ECG-Based Heartbeat Classification for Arrhythmia Detection Using Artificial Neural Networks

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Abstract. Cardiovascular disease (CVD) has quickly grown in prevalence over the previous decade, becoming the major cause of human morbidity on a global scale. Due to the massive number of ECG data, manual analysis is regarded as a time-consuming, costly and prone to human error task. In the other hand, computational systems based on biomedical signal processing and machine learning techniques might be suited for supporting arrhythmia diagnostic processes, while solving some of those issues. In general, such systems involve five stages: acquisition, preprocessing, segmentation, characterization, and classification. Yet numerous fundamental aspects remain unresolved, including sensitivity to signal fluctuation, accuracy, computing cost, generalizability, and interpretability. In this context, the present study offers a comparative analysis of ECG signal classification using two artificial neural networks created by different machine learning frameworks. The neural nets were built into a pipeline that aims to strike an appropriate balance among signal robustness, variability, and accuracy. The proposed approach reaches up to 99% of overall accuracy for each register while keeping the computational cost low.

Keywords: ANN · ECG · Multi layer perceptron · Neural network

1 Introduction

Cardiovascular disease (CVD) has quickly grown in prevalence over the previous decade, becoming the major cause of human morbidity on a global scale [1]. It is estimated to account for 30% of fatalities globally [4]. Cardiac arrhythmia is

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a particular CVD that refers to an irregular heartbeat. Although the majority of arrhythmias are harmless, some are dangerous or even life-threatening [2]. For example, atrial fibrillation may result in strokes and cardiac arrest [3], which is very hazardous and should be treated promptly. Additionally, the expense of cardiovascular disease-related therapies, including medicine, is quite expensive [5]. The electrocardiogram (ECG) is the most often used measuring technique for diagnosing CDV and is the primary tool for diagnosing CVD both in and out of hospitals. An ECG signal is made up of a sequence of periodic beats that depict the electrical activity of the heart throughout time [6].

Currently, the enormous amount of ECG data makes manual analysis by physicians a time-consuming, costly, and prone to human error activity [7]. Additionally, ECG signals are often constituted of several frequency components and even noise, which complicates the task of extracting discriminative features manually, so it is recommended to use an artificial intelligence-based technique.

Wavelet shape transforms (WT) or short-time Fourier transforms are employed for this propose; in general, WT produces more accurate time-frequency analysis findings than Fourier transform. As a result, computational system that include biomedical signal processing and machine learning techniques are well suited for this job supporting arrhythmia diagnosis processes [8]. In general, these systems provide aid with machine learning at five stages: acquisition, preprocessing, beat segmentation, characterization, and classification. There are a variety of methods for classifying ECG signal beats for these purposes.

Some studies have addressed the cardiac arrhythmia identification problem from the perspective of classical machine learning pipelines [9,10]. Various techniques, including artificial neural networks, support vector machines, multi-view based learning, and linear discriminates, are utilized for these goals [11]. Despite these approaches superior performance, some fundamental concerns like as sensitivity to signal fluctuation, accuracy, computing cost, generalizability, and interpretability remain unresolved. With the fats development of artificial neural networks in recent years, approaches based on machine learning have garnered more interest.

This article presents a comparative analysis of ECG signals processing approaches in this respect. To this end, an artificial neural network technique capable of identifying and categorizing cardiac arrhythmia-related beats is created and developed within a framework that finds an optimum balance between signal robustness, variability, and accuracy. To develop an automated approach for ECG signal categorization based on multi layer perceptron technique and artificial neural network (ANN). Where ANN is a machine learning technique that is capable of simulating the human visual system and has been effectively used to image classification and video recognition [12,13].

The ECG beat signal is transformed into the time-frequency domain using continuous wavelet transform (CWT) [13,14], and features are extracted from the 2D scalogram consisting of the previously decomposed time frequency components using ANN. To fully use all available information for ECG signal clas-

sification, we extract and combine RR interval features into our ANN. This is accomplished with the assistance of the MIT-BIH arrhythmia database [15]. The created technique is compared to current and suggested multi layer perceptron technique in the literature [16]. Comparative analysis of EEG signal processing approach enables the optimal trade-off between robustness, signal variability, and accuracy. In comparison to typical machine learning systems, the ANN technique are promising.

