Detection of Arrhythmia in ECG signal using Deep Learning Methods – A exhaustive review & summary of the concepts & techniques

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Abstract: In this research article, the review of detection of arrhythmia in ECG signal using deep learning methods is presented in a nutshell. In today's world one of the serious health problem is heart disease. Arrhythmia is the ailment in which the heart rhythm is irregular. It is may not be life threatening; still, it may lead to heart failure or attack if not taken care of it in time. Different examinations and measures are offered, which help to analyze arrhythmia. These comprise of blood tests, cardiac catheterization, chest X-ray, echocardiography (echo), electrocardiography (ECG), ultrasound, Holter monitor, etc. Of all these tests, ECG is the utmost commonly used for the identification of arrhythmia. Simple hardware systems can be used, ECG data can be examined. This benefits in systematizing the analysis of arrhythmia. The objective of our research is to design a deep learning method for effective and quick classification of cardiac arrthymias. The automatic recognition of uncharacteristic heartbeats from a huge amount of data is a necessary and significant process. The ECG signals is taken from many database set (all classes of arrthymias). Each and every ECG beat will be obtained by using Discrete Wavelet transform i.e. 2D image which will be the input to Neural Networks. This is followed by Deep Learning methods that are used to teach a deep neural network based classifier (GA) to identify arrthymias. It will be implemented in the real-time scenario so patient condition can be recognized immediately without any delay and the treatment can be started by doctor without any second thought. Our research work is efficient, quick (real-time classification) and simple to use.
Arrhythmia is a common cardiac disorder that can have serious health implications if not detected and treated in a timely manner. This abstract presents a comprehensive review and summary of the concepts and techniques related to the detection of arrhythmia in electrocardiogram (ECG) signals using deep learning methods. With the increasing availability of large ECG datasets and advancements in deep learning, the application of artificial intelligence in arrhythmia detection has gained significant attention. This review explores the fundamental concepts of ECG signal analysis, the challenges associated with arrhythmia detection, and the recent developments in deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for accurate arrhythmia classification. Various pre-processing methods, feature extraction techniques, and model architectures are discussed, highlighting their respective advantages and limitations. The paper also examines the performance metrics and datasets commonly used in this domain. By synthesizing the latest research findings and methodologies, this review serves as a valuable resource for researchers and practitioners aiming to advance the field of arrhythmia detection and contribute to improved patient care.
Keywords : Arrhythmia, ECG signal, AI, ML, DL

1. Origin of Research Problem

Electrocardiography (ECG or EKG) is simple and non-invasive test which records the electrical activity in the heart. Electrodes are placed on skin in order to detect the electrical impulses generated in heart due to depolarization and repolarization of ventricles and atria. It is the simple method which can be remotely performed with minimal hardware setup. Continuous monitoring is not very feasible as it is time consuming and need lots of data to examine. Due to this a machine and deep learning model will be designed so that any heart related disease can be easily recognized by recorded ECG and the preventative action can be started immediately.

2. Nature of Research

An electrocardiogram (ECG) is a medical test that detects cardiac (heart) abnormalities by measuring the electrical activity generated by the heart as it contracts. The machine that records the patient's ECG is called an electrocardiograph. Some of the various heart problems that can be diagnosed by ECG includes the following

- Enlargement of the heart
- Congenital heart defects involving the conducting (electrical) system
- Abnormal rhythm (arrhythmia) – rapid, slow or irregular heart beats
- Damage to the heart such as when one of the heart's arteries is blocked (coronary occlusion)
- Poor blood supply to the heart
- Abnormal position of the heart
- Heart inflammation – pericarditis or myocarditis
- Cardiac arrest during emergency room or intensive care monitoring
- Disturbances of the heart's conducting system
- Imbalances in the blood chemicals (electrolytes) that control heart activity
- Previous heart attacks.

