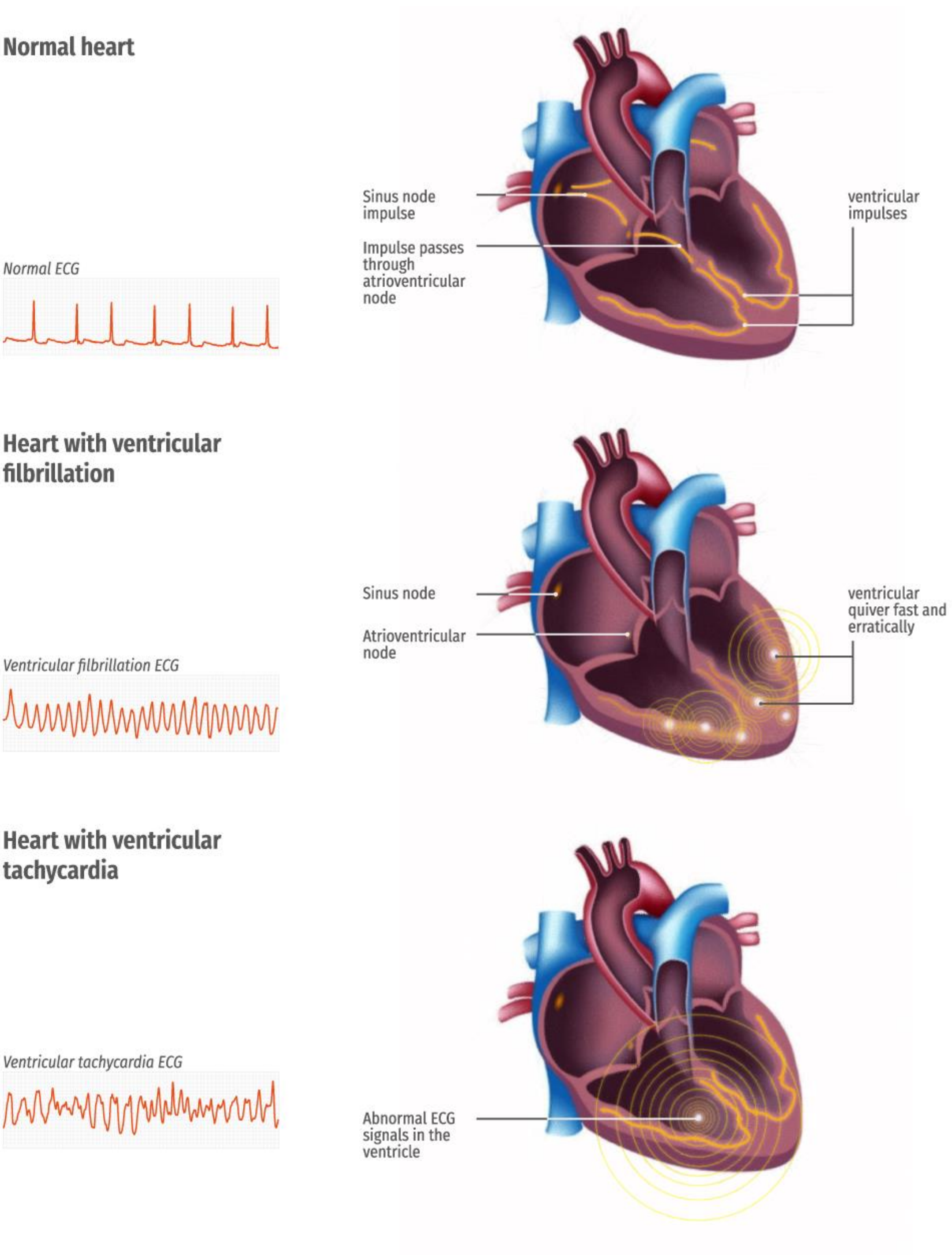

Figure 1. Illustration of normal, VT and and Vfib ECG signal.

2. Proposed Methodology

2.1 Data Used

The ECG signals used in this study are obtained from *three* publicly available databases, namely MIT-BIH arrhythmia database (MITDB) [20,21], MIT-BIH malignant ventricular arrhythmia database (VFDB) [20,22] and Creighton University ventricular tachyarrhythmia database (CUDB) [20,23]. The summary of the acquired ECG data from the *three* databases is shown in Table 1. Also, Table 2 presents different ECG rhythms used and the annotations and number of segments are given in Table 3. The summary of 2 seconds shockable and non-shockable ECG segments is given in Table 4. Example shockable and non-shockable segments are shown in Figure 2.

