Heart Disease Prediction through ECG filtering and classification Methodologies based on Machine Learning and Deep Learning Techniques

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Abstract.

Heart ailment affects around 1.5 billion people worldwide, making its early detection and prevention as one of the most critical duties for any health sector. For the identification and assessment of heart arrhythmias like atrial fibrillation, an electrocardiogram (ECG) is commonly employed. In order to deliver an accurate result, most computer-based automated cardiac anomaly tracking techniques need good recognition of ECG elements like QRS complexes. But, ECGs are frequently polluted by noise and aberrations, particularly when collected with wearable sensors, making reliable detection of QRS spikes difficult. The majority of current denoising approaches were tested using artificial noise applied to a clear ECG signal, and legitimately noisy ECG signals were not considered. Furthermore, most of them are perfect and sampling frequency based, and therefore takes a long time to compute. This study examines the core concepts of several denoising methods in depth. Likewise, ECG categorization is crucial in detecting and classifying heart abnormalities. Conventional signal processing approaches, as well as machine learning (ML) and its sub-categories, like deep learning, are common methods for analysing and categorizing ECG signals, with the goal of developing applications for the earlier identification and therapy of cardiac diseases and arrhythmia. This research paper provides a comprehensive analysis of the research on ECG signal assessment for arrhythmia categorization. Furthermore, comparative assessment is done in this work.

Keywords. ECG filtering, disease classification, machine learning, deep learning.

1. INTRODUCTION

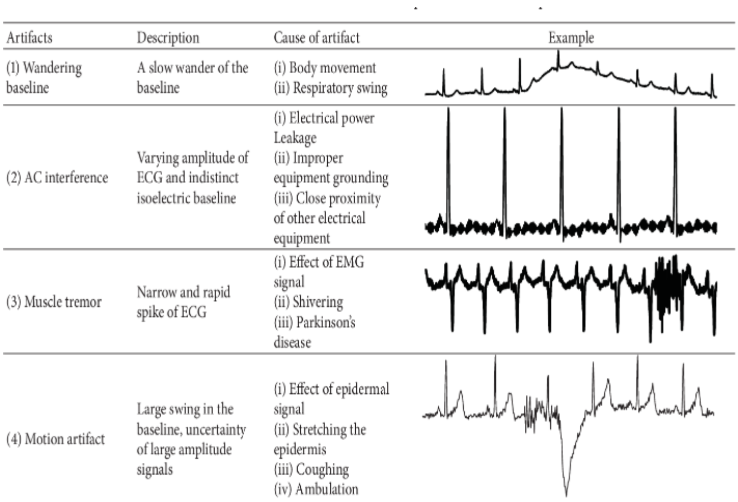
Heart anomaly deaths are expected to rise to 2.34 billion by 2030, accounting for 35 percent of all fatalities (W.H.O, 2018) [1.] The cardiovascular disease (CVD) is the largest reason of death universally, causing over 30% of all fatalities. The heart is a muscular cone-shaped structure that pumps at periodic intervals to supply blood to the body's many organs [2, 3]. Heart attack is caused by a blockage in a blood vessel that supplies blood and oxygen to the heart. CVDs are mostly caused by poor nutrition, cholesterol, tobacco, and other changes in lifestyle. According to WHO main data, 7.4 million people died from heart attacks in 2015, with the majority of these deaths occurring in poor and middle revenue economies [4, 5]. The fatality rate owing to cardiovascular disease in India is around 275 per 100,000 populations. With the existing burden of CVDs, India would lose $237 billion in production [5]. It is estimated that with good health care, 90 percent of CVDs can be avoided. As a result, a complete categorization approach at the national level is required for successful control of CVD risk variables.

The present heart diagnosis core includes clinical signs, ECG pattern analysis, and testing of essential cardiac troponins [6, 7]. ECG waveforms are tracings of the heart's electric activities, and they are significant diagnostic tool for assessing heart health. Much of cardiology and electrophysiology is based on the 12-lead ECG. With variations in the timing and structure of the captured waveforms, it offers special information about the anatomy and electrical conduction system of the heart, as well as overall diseases. Following ECG capture, computer-generated readings are routinely supplied, based on predetermined criteria and computational pattern classification [8]. Existing practices, on the other hand, miss many of the specialised insights and details that experienced cardiologists and electrophysiologists can notice. Doctor reads might be inaccurate and varies based on their experience. It would be a tremendous success, comparable to the development of dependable automated vehicles, to produce trustworthy ECG readings, not least in terms of safety, so that crucial and prompt ECG readings of severe cardiac problems can lead to quick and cost-effective action. To perform a comprehensive ECG assessment, you must be able to recognise the distinct waveforms and their connections, measure the epochs between the waveforms portraying particular electrical activities in various zones of the heart, identify the conditions that affect the anomalies seen on ECGs, comprehend the biology/physiology behind the rhythm disturbances, biologically localise the site of the disturbance, and make assumptions about the future.