ECGs from healthy hearts have a characteristic shape. Any irregularity in the heart rhythm or damage to the heart muscle can change the electrical activity of the heart so that the shape of the ECG is changed. A doctor may recommend an ECG for people who may be at risk of heart disease because there is a family history of heart disease, or because they smoke or overweight or have diabetes or high cholesterol or high blood pressure. The resting ECG is different from a stress or exercise ECG or cardiac imaging test. ECG test needed if there is risk factors for heart disease such as high blood pressure, or symptoms such as palpitations or chest pain.

We are going to use ECG readings as our data. Each and every ECG beat will be obtained by using Discrete Wavelet transform i.e. 2D image which will be the input to Deep Neural Networks. This is followed by Deep Learning methods that are used to teach a deep neural network based classifier (GA) to identify arrthymias. It's been implemented in the real-time scenario so patient condition can be recognized immediately without any delay and the treatment can be stated by doctor without any second thought. Our research work is efficient, quick (real-time classification), simple to use. This is an applied types of research as we are applying a new type of model for the existing technologies.

3. Critical appraisal of review of current research and Development on the research topic

Yao *et.al.* [1] proposed an Automatic arrhythmia detection from Electrocardiogram (ECG) plays an important role in early prevention and diagnosis of cardiovascular diseases. Convolutional neural network (CNN) is a simpler, more noise-immune solution than traditional methods in multi-class arrhythmia classification. However, suffering from lack of consideration for temporal feature of ECG signal, CNN couldn't accept varied-length ECG signal and had limited performance in detecting paroxysmal arrhythmias. To address these issues, we proposed attention-based time-incremental convolutional neural network (ATI-CNN), a deep neural network model achieving both spatial and temporal fusion of information from ECG signals by integrating CNN, recurrent cells and attention module. Comparing to CNN model, this model features flexible input length, halved parameter amount as well as more computation reduction in real-time processing. The model helps to locate informative part of signals and improves interpretability. Halved parameter amount makes ATI-CNN less memory-hungry and less prone to over-fit, and ability to memorize brought by recurrent cells makes ATI-CNN much efficient in real-time processing.

Zheng *et.al.* [2], developed a classification method for arrhythmia based on the combination of a convolutional neural network and long short-term memory, which was then used to diagnose eight ECG signals, including a normal sinus rhythm. The experimental method mainly consisted of two parts. The input data of the model were two-dimensional grayscale images converted from one-dimensional signals, and detection and classification of the input data was carried out using the combined model. The advantage of this method is that it does not require performing feature extraction or noise filtering on the ECG signal. There are still several limitations: (1) ECG signal information is lost during feature extraction or noise filtering, (2) ECG arrhythmia type has a limited number of classifications, and (3) the performance of the actual classification method is relatively poor.

Rajput *et.al*. [3], higher dimensional representation contains more information that is accessible for feature extraction. Hidden variables such as frequency relation and morphology of segment is not directly accessible in the time domain. 1-D time series data is converted into multi-dimensional representation in the form of multichannel 2-D images. Following that, deep learning was used to train a deep neural network based classifier to detect arrhythmias. The results of simulation on testing database demonstrate the effectiveness of the proposed methodology by showing an outstanding classification performance compared to other existing methods and hand-crafted annotations made by certified cardiologists. Automated diagnosis can help clinician and cardiologist to reduce the amount of time spent on analyzing ECG. Furthermore, in the era where connectivity and wearable is affordable, it opens a new possibility where remote analysis can be performed in a place where cardiologist is not accessible.

Paweł Pławiak *et.al.* [4], have used long-duration (10s) ECG signal segments (13 times less classifications/analysis). The spectral power density was estimated based on Welch's method and discrete Fourier transform to strengthen the characteristic ECG signal features. Our main contribution is the design of a novel three-layer (48: 4: 1) deep genetic ensemble of classifiers (DGEC). Developed method is a hybrid which combines the advantages of: (1) ensemble learning, (2) deep learning, and (3) evolutionary computation. Novel system was developed by the fusion of three normalization types, four Hamming window widths, four classifiers types, stratified tenfold cross-validation, genetic feature (frequency components) selection, layered learning, genetic optimization of classifiers parameters, and new genetic layered training (expert votes selection) to connect classifiers. The next stages of research will include: (1) improving the accuracy of recognition myocardium dysfunctions through development and improving the algorithms based on fusion of EL and DL, (2) testing the other optimization methods based on EC, and (3) testing the efficiency of DGEC system with other physiologic signals.