The following is the organization of the paper. Section 2 discusses the currently available approaches. Section 3 discusses the suggested approach for classifying ECG signals. Section 4 contains the results. Section 5 contains the discussion and conclusion of the results. This paper closes with Sect. 5.

2 Existing Methods

Alaa Sheta et al. [17] diagnosed obstructive sleep apnea from ECG signals using machine learning and deep learning classifiers, achieving an accuracy of up to 86.25%. Alaa Sheta et al. used the following popular classifiers: decisio tree (DT), linear discriminate analysis (LDA), k-nearest neighbors (KNN), logistic regression (LR), Naive Bayes (NB), support vector machine (SVM), ensemble decision tree (EDT), and boosted tress (BT).

2.1 Convolutional Neural Network (CNN)

Serkan K. et al. [18] provide an overview of the primary signal processing applications that use CNNs. The research reveals that using a methodical methodology, CNNs may attain a performance of up to 97.6% with minimum computing complexity. Xiaolong Z. et al. [19] utilizes a double beat ECG coupling matrix to propose a CNN based framework for heartbeat categorization. This two-dimensional encoded dual beat ECG coupling matrix effectively represents both the morphology and rhythm of the heartbeat. The suggested technique was validated against the MIT-BIH database and demonstrated more than 90% accuracy.

2.2 K Nearest Neighbour (KNN)

Vedavathi G et al. [20] Propose a classification method for cardiac arrhythmias based on the K-Nearest Neighbor (K-NN) classifier. This method involves phases such as data preprocessing, module extraction, and feature classification. This approach is applied to the MIT-BIH database of ECG signals, which are then categorized using the KNN method. The dataset achieves a classification accuracy of 98.4%, illustrating the accuracy of K-NN classifiers.

2.3 Deep Neural Network (DNN)

Raghu N et al. [21] classified arrhythmias based on ECG signals using Deep neural networks. They compared their results to those obtained using neural

network (NN) and support vector machine (SVM) approaches, which produced much lower results than the DNN classifier. The suggested DNN classifier is used to execute 100 iterations on the MIT-BIH database, obtaining an accuracy of around 98.33%. The authors conclude that by properly characterizing the data, it is essential to increase the suggested method's accuracy.

2.4 Fog Computing Based (FCB)

Alessandro S. et al. [22] assessed the end-to-end method's capacity to recognize beats and categorize them into four categories: normal beats, supraventricular ectopic beats (VEBs), and ventricular ectopic beats. Beats generated from the fusion of normal and VEBs, as well as any beats that do not belong into the MIT-BIH arrythmia database's N, S, V, or F classifications. The resultant method obtains an accuracy of 89.1% in classifying arrhythmias. These findings are significant because the suggested technique minimizes power consumption by using hardware assisted execution of machine learning algorithms.

3 Methodology

3.1 Comparative Methodology

Artificial learning has become the most widely used artificial intelligence technique in recent years, making significant improvements in a variety of fields, including voice recognition, computer vision, and image processing [12,13]. Artificial intelligence approaches have shown their ability to significantly cut time and physical labor. Concentrating on artificial intelligence technologies, the literature has several uses for ECG data [17]. To facilitate cardiovascular health management, the majority of these approaches use artificial neural networks in ECG diagnosis [18–21].

To do this, a ECG signal monitoring method is carried out in a pipeline that aims to strike an appropriate balance between the signal's resilience and variability and accuracy. The proposed machine learning process, as shown in Fig. 1, identifies beats associated with cardiac arrhythmias through several preprocessing, segmentation, and characterization techniques. The resulting data is then fed to the neural nets, which are compared for better performance.

3.2 Database

The code for this work is written in Python and utilizes the MIT-BIH arrhythmia database as a reference dataset for evaluating the ANN and multilayer perceptron technique for developing comparative research. The MIT-BIH arrhythmia database is a freely accessible dataset that contains the data essential for detecting cardiac arrhythmias with 48 half-hourly two-channel ambulatory ECG recordings from 47 participants are included in the database, 23 records were chosen D analog ECG recordings [15].