Table 1. Database summary.

Database	No. of ECG signals	Lead(s)	Lead used	Frequency sample (Hz)	ECG signal duration (minute)
MITDB	48	• Modified lead II (MLII) • V5	Modified lead II (MLII)	360 (resampled to 250)	30
VFDB	22	• Lead I • Lead II	Lead I	250	30
CUDB	35	• Lead I	Lead I	250	8

Table 2. ECG rhythm used.

Shockable VA rhythm	Non-shockable VA rhythm
Ventricular fibrillation	Normal sinus rhythm
Ventricular flutter	Ventricular bigeminy
Rapid ventricular tachycardia	Ventricular ectopic beats
	Ventricular escape rhythm

Table 3. ECG annotations used and the total number of segments obtained from each database.

Type	Used Physionet Annotations		Database
Non-shockable	B	Ventricular Bigeminy	MITDB, VFDB
	N	Normal Sinus Rhythm	MITDB, VFDB, CUDB
	HGEA	High grade ventricular ectopic activity	VFDB
	NSR	Normal Sinus Rhythm	VFDB
	VER	Ventricular escape rhythm	VFDB
Shockable	VFL	Ventricular flutter	MITDB, VFDB
	VT	Ventricular tachycardia	MITDB, VFDB
	VF	Ventricular fibrillation	VFDB
	VFIB	Ventricular fibrillation	VFDB, CUDB

Table 4. Total number of 2sec ECG segments obtained

2 seconds ECG episodes	Obtained
Non-shockable	48095
Shockable	6001

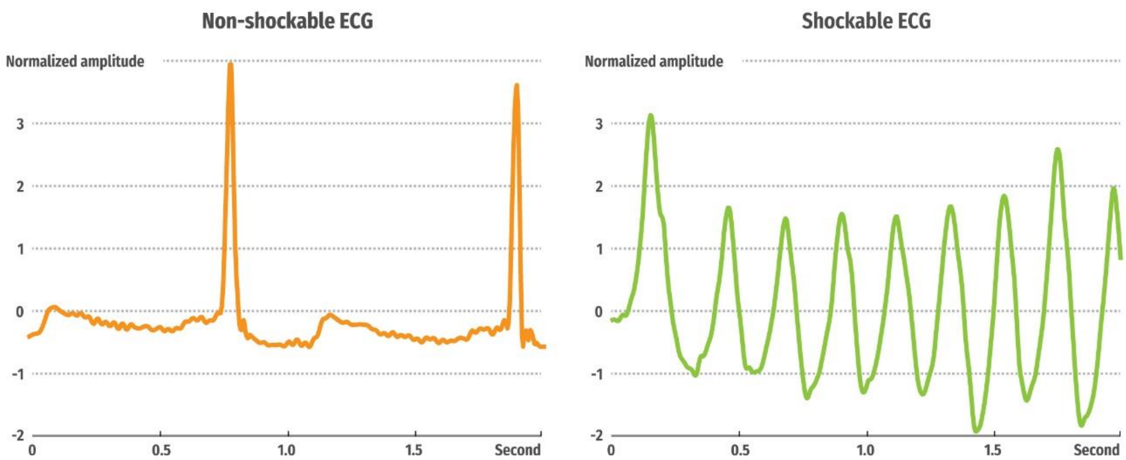

Figure 2. Illustration of shockable and non-shockable ECG segments.

2.2 Pre-Processing and Synthetic Data Generation

The ECG signals obtained from the MITDB database were sampled at 360Hz rate whereas signals in the other two databases (CUDB and VFDB) were sampled at 250 Hz rate. Therefore, to ensure standardization across the databases, the ECG signals obtained from MITDB are down-sampled to 250 Hz. Daubechies wavelet 6 (db6) is implemented on the ECG signals for noise and baseline wander removal [24]. After which, the signals are segmented according to shockable and non-shockable rhythms using ground truth annotations provided in the respective databases.

Each segment was Z-score normalized to address the problem of amplitude scaling and eliminate the offset effect before feeding into a 1D deep convolutional network for training and testing. The 2 second ECG segments contain 500 samples.