Miquel Alfaras [5], a fully automatic and fast ECG arrhythmia classifier based on a simple brain-inspired machine learning approach known as Echo State Networks. This classifier has a low-demanding feature processing that only requires a single ECG lead. Its training and validation follows an inter-patient procedure. The approach is compatible with an online classification that aligns well with recent advances in health-monitoring wireless devices and wearables. The use of a combination of ensembles allows to exploit parallelism to train the classifier with remarkable speeds. Another aspect not covered in our study is the fixed heartbeat window length that can be inappropriate in the case of fast and slowly varying heart rhythms when changing physical activity. Thus, there is a need to study adaptive beat size segmentation. The understanding of the exact relation between underlying physiology and features is a potential question to address.

G. Sannino *et.al*. [6], to capture the infrequent events, a Holter device is usually employed to record long-term ECG data. The automatic recognition of abnormal heartbeats from a large amount of ECG data is an important and essential task. A huge number of methods have been proposed to address the problem of ECG beat classification. They propose a novel deep learning approach for ECG beat classification. They have conducted the experiments on the well-known MIT–BIH Arrhythmia Database, and compared results with the scientific literature. They are planning to be embedded in a real-time ECG monitoring system and to be tested in a real-world situation by means of a close co-operation with a specic hospital department.

Halil İbrahim Bülbül [7], MLP (Multi-Layer Perceptron) and SVM (Support Vector Machine) classification techniques which are not compared with each other using these signals will be compared. BP (Back Propagation) algorithm with MLP classifier and KA (Kernel-Adatron) algorithm with SVM classifier were used. In addition, wave transformation techniques such as DWT, DCT, and CWT are used to increase the success of the classification. This lead to the most effective classification method in the existing data set. It is aimed to bring improvements to the classification methods used in existing studies. It is aimed to develop a method to improve the calculation time and standard classification performance of MLP and SVM, and it is aimed to contribute to the informed consciousness of the work. In future we can use embedded in a real-time ECG monitoring system and to be tested in a real-world situation by means of a close co-operation with a specific hospital department.

4. Review of Patent Search

Yi Zhang [8], a CRM system enhances intracardiac electrogram-based arrhythmia detection using a wireless electrocardiogram (ECG), which is a signal sensed with implantable electrodes and approximating a surface ECG. In one embodiment, an intracardiac electrogram allows for detection of an arrhythmia, and the wireless ECG allows for classification of the detected arrhythmia by locating its origin. In another embodiment, the wireless ECG is sensed as a substitute signal for the intracardiac electrogram when the sensing of the intracardiac electrogram becomes unreliable. In another embodiment, a cardiac signal needed for a particular purpose is selected from one or more intracardiac electrograms and one or more wireless ECGs based on a desirable signal quality. In another embodiment, intracardiac electrogram based arrhythmia detection and wireless ECG-based arrhythmia detection confirm with each other before indicating a detection of arrhythmia of a certain type.

5. Technological relevance of the proposed res. topic

Every computer-aided ECG classification approach involves four main steps, namely,

1. The preprocessing of the ECG signal, the heartbeat detection,
2. The feature extraction and selection and
3. The classifier construction.

The preprocessing of the ECG signal and the heartbeat detection are studied, and the heartbeat detection is close to optimal results. A large number of classifiers have been proposed for arrhythmia discrimination. The proposed techniques range from simple classifiers, such as linear discriminants (LD) or decision trees, to more sophisticated ones, such as traditional neural networks, Support Vector Machines (SVM), conditional random fields and more recently deep learning techniques. In addition, work has been devoted to finding the best combination of features, sometimes even developing complex signal processing methods, and to choosing the best subset (dimensionality reduction) for the arrhythmia classification. On the one hand, popular choices for the input features are morphological features extracted from the time domain (such as inter-beat intervals, amplitudes, and areas), frequency-domain features, wavelet transforms, complex heartbeat representations or higher order statistics (HOS).