A. Noise in ECG

The basic stage in the handling of an ECG signal is noise filtering [12]. The primary noise (PLI) should be reduced at the first phase of processing processes [13], is introduced by an alternating current source from a power source. The signal has a frequency of roughly 50/60 Hz, depending on the country location (Lin and Hu 2008). Europe and India use a 50 Hz AC supply, while the United States and a few other nations use a 60 Hz source. This noise is caused by the human's process of breathing, which causes the ECG signals to shift out of the baseline. Other possible factors include cable motion during ECG signal processing, dirty lead electrodes/wires, or a weak electrode connection [14]. Contraction of heart muscles leads to EMG (electromyogram) noise through ventricular depolarization waves created nearby the electrodes [15].

Contact noise is another sort of noise which is caused by the placement of the heart with reference to the electrodes variance. Baseline disturbances are caused by variations in the electrode–skin conductance [16]. The coupling of conductors, wiring, signal processor/amplifier, and ADC are the key factors of noise [16]. Nurses and doctors in hospitals do not give heed to electrode placement. As a result, common mode noise is produced, necessitating the usage of 50 Hz filtering. Below given figure depicts some most common types of artifact in the ECG signal.



Artifacts	Description	Cause of artifact	Example
(1) Wandering baseline	A slow wander of the baseline	(i) Body movement (ii) Respiratory swing	
(2) AC interference	Varying amplitude of ECG and indistinct isoelectric baseline	(i) Electrical power Leakage (ii) Improper equipment grounding (iii) Close proximity of other electrical equipment	
(3) Muscle tremor	Narrow and rapid spike of ECG	(i) Effect of EMG signal (ii) Shivering (iii) Parkinson's disease	
(4) Motion artifact	Large swing in the baseline, uncertainty of large amplitude signals	(i) Effect of epidermal signal (ii) Stretching the epidermis (iii) Coughing (iv) Ambulation	

Fig.1. Artifacts in ECG signal

B. ECG, its application and arrhythmia recognition

The ECG captures the electrical activity produced by cardiac muscle depolarizations, which travel to the skin in the form of pulsing electrical waves. Despite the fact that the quantity of electricity is so little, it can be effectively detected with ECG electrodes applied to the skin [17]. P waves, QRS complex, and T waves make up the majority of ECG signals. Any rapid change in this value indicates that the heart is experiencing a problem, which could be caused by a variety of factors.

Below given table 1 describes these attributes briefly along with their normal duration.

Attribute	Description	Duration
P	First limited movement of ECG in upward direction	80 ms
PR	Connecting the P and R	50-120 ms
PQ	From P to beginning of QRS complex	120-200
RR	Interval between two consecutive R waves	0.6-1.2s
QRS	It generally starts with the downward movement of Q, larger upward movement of R and ends by forming the downside S wave	80-120
QT	Measured from beginning of QRS and end of T wave	420 ms
T	Modest upward movement of	160ms
ST	Connecting the QRS complex with T wave	80-120 ms

TABLE.I -CHARACTERISTIC OF VARIOUS SEGMENTS OF ECG SIGNAL

The ML algorithms are preferred over manual methods for better categorization results, but a useful algorithm is required to further reduce it [23, 24]. With the advancement of ML and deep learning (DL) techniques, it may be able to uncover formerly unidentified illness patterns. Several systems, such as EEG, ECG, and EMG, have been used to diagnose vital signs [25]. One of the most significant difficulties is the difficulty of organising physiological records, which is hampered by domain expertise, time constraints, and privacy concerns. Another issue is that ECG data is usually uneven, with a small number of labelled ECG signals for each condition, thus the training samples contain numerous normal ECG signals, making it hard to categorise the ECG signals with disorders due to the asymmetry in the initial data. Based on the characteristic of ECG signal, we can obtain the information about following abnormalities as mentioned in below given table 2

S.No.	Heart related abnormality	Attribute information obtained from ECG
1.	Tachycardia	If R-R interval < 0.6 s
2.	Bradycardia	If R-R interval >1.0 s
3.	Dextrocardia	Inverted P wave
4	Myocardial	Ischaemia Inverted T-wave
5	Sinoatrial block	Complete drop out of cycle
6	Hyperkalaemia	Tall T-wave and absence of P-wave
7	Hypercalcaemia	QRS interval 0.1s
8	Sudden cardia death	Irregular ECG

TABLE.II- Attributes and abnormality

Arrhythmias, in which the heartbeat pattern detracts from its normal pattern, are one of the most prevalent cardiovascular diseases. These abnormal patterns must be classified into subclasses, and this knowledge can be used to make exact cure recommendations to patients. The ECG is commonly utilized to identify and anticipate the abnormal behaviour of the heart of human in order to detect cardiologic illnesses.