To overcome the class imbalance problem, synthetic data was generated by varying around 10% of the standard deviation and mean of the Z-scores calculated from the original signals. Through this process the total number of shockable ECG segments increased from 6,001 to 48,095.

2.3 Proposed Convolution Neural Network (CNN) Architecture

CNNs [25] represent a class of neural network models that can process multidimensional data such as whole images or time series because of their complex structure that includes two -or three-dimensional layers of neurons connected within and between the layers [26]. The structure of the CNN is similar to neural network (NN) with an input, hidden, and output layers. However, unlike NN, CNN is an improved version of NN which is both translational and shift invariant [27]. CNNs consist of different types layers such as input, convolution, max pooling, average pooling, rectified linear unit layer etc. and play specific role in the model. Briefly, data gathered at the input layer is split and then transformed while being propagated through the network to the last layer which yields classification scores [18,28–30]. The description of the different layers in the developed model is outlined below:

Signal Input layer: The input signals are initially fed into it and it holds the raw signal values.

Convolutional layer (CONV): This is the main layer that performs most computations including feature extraction and feature selection. It is the first and the compulsory layer of the network after the signal input layer. The CONV layer learns filters. Each filter is convolved with the input and a dot product between of the filter weights and the input is computed. As the filter slides over the input volume, an activation map is produced. Naturally, the model will learn filters that activate when they see significant features [28].

Max-pooling layer: This layer is also called a sub-sampling layer. Its purpose is to progressively reduce the number of parameters and computational burden in the structure. Furthermore, it helps to manage the overfitting problem [28,31].

Fully-connected layer (FC): This layer has full connections to all activations in the previous layer. Their activations can thus be determined through a matrix multiplication [28]. Details of the CNN model proposed in this study are given below.

Table 5. Details of the CNN structure.

Layers	**Type**	**No. of neurons (output layer)**	**Kernel size for each output feature map**	**Stride**
0-1	Convolution	496 x 3	5	1
1-2	Max-pooling	248x 3	2	2
2-3	Convolution	244 x 5	5	1
3-4	Max-pooling	122 x 5	2	2
4-5	Convolution	118 x 10	5	1
5-6	Max-pooling	59 x 10	2	2

6-7	Convolution	56x 10	4	1
7-8	Max-pooling	28 x 10	2	2
8-9	Fully-connected	10	-	-
9-10	Fully-connected	5	-	-
10-11	Fully-connected	2	-	-

The proposed CNN model is shown in Figure 3.