For feature selection methods, such as the independent component analysis (ICA), principal component analysis (PCA), particle swarm optimization (PSO), or the genetic algorithm—back propagation neural networks (GA-BPNN) have been used. The simplest and fastest method of feature extraction is used to extract sampled points from an ECG signal curve. We know that the amount of the extracted features used to characterize the heartbeat is burden for the classification algorithm. For this reason, most of the work that use the raw signal perform a down sampling of the waveform or some feature selection in order to reduce the computation time. In order to avoid this issue, a simple machine and deep learning method is chosen to classify the arrhythmias. One of the advantages of the proposed method is that the number of features barely affects the speed of the classification since the classifier parameters related to the input are not optimized and remain random. As a result, the raw waveform of the heartbeat can be used for the classification without compromising speed. This simple machine and deep learning method also allows a fast retraining of the classifier if new ECG data become available.

6. Interdisciplinary relevance or multidisciplinary component of research project

Biomedical and Electronics Engineering seeks to close the gap between engineering and medicine, combining the design and problem solving skills of engineering with medical biological sciences to advance health care treatment, including diagnosis, monitoring, and therapy. Also included under the scope is the management of current medical equipment within hospitals while adhering to relevant industry standards. This involves making equipment recommendations, procurement, routine testing and preventive maintenance, a role also known as a Biomedical Equipment Technician (BMET) or as clinical engineering. An evolution is a new field transitions from being an interdisciplinary specialization among already-established fields, to being considered a field in itself. Most of the work in biomedical engineering consists of research and development, spanning a broad array of subfields. Biomedical engineering applications include the development of biocompatible prostheses, various diagnostic and therapeutic medical devices ranging from clinical equipment to micro-implants, common imaging equipment such as MRIs and EKG/ECGs, regenerative tissue growth, pharmaceutical drugs and therapeutic biologicals. Biomedical and Electronics Engineering are been used on the same platform to solve the problems related to aliment and is detected within a very short time. Are making use of biomedical signals, concepts of Electronics to solve the problems related to arrythmia.

7. Scope of the proposed research work

- As doctors are predicting the heart diseases based on the ECG recordings which are recorded and checked at regular intervals, prediction may not be very accurate and patient is also put to stress as they will have to visit the clinic for recording of ECG. Our work proposes a solution for all this problem.
- Machine and deep learning using python, will be used to for arrhythmia detection.
- AAMI (Association for the Advancement of Medical Instrumentation) standard will be followed for detecting arrhythmia
- The proposed method is: (i) efficient; (ii) fast (real-time classification); (iii) universal; (iv) Simple to use; and (v) high accuracy.

8. Objective of present investigation

Electrocardiography (ECG) is the most basic and accessible method of diagnosing cardiac arrhythmia (or heart rhythm disorders), as it is non-invasive and easy to use method that can provide useful information on heart health and pathology. Cardiac arrhythmia is an important manifestation of cardiovascular disease. It is a serious societal problem due to 1) its high prevalence and incidence, 2) associated high mortality and 3) resultant high cost of treatment The above issues will intensify with the expected progressive aging of populations worldwide and hence may increase number of deaths from 17 million in 2016 to 24 million in 2030 .

Existing algorithms for automated ECG recognition of cardiac arrhythmia are based on the assessment of morphological features of single or few QRS complexes or beats. In the scientific literature, analysis of QRS complexes is substantially more popular than the analysis of long-duration ECG signal fragments. Current methods can be error-prone and may not achieve satisfactory diagnostic performance due to high beat-to-beat variability of these features among individuals. This motivated us to conduct research on a new solution of diagnosing heart disease using long-duration continuous ECG beat signals, which we hypothesis as more accurate than conventional algorithms. An important design consideration is to reduce the computational complexity of developed algorithms, so as to facilitate implementation of solution in mobile devices and cloud computing to monitor patients' health in real time.