C. Machine learning and its use in detecting heart abnormalities utilizing ECG signals

With the advancement of ML algorithms in recent times, a growing percentage of automatic identification approaches for arrhythmias have been implemented [3]. The ML approaches typically necessitate feature extraction by hand. After that, features are retrieved using a number of mathematical approaches like PCA, wavelet transform, LDA, ICA, and PCA. To perform the categorization, the collected characteristics are fed into a classifier [27, 28, and 29]. The SVM [30, 31], decision tree [32, 34], and artificial neural network [34] are examples of classifiers. Conventional ECG signal feature extraction algorithms are difficult to use and are limited by specific skill fields. Furthermore, the capacity to fit nonlinearly is limited. As a result, the retrieved features may not always reflect the best features, and even essential ECG signal information may be missing. The DL methods have been applied to the rapid recognition of arrhythmias to circumvent the drawbacks of ML techniques. Deep learning, unlike ML methods, does not need the manual retrieval of features. (CNNs are a sort of dDL methods that can mechanically retrieve significant aspects of ECG signals by stacked layers and aren't bound by domain expertise [17]. Authors in [35] developed a deep convolutional network for detecting arrhythmias, as well as focused loss to alleviate data imbalance difficulties. Authors in [36] suggested a CNN based ECG categorization approach in which fuzzy sets were employed to minimise the symmetry of retrieved ECG image characteristics, and the network was improved utilizing residual structures [36]. Furthermore, because of its superior enactment in handling of temporal data, LSTM has been frequently used in the categorization of ECG signals. Kim and Pyun suggested a two-way LSTM-based automatic arrhythmia detection mechanism, and testing findings revealed that it outperformed classic LSTM [37]. Sharma et al. treated the RR interval using Fourier–Bessel expansion and then sent the modified data into the LSTM for ECG categorization, with effective outcomes [38].

D. Work contribution, objectives and organization

ECG signals play a significant role in health monitoring specifically, monitoring the health of heart. Currently, the demand of automated heart disease prediction systems has increased. In this field, ECG plays a significant role. Several techniques have been introduced for ECG filtering and classification. In this work, we study about these techniques of ECG signal filtering and classification. Moreover, we present a comparative analysis based on these techniques.

2. RELATED WORKS

A. ECG signal filtering procedures

The accumulated ECG signal is frequently mixed with a lot of noise, which makes signal analysis difficult. As a result, the most crucial step in data handling is to denoise the accumulated signal in order to improve its usefulness.

ECGs are frequently polluted by a number of noise sources, such as motion artefacts, poor electrode contact with the muscle, skin and PLI, all of which can affect ECG morphology and contribute to heart arrhythmia misidentification. Because of motion artefacts, noise is more pronounced in ECGs from hold able technology. As a result, removing noise and artefacts from ECG signals is extremely significant and essential to enhance the usefulness of ECGs. Alternatively, Denoising of ECG signals is difficult, particularly when the noise frequency and the signal frequency are the same. Numerous denoising methods have been recommended in this research area over the last few generations. DWT decomposition [39-42], adaptive filtering [12, 40], EMD and EEMD [41], NLM [43], and neural networks (NN) [23, 24] are the most well-developed approaches. While numerous approaches demonstrated positive denoising results, they each have their own set of benefits and drawbacks. The primary downside of adaptive filtering is that it needs an allusion signal that is not always accessible; likewise, the main drawback of NLMS is that its effectiveness relied upon the bandwidth selection of a parameter that relies upon the standard deviation of noise, which may not be accessible in actual time. Furthermore, DL centered techniques operate as a black box, necessitating additional data for training and being arithmetically costly. As a result, DL-based denoising might not be appropriate for actual circumstances, particularly in wearable gadget appliances.

In real applications, conventional noise filtering systems have some drawbacks. Noise removal approaches are frequently in a one-to-one association, which is insufficient to address the real requirements of ECG signal noise removal. Kumar et al. [39], for instance, suggested a static wavelet transform-based denoising approach. Numerous investigations have been done on conventional ECG noise reduction techniques. Xiong et al. [40] investigated spectral power fluctuations through the motion artefact input process and developed a cosine transform DCT-LMS approach to eliminate mobility artefacts from the ECG. The noisy ECG signal is initially adjustably disintegrated into vibratory elements known as IMFs employing EMD or its variations, refer to El Bouny et al. [41]. As a result, through a novel parameter originated from the HOS, the 4th order cumulant or kurtosis, the acquired modes are divided into 2 sets: noisy signal modes and usable signal modes. Then, to minimise noise and maintain the QRS complex, a customized shrinkage method relies upon the Interval thresholding approach is dynamically implemented to every chosen IMF from the noise-dominant clusters. The total filtered ECG signal is then rebuilt by merging the threshold IMFs with the smaller frequency meaningful IMFs that were left untreated. Wang et al. [42] employ a filter bank with 2 adjustable Kalman filters (KF), one for denoising the big frequency QRS complex and the other for denoising the small frequency T and P waves. The EM algorithm is used to estimate and repeatedly update the parameters of these filters. They employed Bryson and Henrikson's methodology for the estimate and updating steps within the KF bank to deal with stochastic noises like muscular artefact (MA) noise. Singh et al. [43] used EMD to apply the NLM approach to deconstruct the signal into IMFs. To achieve the ultimate denoised output, the IMFs are then threshold using the immediate half period standard and soft-thresholding. In addition, to save time and money, the modified EMD is utilised instead of the normal EMD.