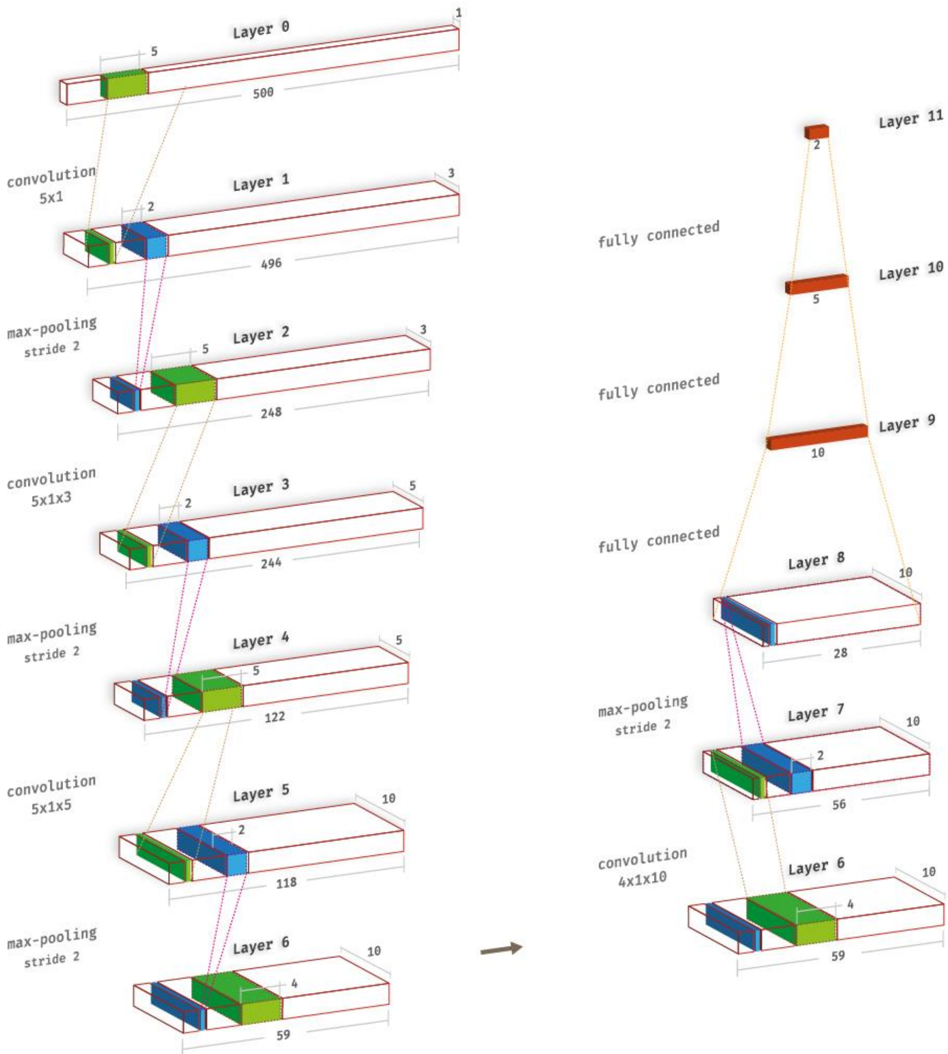

Figure 3. Architecture of the proposed CNN model.

During training of the CNN the following parameters are tuned.

- Epochs: An epoch is a single pass of the training dataset through the network. The maximum epoch limit is set to 40 which is found to be sufficient for this dataset.
- Minibatch: Minibatches are used to train the network in a sequential manner. Here, the minibatch size is set to 10. This means that after training with 10 segments, the algorithm will update the weights of the network in batches and proceed to the next iteration (epoch).
- Learning rate: The learning rate is the speed at which the network trains itself. In this work, the learning rate is set to 0.001.
- Lambda: This is the regularization parameter is set to 0.2 [32].
- Momentum: The momentum is set to 0.7.

Leaky rectifier linear unit (LReLU) [32] is used in CNN as the activation function for layer 1, 3, 5, 7 9, 10. For layer 11, softmax function is used. Xavier initialization [32] is used for the weights of layer 1, 3, 5, 7, 9 and 10. Biases is set to a value of 1 for layer 1, 3 and 5. On the other hand, the value of the biases at the layer 4 is randomly generated based on Gaussian distribution [32].

2.4 k-fold stratified cross validation

In this work, 10-fold cross validation is performed to assess the ability of the proposed CNN to classify shockable versus non-shockable waves. Initially, the entire set of segments is partitioned into *ten* equal parts. First nine parts are used to train the CNN model and rest are used to test. This process is repeated nine more times by considering the remaining folds for training and testing. Average classification results from all ten experiments are used to assess the performance: sensitivity, specificity, positive predicted value (PPV) and accuracy are computed.

3. Results

In this work, shockable (6001) and non-shockable (48095) ECG segments are analyzed by a novel CNN model developed by the authors using MATLAB software. The CNN model is trained on a workstation PC with two Intel Xeon 2.40 GHz (E5620) processors and 24 GB of RAM. During the training, the weights of neurons in the CNN are adjusted to minimize the error between the predicted and ground truth label of ECG segments. Typically, 1389.533 sec are needed to complete one epoch of training.

Next, the developed CNN model is tested. Table 6 shows the performance in terms of confusion matrix across the *ten* folds. Table 7 presents overall classification results across for ten folds. It can be observed from Table 6 that 91.04% of ECG segments are correctly classified as non-shockable. Also, 95.32% of ECG segments are correctly classified as shockable.

Table 6. Confusion matrix across all 10 folds.

Original/Predicted	Non-shockable	Shockable	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Non-shockable	43790	4305	93.18	95.11	91.04	95.32
Shockable	2250	45845	93.18	91.41	95.32	91.04

Table 7. Overall classification result across all 10 folds.

TP	TN	FP	FN	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
45845	43790	4305	2250	93.18	91.41	95.32	91.04

4. Discussion

The detection of life-threatening ventricular arrhythmias is extremely difficult as the ECG waveforms with arrhythmias are irregular, fluctuate, and are corrupted by noise. Hence, it is utmost important to capture the VAs within a short duration of ECG rhythms. In this work, a novel CNN based algorithm for the automated identification of shockable and non-shockable ECG episodes is presented. The proposed technique can distinguish the life-threatening shockable waves from non-shockable ones with an accuracy, sensitivity and specificity of 93.18%, 95.32% and 91.04% respectively.