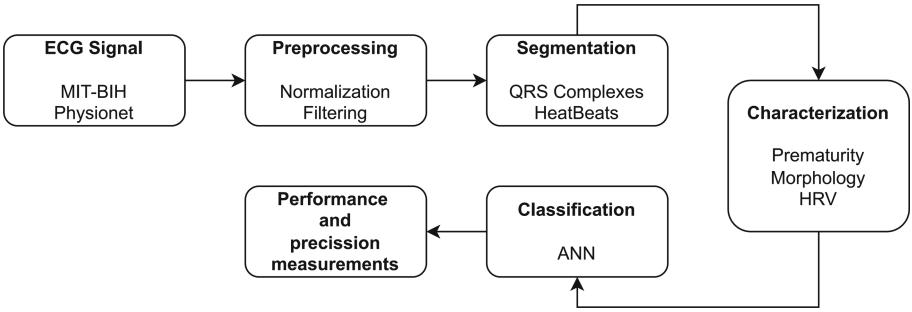


Fig. 1. Diagram depicting the steps for detecting cardiac arrhythmias. This identifies beats associated with cardiac arrhythmias through acquisition, preprocessing, segmentation, characterization, and classification techniques.

The remaining 25 records were collected from prior ambulatory ECG recordings and similarly exhibit rare but clinically severe arrhythmias. Each record has two leads and operates at a sampling rate of 360 samples per second with a resolution of 11 bits in the range of 10 mv ECG signals. The first lead is modified lead II (ML II), while the second lead is one of the following: lead VI, VII, V2, V4, or V5. Due to the prevalence of ML II in recordings, we will utilize it to classify ECGs in this study. Two or more cardiologists name each tape independently and classify into one of fifteen arrhythmia categories. As shown in Table 1 the annotations used are those from the original MIT-BIH database, which have

Table 1. Main categories of beats present in the MIT-BIH database. Where you can see the division of the superclasses N, SVEB, VEB, F and Q respectively.

Group	Annotation	Description
N	N	Normal beat
Any heartbeat not categorized as	L	Left bundle branch block beat
SVEB, VEB, F or Q	R	Right bundle branch block beat
	e	Atrial escape beat
	j	Nodal (junctional) escape beat
SVEB	A	Atrial premature beat
Supraventricular ectopic beat	a	Aberrated atrial premature beat
	S	Supraventricular premature beat
	J	Nodal (junctional) premature beat
VEB	V	Premature ventricular contraction
Ventricular ectopic beat	E	Ventricular escape beat
	!	Ventricular flutter wave
F - Fusion beat	F	Fusion of ventricular and normal beat
Q	Q	Unclassifiable beat
Unknown beat	/	Paced beat
	f	Fusion of paced and normal beat

been grouped by superclasses respectively according to the previous article by Eduardo Jose et al. [23].

3.3 ECG Signal Preprocessing

Clinically obtained ECG signals are often disrupted by a variety of noise sources, including baseline drift, electromyography disturbances, and power line interference, making it impossible to extract usable information from the ECG signal without processing. As a result, prior to further processing, a normalization and filtering step is required. Geometric normalization was used to normalize the signals in question [24], as expressed in Eq. (1). This normalization reduces the signal to noise ratio. The term $E\{s\}$ denotes the expectation operator, the arithmetic mean is considered in the instance is considered, correcting for the impact of a zero-mean transformation.

$$s \leftarrow \frac{s - E\{s\}}{\max |s|} \tag{1}$$

Due to the fact that excessive filtering would result in the loss of vital information, we eliminate just the noise: the baseline deviation, which has a significant effect on the categorization of ECG signals. The patient's respiration or movement causes base-line drift. In accordance with prior work [25], a simple 1s window with overlap filter is used to decrease signal disruptions and artifacts. The influence of noise on the ECG signal is seen in Fig. 2. In comparison to other filtering approaches, the simple 1s window with overlap filter effectively removes outliers without causing phase distortion [26].