In the field of ECG noise reduction, DL has appealed an increasing number of in-depth research projects. Deep Filter is a DL BLW filtering solution developed by Romero et al. [44]. The suggested model is built on multipath modules and is completely convolutional. This method employs multipath modules, which stack many convolutional layers on top of each other and allow the backpropagation technique to select not just the weights but also the optimum route for the signal to take. The MKLANL filter component that is motivated by the beginning component has been used in this technique. Using a fully convolutional network, Chiang et al. [45] suggested a DAE (FCN). However, in terms of the DAE architecture, the suggested FCN-based DAE can conduct compression. Noise suppression based on Dl method is presented by Qiu et al. [46]. The process is broken into two parts, and two concepts are created for each level. A 1D U-net prototype is intended for ECG signal denoising in the initial step to remove as much noise as feasible. In the second part, the 1D DR-net model is utilised to rebuild the ECG signal and rectify the waveform deformation generated by the previous phase's reduction of noise. In this research, the convolution approach is used to build the U network and the DR network in order to perform complete projecting from noisy ECG signals to pure ECG signals. Several techniques are reported in this section. Below given table 3 shows the comparative analysis of this techniques.

B. Machine learning and deep learning centered procedures for ECG categorization

Deep neural networks (DNNs) have recently exhibited promise in the processing of ECG data [58], providing yet another possibility to increase the efficiency and flexibility of automated ECG categorization. The DNNs may incorporate multiple feature representations and classifiers to construct a complete multilayer model [59] based on various network structures, which can solve the limitations of classic ML method models with autonomous input and output. Furthermore, some new DNN approaches have been proposed, like residual blocks [60], DCNN [61], deep residual CNN [62], RNN with LSTM [37,54], and Bi-LSTM network [23,37, 38].

Duan et al. [63] presented a MADNN technique to improve the ability of retrieving ECG characteristics on multiple scales by merging kernel and branch-wise attention components, resulting in a complete score of 0.447 on the concealed testing set. By combining remaining CNN and a class-wise attention method, Liu et al. [64] suggested a unique multilevel classifier for twelve lead ECG records that can achieve challenge metric scores of 0.5501 0.0223, suggesting a promising approach for ECG classification. He et al. [65] employed the attention method to acquire an attention distribution on a record of retrieved characteristics, and then combined the attention coefficients into one feature vector and utilized for concluding prediction. By using Deep Heart system, the complete score with 5 cross confirmation of the training set is approximately 0.55, indicating that it has prospective real-world applications. Therefore, there it is difficult to get clinical application categorization precision.

The CNN and RNN are utilised by Wang et al. [49] to combine space and time information from ECG data. These networks, on the other hand, neglect the various contributions of global and local segments of an ECG feature map, as well as the correlation link between the two. A novel CNN with NCBAM is suggested to autonomously categorize ECG heartbeats in order to address this issue. A thirty three layer CNN model is followed by an NCBAM component in this technique. To recover spatial and channel information, pre-processed electrocardiogram (ECG) signals are input into the CNN framework.

Chen et al. [50] propose an automated technique for distinguishing between normal and abnormal ECG readings. The authors present a multi-channel multi-scale DNN framework that is a complete framework for classifying ECG data without the need for feature extraction. To increase the performance of the DNN model, convolutional layers are employed to mine key characteristics, and LSTM and attention are integrated.

They have divided ECG signals into separate pulses, collected characteristics from every pulse, and then categorised these pulses using ML approaches, as Sharma et al. [51] built a separator for computerized identification of patients with HCM. The authors defined a patient as having HCM if the number of HCM heartbeats was equal to as or more than the number of control heartbeats. Authors retrieved previously utilised features and few fresh morphological characteristics from ECG signals for this categorization experiment. The authors used random forests and SVM classifiers to discriminate between HCM and non-HCM patients' heartbeats.

Gaddam et al. [52] developed a DL based method for categorising various cardiac arrhythmias. With the use of Continuous Wavelet, 1-D ECG signals are first translated into 2-D scalogram images (CWT). To test the suggested technique, four distinct types of ECG waveforms were chosen: arrhythmia datasets, Normal Sinus Rhythm dataset and BIDMC congested cardiac arrest dataset. The purpose of this study is to elaborate a transferable DL procedure for automatic classification of the 4 cardiac illnesses stated above. When compared to other approaches, this scheme uses 2D scalogram images to train the deep CNN and displays superior efficiency.

Maghawry et al. [53] stated that, it's difficult to find the best setup for a Dl system for a certain issue area. The purpose of this study is to deliver an operative method for classifying cardiac heartbeats into 5 categories using an optimised CNN. A customised evolutionary algorithm was used to find the best structure of hyper parameter values for the CNN model. This technique does not involve any pre-processing of ECG readings. To counteract the dataset's uneven nature, the resampling method is used. The classification performance of this technique was 98.45 percent.