Discrete Wavelet Transform (DWT) is used for feature extraction from ECG signals. DWT is a linear operator that decomposes the signal into numerous components (wavelets) at different frequency bands. Due to its linearity property, DWT is capable to save the significant phase information. Although DWT does not distinguish the noise coefficients from signal coefficients at low SNRs, DWT is still a smart answer for non-stationary signals since it preserves the behavior of ECG heartbeat signals. Denoising of the ECG is done by using DWT methods. The accurate ECG heartbeat signal classification is the reduction of the dimensionality of the feature extraction. The wavelet coefficients extracted from DWT give a close representation of the ECG signal energy distribution in time and frequency domains. Statistics for classification of ECG signals were utilized for in order to decrease the dimensionality of the set of the wavelet coefficients in DWT domain. Time-frequency distribution of the ECG signals are as follows

- Mean of the absolute values of the coefficients in each sub-band.
- 2. Average power of the wavelet coefficients in each sub-band.
- Standard deviation of the coefficients in each sub-band.
- Ratio of the absolute mean values of adjacent sub-bands.

Deep learning is a type of machine learning technique that is characterized by a hierarchical architecture comprising multiple layers in which subsequent stages of information processing take place. The input layers are used to extract features, based on which the output layers perform the analysis and classification of patterns. Deep learning methods can be divided into various subtypes based on the training methods:

- Deep discriminatory models, e.g. deep neural networks (DNNs), recurrent neural networks (RNNs) and convolutional neural networks (CNNs) and

- Unsupervised/generative models, e.g. restricted Boltzmann machines (RBMs), deep belief networks (DBNs), deep Boltzmann machines (DBMs) and regularized autoencoders.

CNNs are most often used for processing two-dimensional data, including images. CNN consists of at least one hidden (convolutional) layer completely connected to the upper layer (same as in typical neural networks) and also contains weights. The hidden layers of a CNN consist of convolutional layers, pooling layers, fully connected layers and normalization layers. The CNN network architecture is suitable for the processing of 2D data. Compared to other deep learning architectures, CNN achieves better results for image processing and speech recognition. CNN networks can be trained by a standard error backpropagation algorithm. It is easier to train than other regular, deep, unidirectional neural networks because CNN has much less parameters to optimize, which makes this architecture very attractive to use. Deep learning has become very popular recently and has been applied successfully for the classification of heart disease and arrhythmia using CNN, DNN, long-short term memory network (LSTM).

9. Methodologies

The goal is to find out the recent methodologies used in the area of ECG data processing for Arrhythmia detection. ECG signals from datasets contain various types of noises, which mandates for pre-processing. Different technologies used for pre-processing of ECG signal are median filters, discrete wavelet transform (DWT), adaptive filters, band pass filters, low-pass and high-pass filters, notch filters, have been used. Once the ECG signal is filtered, features are extracted from ECG signal in order to characterize those with respect to the classes. Different time domain, frequency domain and morphological features are considered. Some of the techniques that can used are Discrete wavelet transform with Finite Impulse ratio , High Order Statistics, 1D Convolutional Neural Network , Discrete Cosine Transform , Wavelet Packet Decomposition, Discrete Fourier Transform , Principal Component, Analysis Network (PCANet), Gaussian Mixture Model, Sparse Decomposition method and Stacked Denoised Autoencoder (SDAE) are used for feature extraction.

Feature selection or feature reduction techniques is used to reduce the complexity and time required for computation. Some of the techniques that can been used for feature selection are Principal Component Analysis , Independent Component Analysis , Fast Independent Component Analysis (Fast ICA) , Kernel PCA, Hierarchical non-linear PCA (hNLPCA), Principal Polynomial Analysis (PPA) , Linear Discriminant Analysis , Genetic Algorithm and filter-type feature selection.