Our proposed method segmented the 2 seconds ECG segments to capture the shockable rhythms occurring before the waveforms changes due to sudden cardiac death (or before progression to SCD stage). When juxtaposing the performance of this method to performances of other techniques collected in Table 8, it becomes apparent that the proposed method outperforms the state-of the art. The main point is that the CNN model can correctly classify short (2 seconds) time segments of ECG, while other methods can do the same in time that is 2-4 times longer. The other novelty of our work is in the use of *three* databases consisting of total 54096 ECG segments (6001 shockable and 48095 non-shockable). To best of our knowledge this is the first study that shows the application of a CNN model to the classification of shockable and non-shockable episodes. It is non-selective and can deal with of a spectrum of shockable (VT, VFib, and VFL) and non-shockable (NSR, VB, VEB, and VER) episodes, which is the largest comparing to the datasets used in individual studies shown in Table 8. The proposed solution is highly sensitive in capturing the shockable rhythms. The false positive rate is low (high specificity), and thus can help in avoiding unnecessary defibrillations. In future, we would like to extend our work and develop a model able to analyze shorter segments (<2sec) and thus further diminish the delay arising from hands-off time in AEDs. Nevertheless, it is noted that the performance of the present proposed CNN model can be improved. Therefore, in our future work, we will perform bagging algorithm and data augmentation.

The advantages of proposed algorithm are as follows:

- CNN is invariant to translation; hence it is very sensitive in capturing the shockable rhythms with low-false positive rate.
- Does not require handcrafted feature for the classification.
- It is robust as shown through the 10-fold cross-validation.
- Does not require R peak detection or any other ECG pre-processing.
- Feature extraction, statically analysis, feature ranking and classification steps are not needed.

- As per Table 8, proposed model yields high performance even for smallest duration (2 seconds) data.

The drawbacks of proposed algorithm are as follows:

- Requires a huge data set to train.
- Training time of CNN is longer comparing to models shown Table 8.

Table 8. **Summary of automated shockable and non-shockable ventricular arrhythmia.**

Author, **(Year):**	**ECG signals obtained from:**	**Approaches:**	**Length of ECG segments: (seconds)**	**Performance:**
Jekova, (2000) [33]	AHA, CUDB, VFDB	• 5 different algorithms implemented • VF filter achieved highest performance	8	• SEN: 94% • SPEC: 91%
Jekova et al, (2004) [34]	AHA, CUDB, VFDB	• Band pass digital filtration	8	• SEN: 94.4% • SPEC: 95.9%
Amann et al, (2005) [35]	AHA, CUDB, BIH-MIT	• 12 different algorithms implemented • Signal comparison algorithm achieved highest performance	8	• SEN: 71.2% • SPEC: 98.5% • ACC: 96.2%
Amann et al, (2007) [36]	AHA, CUDB, BIH-MIT	• Time-delay based algorithm	8	• SEN: 79% • SPEC: 97.8% • ACC: 96.2%
Jekova et al, (2007) [37]	AHA, CUDB, VFDB	• Discriminant Analysis	10	• SEN: 94.1% • SPEC: 93.8%

Fokkenrood et al, (2007) [38]	BIH-MIT, CUDB, VFDB	• Improved amplitude distribution analysis	6	• SEN: 97% • SPEC: 98% • ACC: 98%
Alonso-Atienza et al, (2014) [39]	BIH-MIT, CUDB, VFDB	• Complexity, morphological, spectral features • Support vector machine classifier	8	• SEN: 92% • SPEC: 97%
Li et al, (2014) [40]	AHA, CUDB, VFDB	• Genetic algorithm • Support vector machine classifier	5	• SEN: 96.2% • SPEC: 96.2% • ACC: 96.3%
Tripathy et al, (2016) [41]	BIH-MIT, CUDB, VFDB	• Variational mode decomposition • Entropies features • Random forest Classifier	5 8	(5 seconds) • SEN: 96.54% • SPEC: 97.97% • ACC: 97.23% (8 seconds) • SEN: 94.37% • SPEC: 94.73% • ACC: 94.07%
Present work	**CUDB, MITDB, VFDB**	• **Convolution neural network**	**2**	• **SEN: 95.32%** • **SPEC: 91.04%** • **ACC: 93.18%**