Jiang et al. [57] developed a method for automatically implementing ECG categorization using a hybrid HADL network. The HADLN approach was validated using data from the PhysioNet 2017 competition. This paper's primary contributions can be summarised as follows: (1) The ResNet portion extracts local features by superimposing 16 residual blocks, while the bidirectional LSTM network extracts global characteristics in parallel. Furthermore, the universal characteristic from Bi-LSTM and the local feature from Res Network were fused characteristics, that were able to mine numerous characteristics from the initial ECG data; (2) in this article, an alteration of the basic attention method was postulated to empower local feature representations from Res-Network using weight parameters measured from compound characteristics.

Achieving better classification with less computational complexity is a tedious task. Several deep learning based techniques are reported in this section, we present a comparative study based on these techniques. Below given table 3shows the comparative analysis.

Author	**Objective**	***Technique***	**Performance (max or min values in experiments)**
Wang et al. [49]	ECG classification	CNN with on-local convolutional block attention module	AUC=0.9314 F_{max} =0.8507
Chen et al. [50]	ECG classification	Multi-channel with DNN	NA
Sharma et al. [51]	Segmentation and arrhythmia disease classification	Hybrid of deep learning method and cuckoo search algorithm	Accuracy=98.53% precision = 98.24 Recall = 95.68%
Gaddam et al. [52]	Arrhythmias	Transferred Deep Learning with Continuous Wavelet(CWT)	Accuracy =95.67% Precision = 93.12% Sensitivity=94.21% Specificity=95.31%
Maghawry et al. [53]	Heartbeats segmentation Classifier	Optimization with genetic algorithm and CNN	Accuracy= 98.45%
Pokaprakarn et al. [54]	Cardiac Rhythm Classification	CNN with RNN configuration	F1 score =0.89
Ganeshkumar et al. [55]	ECG classification	Grad-CAM technique to obtain the activation maps for class and trained by CNN	Precision = 0.986 Recall = 0.949 F1-score = 0.967 Accuracy = 96.2%
Essa et al. [56]	ECG segmentation and classification	Two technique: CNN-LSTM and (RRHOS-LSTM	Accuracy= 95.81% Sensitivity= 98.03 Specificity = 80.27
Jiang et al. [57]	Arrhythmia Classification	Combination of ResNet and Bi-LSTM with attention mechanism	Precision =0.866 Recall =0.859 Accuracy =0.867 F1-score = 0.880
Hong et al. [59]	Heart disease prediction	MultIlevelkNowledge-guided Attention	ROC-AUC=0.9488 ± 0.0081

		networks	PR-AUC=0.9436 ± 0.0082 F1=0.8342 ± 0.0352
Li et al. [62]	Heartbeat classification	deep residual network (ResNet)	Accuracy= 99.06% Sensitivity= 93.21% positive predictivity= 96.76%
Duan et al. [63]	Arrhythmia classification	Multi-scale deep neural network	validation score = 0.446, full test set score = 0.236
He et al. [65]	Arrhythmias	DNN with Gated Recurrent Unit (BiGRU)	

TABLE.III - COMPARATIVE ANALYSIS FOR DEEP LEARNING TECHNIQUES

3. CONCLUSION

The ECG is a useful technique for detecting problems in cardiac function. Early detection of myocardial infarction (MI) can protect lives and is a difficult undertaking, however computerized analysis of MI can be performed with ECG examination and categorization using CAD and machine learning approaches. These ECG signals, on the other hand, are subject to sounds such as WGN, coloured noise, PLI, baseline wander, electrode noise, and muscular artefact, among others. As a result, we investigated state-of-the-art ECG filtering algorithms and conducted a comparative analysis to highlight existing techniques' limitations.

In addition, this study provided a thorough examination of various classical and ML techniques utilised in each level of ECG signal processing, particularly for the ECG categorization process. The ML algorithms for detecting ECG fiduciary details like R-peaks and QRS complexes have been proposed, both fully automated and partially automated. In a recently published study, deep learning algorithms produce more efficient recognition and categorization outcomes. In this paper, we established a phases-centered framework for ECG signal study, where the majority of ECG literature can be classified into one or more phases of a project. Scholars are engaged to the vast body of ECG research literature in this survey paper to gain insights into how the ECG signal passes through various phases/procedures, what is comprised in every phase in context of data attainment, and the methodologies and procedures associated with every phase of ECG signal study. A number of hardware and software tools for this type of research have also been described. The significant obstacles and constraints have also been explored.

4. References

[1] Virani, S. S., Alonso, A., Aparicio, H. J., Benjamin, E. J., Bittencourt, M. S., Callaway, C. W., ... & American Heart Association Council on Epidemiology and Prevention Statistics Committee and Stroke Statistics Subcommittee. (2021). Heart disease and stroke statistics—2021 update: a report from the American Heart Association. Circulation, 143(8), e254-e743.