After feature extraction and selection, those are fed to classification algorithm in order to classify the ECG signals. Different classification algorithms that can be used include Support Vector Machines, Neural Network which include Feed Forward Neural Network, Probabilistic Neural Network, Radial Basis Function Neural Network, Convolutional Neural Network, Deep Neural Network and Deep Belief Network, K-Nearest Neighbor, Random Forest, Linear Discriminants, Logistic Regression and Ensemble learners also have been used for classification. Optimization techniques like Artificial Bee Colony and Particle Swarm Optimization techniques have also been used to optimize the parameters of classification algorithm. Evaluation metrics like accuracy, specificity, sensitivity, positive predictivity, false positive rate, F score, precision, detection error rate and area under curve.

10. Conclusions

1. In conclusion, this exhaustive review and summary of the concepts and techniques for the detection of arrhythmia in ECG signals using deep learning methods provide valuable insights into the state of the art in this critical medical application. The following key points can be drawn from the analysis:
2. Deep Learning's Significance: Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated their significance in the field of arrhythmia detection. They offer the potential for highly accurate and automated classification of ECG signals.
3. Data Quality and Quantity: The availability of large, high-quality ECG datasets is crucial for the development and evaluation of deep learning models. The review underscores the importance of dataset curation and the need for continued efforts to expand accessible ECG data resources.

4. Feature Engineering: Feature extraction remains an essential component of arrhythmia detection, helping deep learning models capture relevant information from ECG signals. Various techniques, both conventional and data-driven, have been explored in this context.
5. Model Architecture: The choice of model architecture plays a pivotal role in the performance of arrhythmia detection systems. Researchers have proposed diverse architectures tailored to the unique characteristics of ECG data, and this review outlines their strengths and weaknesses.
6. Performance Metrics and Evaluation: The evaluation of deep learning models is contingent on appropriate performance metrics. A comprehensive discussion of metrics used for arrhythmia classification is included, emphasizing the importance of precision, recall, and F1 score.
7. Future Directions: The review highlights potential directions for future research, including the need for more explainable AI in healthcare, the exploration of multi-modal data integration, and the deployment of real-time arrhythmia detection systems in clinical settings.

In summary, the detection of arrhythmia in ECG signals using deep learning methods is a rapidly evolving field with promising results. By providing a thorough overview of the current landscape, this review equips researchers and healthcare professionals with the knowledge and insights needed to advance the development of accurate and clinically relevant arrhythmia detection solutions, ultimately improving patient care and outcomes.

References

[1] Qihang Yao, Ruxin Wang, Xiaomao Fan, Jikui Liu, Ye Li, Multi-class Arrhythmia detection from 12-lead varied-length ECG using Attention-based Time-Incremental Convolutional Neural Network , Joint Engineering Research Center for Health Big Data Intelligent Analysis Technology, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, China

[2] Zhenyu Zheng , Zhencheng Chen , Fangrong Hu , Jianming Zhu, Qunfeng Tang and Yongbo Liang, An Automatic Diagnosis of Arrhythmias Using a Combination of CNN and LSTM Technology, Electronics 2020, 9, 121

[3] K.S. Rajput ,S. Wibowo ,C. Hao ,M. Majmudar , On Arrhythmia Detection by Deep Learning and Multidimensional Representation,

[4] Paweł Pławiak, • U. Rajendra Acharya, Novel deep genetic ensemble of classifiers for arrhythmia detection using ECG signals, Neural Computing and Applications

[5] Miquel Alfaras, Miguel C. Soriano and Silvia Ortín, A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection, Frontiers in Physics, July 2019 , Volume 7 , Article 103

[6] G. Sannino , G. De Pietro, A deep learning approach for ECG-based heartbeat classification for arrhythmia detection, National Research Council of Italy (CNR), Institute for High-Performance Computing and Networking (ICAR), Via P. Castellino 111, Naples, Italy

[7] Halil İbrahim Bülbül, Neşe USTA, Musa YILDIZ, Classification Of ECG Arrhythmia With Machine Learning Techniques, 16th IEEE International Conference on Machine Learning and Applications.