*ACC: Accuracy, SEN: Sensitivity, SPEC: Specificity
AHA: American Heart Association Fibrillation database
MIT-BIH Malignant Ventricular Arrhythmia Database: VFDB
Creighton University ventricular tachyarrhythmia database: CUDB
Boston's Beth Israel Hospital and MIT arrhythmia database: BIT-MIH

5. Conclusion

In this work, the problem of having a fast and reliable algorithm to correctly identify shockable ECG signals is addressed by using a CNN model. We achieved a high performance of 93.18% with the proposed model using only a short duration (2 seconds) of ECG data. Its excellent performance indicates that the algorithm possesses the potential to be installed in AED devices to save life and reduce damage inflicted to the heart muscle by a wrong classification of ventricular arrhythmias.

6. References

[1] N. J. Finch and R. B. Leman, "Clinical trials update: Sudden cardiac death prevention by implantable device therapy," *Critical Care Nursing Clinics of North America*, vol. 17, no. 1. pp. 33–38, 2005.

[2] D. P. Zipes and H. J. J. Wellens, "Sudden cardiac death," *Circulation*, vol. 98, no. 21, pp. 2334–2351, 1998.

[3] D. P. Zipes, A. J. Camm, and M. Borggrefe, "ACC/AHA/ESC 2006 Guidelines for management of patients with ventricular arrhythmias and the prevention of sudden cardiac death," *J. Am. Coll. Cardiol.*, vol. 48, no. 5, p. e247, 2006.

[4] F. J. Jaeger, "Cardiac arrhythmias," *Disease Management, Cleveland Clinic Center of Continuing Education*, 2010. .

[5] M. C. S. Hall, "Modern management of arrhythmias," *Postgrad. Med. J.*, vol. 82, no. 964, pp. 117–125, 2006.

[6] C. T. Pedersen *et al.*, "EHRA/HRS/APHRS Expert consensus on ventricular arrhythmias," *Europace*, vol. 16, no. 9, pp. 1257–83, 2014.

[7] E. J. Benjamin *et al.*, "Heart Disease and Stroke Statistics-2017 Update A Report From the American Heart Association," *Circulation*, vol. 135, no. 10, pp. E146–E603, 2017.

[8] M. Josephson and H. J. J. Wellens, "Implantable defibrillators and sudden cardiac death," *Circulation*, vol. 109, no. 22, p. 2685 LP-2691, 2004.

[9] National Heart Lung and Blood Institute, "What is an automated external defibrillator?," 2011. .

[10] Mayo Clinic Staff, "Heart Arrhythmia," 2016. [Online]. Available: http://www.mayoclinic.org/diseases-conditions/heart-arrhythmia/symptoms-causes/dxc-20188128. [Accessed: 04-Jul-2017].

[11] R. Acharya U, N. Kannathal, L. M. Hua, and L. M. Yi, "Study of heart rate variability signals at sitting and lying postures," *J. Bodyw. Mov. Ther.*, vol. 9, no. 2, pp. 134–141, 2005.

[12] D. Biarent *et al.*, "European resuscitation council guidelines for resuscitation 2010 Section 6. Paediatric life support," *Resuscitation*, vol. 81, no. 10, pp. 1364–1388, 2010.

[13] M. E. Kleinman *et al.*, "Part 10: Pediatric basic and advanced life support: 2010 International consensus on cardiopulmonary resuscitation and emergency cardiovascular care science withtreatment recommendations," *Circulation*, vol. 122, no. suppl_2, pp. S466–S515, 2010.

[14] M. Rasooli *et al.*, "Analysis of electrocardiogram pre-shock waveforms during ventricular fibrillation," *Biomed. Signal Process. Control*, vol. 21, pp. 26–33, 2015.

[15] S. G. Priori *et al.*, "2015 ESC Guidelines for the management of patients with ventricular arrhythmias and the prevention of sudden cardiac death," *Eur. Heart J.*, vol. 36, no. 9, pp. 2793–2867, 2015.

[16] C. D. Deakin, J. P. Nolan, K. Sunde, and R. W. Koster, "European Resuscitation Council Guidelines for Resuscitation 2010 Section 3. Electrical therapies: Automated external defibrillators, defibrillation, cardioversion and pacing," *Resuscitation*, vol. 81, no. 10, pp. 1293–1304, 2010.