[2] Giosuè, A., Calabrese, I., Lupoli, R., Riccardi, G., Vaccaro, O., & Vitale, M. (2022). Relations Between the Consumption of Fatty or Lean Fish and Risk of Cardiovascular Disease and All-cause Mortality: A Systematic Review and Meta-analysis. Advances in Nutrition.

[3] Sahoo, S., Dash, M., Behera, S., & Sabut, S. (2020). Machine learning approach to detect cardiac arrhythmias in ECG signals: a survey. Irbm, 41(4), 185-194.

[4] Yusuf S, Rangarajan S, Teo K, et al. Cardiovascular risk and events in 17 low, middle, and high-income countries. N Engl J Med 2014;371:818–27.

[5] Gupta R, Mohan I, Narula J. Trends in coronary heart disease epidemiology in India. Ann Glob Health 2016;82(2):307–15

[6] Cho, Y., Kwon, J. M., Kim, K. H., Medina-Inojosa, J. R., Jeon, K. H., Cho, S., ... & Oh, B. H. (2020). Artificial intelligence algorithm for detecting myocardial infarction using six-lead electrocardiography. Scientific reports, 10(1), 1-10.

[7] Sangaiah, A. K., Arumugam, M., & Bian, G. B. (2020). An intelligent learning approach for improving ECG signal classification and arrhythmia analysis. Artificial intelligence in medicine, 103, 101788.

[8] Zhang, J., Liang, D., Liu, A., Gao, M., Chen, X., Zhang, X., & Chen, X. (2021). MLBF-Net: a multi-lead-branch fusion network for multi-class arrhythmia classification using 12-Lead ECG. IEEE Journal of Translational Engineering in Health and Medicine, 9, 1-11.

[9] Cho, Y., Kwon, J. M., Kim, K. H., Medina-Inojosa, J. R., Jeon, K. H., Cho, S., ... & Oh, B. H. (2020). Artificial intelligence algorithm for detecting myocardial infarction using six-lead electrocardiography. Scientific reports, 10(1), 1-10.

[10] Makimoto, H., Höckmann, M., Lin, T., Glöckner, D., Gerguri, S., Clasen, L., ... & Kelm, M. (2020). Performance of a convolutional neural network derived from an ECG database in recognizing myocardial infarction. Scientific reports, 10(1), 1-9.

[11] Siontis, K. C., Noseworthy, P. A., Attia, Z. I., & Friedman, P. A. (2021). Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nature Reviews Cardiology, 18(7), 465-478.

[12] Shaddeli, R., Yazdanjue, N., Ebadollahi, S., Saberi, M. M., & Gill, B. (2021, September). Noise Removal from ECG Signals by Adaptive Filter Based on Variable Step Size LMS Using Evolutionary Algorithms. In 2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE) (pp. 1-7). IEEE.

[13] Islam, M., Rastegarnia, A., & Sanei, S. (2021). Signal artifacts and techniques for artifacts and noise removal. In Signal processing techniques for computational health informatics (pp. 23-79). Springer, Cham.

[14] Niederhauser T, et al. A baseline wander tracking system for artifact rejection in long-term electrocardiography. IEEE Trans Biomed Circ Syst. 2016;10(1):255–65.

[15] Mortezaee, M., Mortezaie, Z., & Abolghasemi, V. (2019). An improved SSA-based technique for EMG removal from ECG. Irbm, 40(1), 62-68.

[16] Rodrigues J, Belo D, Gamboa H. Noise detection on ECG based on agglomerative clustering of morphological features. Comput Biol Med. 2017;87:322–34

[17] Ullah, A., Tu, S., Mehmood, R. M., & Ehatisham-ul-haq, M. (2021). A hybrid deep CNN model for abnormal arrhythmia detection based on cardiac ECG signal. Sensors, 21(3), 951.

[18] Li, Z., Feng, X., Wu, Z., Yang, C., Bai, B., & Yang, Q. (2019). Classification of atrial fibrillation recurrence based on a convolution neural network with SVM architecture. IEEE Access, 7, 77849-77856.

[19] Wasimuddin, M., Elleithy, K., Abuzneid, A. S., Faezipour, M., & Abuzaghleh, O. (2020). Stages-based ECG signal analysis from traditional signal processing to machine learning approaches: A survey. IEEE Access, 8, 177782-177803.

[20] Alfaras, M., Soriano, M. C., & Ortín, S. (2019). A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection. Frontiers in Physics, 7, 103.

[21] Sree, V., Mapes, J., Dua, S., Lih, O. S., Koh, J. E., Ciaccio, E. J., & Acharya, U. R. (2021). A novel machine learning framework for automated detection of arrhythmias in ECG segments. Journal of Ambient Intelligence and Humanized Computing, 12(11), 10145-10162.

[22] Farooq, A., Seyedmahmoudian, M., & Stojcevski, A. (2021). A wearable wireless sensor system using machine learning classification to detect arrhythmia. IEEE Sensors Journal, 21(9), 11109-11116.