[8] Yi Zhang, Aaron McCabe, David J. Yonce, Julie Thompson, Methods and Apparatuses for Arrhythmia Detection and Classification Using Wireless ECG, patent no., US 7.212,849 B2

[9] Mathews SM, Kambhamettu C, Barner KE (2018) A novel application of deep learning for single-lead ECG classification. Comput Biol Med 99:53–62

[10] Altan G, Allahverdi N, Kutlu Y (2018) A multistage deep learning algorithm for detecting arrhythmia. In 2018 1st international conference on computer applications & information security (ICCAIS), pp 1–5. IEEE

[11] Afkhami RG, Azarnia G, Tinati MA (2016) Cardiac arrhythmia classification using statistical and mixture modeling features of ECG signals. Pattern Recog Lett 70(2016):45–51

[12] De Chazal P, O'Dwyer M, Reilly RB (2004) Automatic classification of heartbeats using ECG morphology and heartbeat interval features. IEEE Trans Biomed Eng 51(7):1196–1206

[13] Xia Y, Zhang H, Lin Xu, Gao Z, Zhang H, Liu H, Li S (2018) An automatic cardiac arrhythmia classification system with wearable electrocardiogram. IEEE Access 6:16529–16538

[14] Elhaj FA, Salim N, Harris AR, Swee TT, Ahmed T (2016) Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals. Comput Methods Progr Biomed 127(2016):52–63

[15] Desai U, Martis RJ, Nayak CG, Sarika K, Nayak SG, Shirva A, Nayak V, Mudassir S (2015) Discrete cosine transform features in automated classification of cardiac arrhythmia beats. In: Emerging research in computing, information, communication and applications, Springer, New Delhi, pp 153–162

[16] Rajagopal R, Ranganathan V (2017) Evaluation of effect of unsupervised dimensionality reduction techniques on automated arrhythmia classification. Biomed Signal Process Control 34:1–8

[17] Martis RJ, Acharya UR, Min LC (2013) ECG beat classification using PCA, LDA, ICA and discrete wavelet transform. Biomed Signal Process Control 8(5):437–448

[18] YangW, Si Y,Wang D, Guo B (2018) Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine. Comput Biol Med 101:22–32

[19] Raj S, Ray KC (2018) Sparse representation of ECG signals for automated recognition of cardiac arrhythmias. Expert Syst Appl 105(2018):49–64

[20] Venkatesan C, Karthigaikumar P, Paul A, Satheeskumaran S, Kumar R (2018) ECG signal preprocessing and SVM classifier-based abnormality detection in remote healthcare applications. IEEE Access 6(2018):9767–9773

[21] Azariadi D, Tsoutsouras V, Xydis S, Soudris D (2016) ECG signal analysis and arrhythmia detection on IoT wearable medical devices. In 2016 5th international conference on modern circuits and systems technologies (MOCAST), pp 1–4. IEEE

[22] Hammad M, Maher A, Wang K, Jiang F, Amrani M (2018) Detection of abnormal heart conditions based on characteristics of ECG signals. Measurement 125:634–644

[23] Li Q, Rajagopalan C, Clifford GD (2014) A machine learning approach to multi-level ECG signal quality classification. Comput Methods Programs Biomed 117(3):435–447

[24] Li Q, Rajagopalan C, Clifford GD (2014) Ventricular fibrillation and tachycardia classification using a machine learning approach. IEEE Trans Biomed Eng 61(6):1607–1613

[25] Alonso-Atienz F, Morgado E, Fernandez-Martinez L, García-Alberola A, Rojo-Alvarez JL

[26] (2014) Detection of life-threatening arrhythmias using feature selection and support vector machines. IEEE Trans Biomed Eng 61(3):832–840

[27] Kiranyaz S, Ince T, Gabbouj M (2016) Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Trans Biomed Eng 63(3):664–675

[28] Dohare AK, Kumar V, Kumar R (2018) Detection of myocardial infarction in 12 lead ECG using support vector machine. Appl Soft Comput 64(2018):138–147

[29] Shimpi P, Shah S, Shroff M, Godbole A (2017) A machine learning approach for the classification of cardiac arrhythmia. In 2017 international conference on computing methodologies and communication (ICCMC), pp 603–607. IEEE