[17] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with

convolutional neural network," *Inf. Sci. (Ny).*, vol. 405, 2017.

[18] U. R. Acharya, H. Fujita, S. L. Oh, M. Adam, J. H. Tan, and K. C. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," *Knowledge-Based Syst.*, vol. 946, pp. 1–10, 2017.

[19] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals," *Inf. Sci. (Ny).*, vol. 416, pp. 190–198, 2017.

[20] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, pp. E215-20, 2000.

[21] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3. pp. 45–50, 2001.

[22] S. D. Greenwald, "The development and analysis of a ventricular fibrillation detector," Massachusetts Institute of Technology, 1986.

[23] F. M. Nolle, F. K. Badura, J. M. Catlett, R. W. Bowser, and M. H. Sketch, "CREI-GARD, a new concept in computerized arrhythmia monitoring systems," *Comput. Cardiol.*, pp. 515–518, 1987.

[24] R. J. Martis *et al.*, "Application of empirical mode decomposition (EMD) for automated detection of epilepsy using EEG signals," *Int. J. Neural Syst.*, vol. 22, no. 6, p. 121102031948003, 2012.

[25] L. Yann, B. Yoshua, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.

[26] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Adv. Neural Inf. Process. Syst.*, pp. 1–9, 2012.

[27] K. Fukushima, "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position," *Biol. Cybern.*, vol. 36, no. 4, pp. 193–202, 1980.

[28] "CS231n Convolutional Neural Networks for Visual Recognition." .

[29] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Inf. Sci. (Ny).*, vol. 405, pp. 81–90, 2017.

[30] I. Goodfellow, Y. Bengio, and A. Courville, "Deep learning," *Nat. Methods*, vol. 13, no. 1, pp. 35–35, 2015.

[31] J. Zhang, Q. Huang, H. Wu, and Y. Liu, "A shallow network with combined pooling for fast traffic sign recognition," *Information*, vol. 8, no. 2, p. 45, Apr. 2017.

[32] J. H. Tan, U. R. Acharya, S. V. Bhandary, K. C. Chua, and S. Sivaprasad, "Segmentation of optic disc, fovea and retinal vasculature using a single convolutional neural network," Feb. 2017.

[33] I. Jekova, "Comparison of five algorithms for the detection of ventricular fibrillation from the surface ECG.," *Physiol. Meas.*, vol. 21, no. 4, pp. 429–39, 2000.

[34] I. Jekova and V. Krasteva, "Real time detection of ventricular fibrillation and tachycardia," *Physiol. Meas.*, vol. 25, no. 5, pp. 1167–1178, 2004.

[35] A. Amann, R. Tratnig, and K. Unterkofler, "Reliability of old and new ventricular fibrillation detection algorithms for automated external defibrillators," *Biomed. Eng. Online*, vol. 4, pp. 60–60, 2005.

[36] A. Amann, R. Tratnig, and K. Unterkofler, "Detecting ventricular fibrillation by time-delay methods," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 1, pp. 174–177, 2007.

[37] I. Jekova, "Shock advisory tool: Detection of life-threatening cardiac arrhythmias and shock success prediction by means of a common parameter set," *Biomed. Signal Process. Control*, vol. 2, no. 1, pp. 25–33, 2007.

[38] S. Fokkenrood, P. Leijdekkers, and V. Gay, "Ventricular tachycardia/fibrillation detection algorithm for 24/7 personal wireless heart monitoring," in *International Conference on Smart Homes and Health Telematics*, 2007, pp. 110–120.

[39] F. Alonso-Atienza *et al.*, "Detection of life-threatening arrhythmias using feature selection and support vector machines.," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 3, pp.

832–40, 2014.

[40] Q. Li, C. Rajagopalan, and G. D. Clifford, “Ventricular fibrillation and tachycardia classification using a machine learning approach,” *IEEE Trans. Biomed. Eng.*, vol. 61, no. 6, pp. 1607–1613, 2014.

[41] R. K. Tripathy, L. N. Sharma, and S. Dandapat, “Detection of shockable ventricular arrhythmia using variational mode decomposition,” *J. Med. Syst.*, vol. 40, no. 4, pp. 1–13, 2016.