[23] Tao, L., Liu, B., & Liang, W. (2021). Automated Detection of Arrhythmia for Hybrid Neural Network of LSTM-Residual with Multi-Information Fusion. Mathematical Problems in Engineering, 2021.

[24] Rasti-Meymandi, A., & Ghaffari, A. (2022). A deep learning-based framework For ECG signal denoising based on stacked cardiac cycle tensor. Biomedical Signal Processing and Control, 71, 103275.

[25] Faust, O., Hagiwara, Y., Hong, T. J., Lih, O. S., & Acharya, U. R. (2018). Deep learning for healthcare applications based on physiological signals: A review. Computer methods and programs in biomedicine, 161, 1-13.

[26] Thomas, T., & Kurian, A. N. (2022). Artificial Intelligence of Things for Early Detection of Cardiac Diseases. In Machine Learning for Critical Internet of Medical Things (pp. 81-102). Springer, Cham.

[27] Ayar, M., Isazadeh, A., Gharehchopogh, F. S., & Seyedi, M. (2021). Chaotic-based divide-and-conquer feature selection method and its application in cardiac arrhythmia classification. The Journal of Supercomputing, 1-27.

[28] Xiong, Y., Wang, L., Wang, Q., Liu, S., & Kou, B. (2021). Improved convolutional neural network with feature selection for imbalanced ECG Multi-Factor classification. Measurement, 110471.

[29] Lee, M., & Lee, J. H. (2022). A robust fusion algorithm of LBP and IMF with recursive feature elimination-based ECG processing for QRS and arrhythmia detection. Applied Intelligence, 52(1), 939-953.

[30] Bhattacharyya, S., Majumder, S., Debnath, P., & Chanda, M. (2021). Arrhythmic heartbeat classification using ensemble of random forest and support vector machine algorithm. IEEE Transactions on Artificial Intelligence, 2(3), 260-268.

[31] Jannah, N., Hadjiloucas, S., & Al-Malki, J. (2021). Arrhythmia detection using multi-lead ECG spectra and Complex Support Vector Machine Classifiers. Procedia Computer Science, 194, 69-79.

[32] Kumari, L. V., & Sai, Y. P. (2021). Classification of ECG beats using optimized decision tree and adaptive boosted optimized decision tree. Signal, Image and Video Processing, 1-9.

[33] Lu, P., Zhang, Y., Zhou, B., Zhang, H., Chen, L., Lin, Y., ... & Xi, H. (2021). Identification of Arrhythmia by Using a Decision Tree and Gated Network Fusion Model. Computational and Mathematical Methods in Medicine, 2021.

[34] Ma, F., Zhang, J., Liang, W., & Xue, J. (2020). Automated classification of atrial fibrillation using artificial neural network for wearable devices. Mathematical Problems in Engineering, 2020.

[35] M. M. Al Rahhal, Y. Bazi, H. Almubarak, N. Alajlan, and M. Al Zuair, "Dense convolutional networks with focal loss and image generation for electrocardiogram classification," IEEE Access, vol. 7, pp. 182225–182237, 2019.

[36] X. F. Yang, Q. P. Hu, and S. H. Li, "Electrocardiogram classification of lead convolutional neural network based on fuzzy algorithm," Journal of Intelligent & Fuzzy Systems, vol. 38, no. 4, pp. 3539–3548, 2020.

[37] B. H. Kim and J. Y. Pyun, "ECG identification for personal authentication using LSTM-based deep recurrent neural networks," Sensors, vol. 20, no. 11, Article ID 3069, 2020.

[38] A. Sharma, N. Garg, S. Patidar, R. S. Tan, and U. R. Acharya, "Automated pre-screening of arrhythmia using hybrid combination of Fourier–Bessel expansion and LSTM," Computers in Biology and Medicine, vol. 120, Article ID 103753, 2020.

[39] Kumar, A., Tomar, H., Mehla, V. K., Komaragiri, R., & Kumar, M. (2021). Stationary wavelet transform based ECG signal denoising method. ISA transactions, 114, 251-262. of arrhythmia disease using ECG signals. Neural Computing and Applications, 33(19), 13123-13143.

[40] Gaddam, P. G., & Sreehari, R. V. (2021, November). Automatic Classification of Cardiac Arrhythmias based on ECG Signals Using Transferred Deep Learning Convolution Neural Network. In Journal of Physics: Conference Series (Vol. 2089, No. 1, p. 012058). IOP Publishing.

[41] Maghawry, E., Gharib, T. F., Ismail, R., & Zaki, M. J. (2021). An Efficient Heartbeats Classifier Based on Optimizing Convolutional Neural Network Model. IEEE Access, 9, 153266-153275.

[42] Pokaprakarn, T., Kitzmiller, R. R., Moorman, R., Lake, D. E., Krishnamurthy, A. K., & Kosorok, M. (2021). Sequence to Sequence ECG Cardiac Rhythm Classification using Convolutional Recurrent Neural Networks. IEEE Journal of Biomedical and Health Informatics.

[43] Ganeshkumar, M., Ravi, V., Sowmya, V., Gopalakrishnan, E. A., & Soman, K. P. (2021). Explainable Deep Learning-Based Approach for Multilabel Classification of Electrocardiogram. IEEE Transactions on Engineering Management.

[44] Essa, E., & Xie, X. (2021). An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification. IEEE Access, 9, 103452-103464.

[45] Jiang, M., Gu, J., Li, Y., Wei, B., Zhang, J., Wang, Z., & Xia, L. (2021). HADLN: Hybrid attention-based deep learning network for automated arrhythmia classification. Frontiers in Physiology, 12.

[46] Parvaneh, S., Rubin, J., Babaeizadeh, S., & Xu-Wilson, M. (2019). Cardiac arrhythmia detection using deep learning: A review. Journal of electrocardiology, 57, S70-S74.

[47] Hong, S., Xiao, C., Ma, T., Li, H., & Sun, J. (2019). MINA: multilevel knowledge-guided attention for modeling electrocardiography signals. arXiv preprint arXiv:1905.11333.

[48] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[49] Wu, Q., Sun, Y., Yan, H., & Wu, X. (2020). Ecg signal classification with binarized convolutional neural network. Computers in biology and medicine, 121, 103800.

[50] Li, Z., Zhou, D., Wan, L., Li, J., & Mou, W. (2020). Heartbeat classification using deep residual convolutional neural network from 2-lead electrocardiogram. Journal of Electrocardiology, 58, 105-112.

[51] Duan, R., He, X., & Ouyang, Z. (2020, September). MADNN: a multi-scale attention deep neural network for arrhythmia classification. In 2020 Computing in Cardiology (pp. 1-4). IEEE.

[52] Liu, Y., Wang, K., Yuan, Y., Li, Q., Li, Y., Xu, Y., & Zhang, H. (2020, September). Multi-label classification of 12-lead ECGs by using residual CNN and class-wise attention. In 2020 Computing in Cardiology (pp. 1-4). IEEE.

[53] He, R., Wang, K., Zhao, N., Sun, Q., Li, Y., Li, Q., & Zhang, H. (2020, September). Automatic classification of arrhythmias by residual network and bigru with attention mechanism. In 2020 Computing in Cardiology (pp. 1-4). IEEE.

[54] Xiong, F., Chen, D., Chen, Z., & Dai, S. (2019). Cancellation of motion artifacts in ambulatory ECG signals using TD-LMS adaptive filtering techniques. Journal of Visual Communication and Image Representation, 58, 606-618.

[55] El Bouny, L., Khalil, M., & Adib, A. (2019). ECG signal filtering based on CEEMDAN with hybrid interval thresholding and higher order statistics to select relevant modes. Multimedia Tools and Applications, 78(10), 13067-13089.

[56] Wang, Z., Zhu, J., Yan, T., & Yang, L. (2019). A new modified wavelet-based ECG denoising. Computer Assisted Surgery, 24(sup1), 174-183.

[57] Singh, P., Shahnawazuddin, S., & Pradhan, G. (2018). An efficient ECG denoising technique based on non-local means estimation and modified empirical mode decomposition. Circuits, Systems, and Signal Processing, 37(10), 4527-4547.

[58] Romero, F. P., Piñol, D. C., & Vázquez-Seisdedos, C. R. (2021). DeepFilter: an ECG baseline wander removal filter using deep learning techniques. Biomedical Signal Processing and Control, 70, 102992.

[59] Ahmed, S. T., Sreedhar Kumar, S., Anusha, B., Bhumika, P., Gunashree, M., & Ishwarya, B. (2018, November). A Generalized Study on Data Mining and Clustering Algorithms. In *International Conference On Computational Vision and Bio Inspired Computing* (pp. 1121-1129). Springer, Cham

[60] Qiu, L., Cai, W., Yu, J., Zhong, J., Wang, Y., Li, W., ... & Wang, L. (2020). A two-stage ECG signal denoising method based on deep convolutional network. bioRxiv.

[61] Bing, P., Liu, W., & Zhang, Z. (2021). DeepCEDNet: An Efficient Deep Convolutional Encoder-Decoder Networks for ECG Signal Enhancement. IEEE Access, 9, 56699-56708.

[62] Wang, T., Lu, C., Sun, Y., Yang, M., Liu, C., & Ou, C. (2021). Automatic ECG classification using continuous wavelet transform and convolutional neural network. Entropy, 23(1), 119.

[63] Ahmed, S. T., Sandhya, M., & Sankar, S. (2020). TelMED: dynamic user clustering resource allocation technique for MooM datasets under optimizing telemedicine network. *Wireless Personal Communications*, *112*(2), 1061-1077.

[64] Chen, C. Y., Lin, Y. T., Lee, S. J., Tsai, W. C., Huang, T. C., Liu, Y. H., ... & Dai, C. Y. (2021). Automated ECG classification based on 1D deep learning network. Methods.

[65] Sharma, P., Dinkar, S. K., & Gupta, D. V. (2021). A novel hybrid deep learning method with cuckoo search algorithm for classification