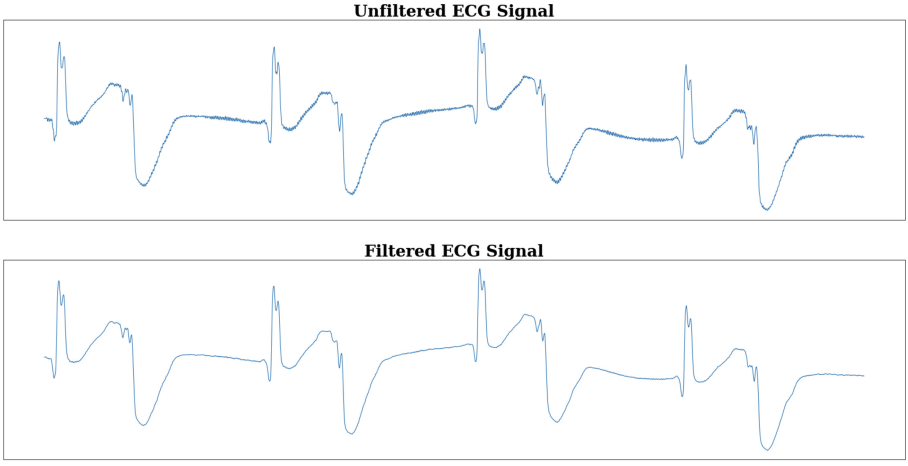


Fig. 2. ECG signal filtering impact

3.4 Hearbeat and QRS Segmentation

To correctly segment individual beats from the ECG signal, the QRS waves and beat reference points must be detected [27]. Numerous studies in the literature demonstrate that this procedure has a success rate of more than 99% [29]. The R peak is used as a reference point in this experiment, and the ECG signal is divided as shown in Eqs. (2) and (3).

$$b_i = y(p_i - 0.3RR_i : p_i - 0.6RR_i) \tag{2}$$

and

$$c_i = y(p_i - \alpha\ F_s : p_i + \beta\ F_s), \tag{3}$$

where p_i denotes the location of the i-th beat's R peak, p_i denotes the i-th beat's QRS complex, RR denotes the vector storing the distance between the R_i peaks, and Fs is the frequency of the vector v between places a and b ($b > a$). Because the times are derived from a dynamic variable, the duration of each extracted time is unique. The complexes were extracted using a 200 ms window width and centered on the R peak it means $\alpha = \beta = 0.1$ s. As seen in Fig. 3, these positions correspond to the most significant beat waves.

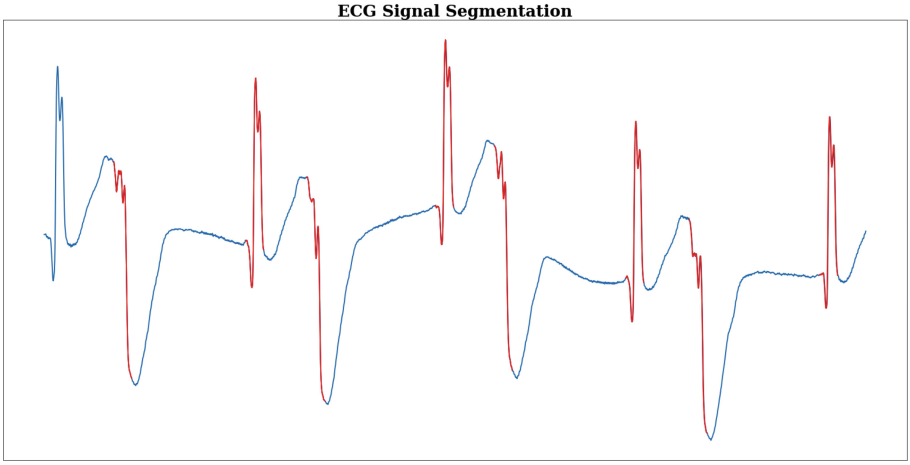


Fig. 3. ECG signal segmentation of QRS complexes.

Typically, arrhythmia alter not only the form of the pulse, but also the surrounding RR intervals (also knowns as peak R intervals). As a result, we include RR interval data into our ANN for ECG categorization. Three extensively utilized characteristics of RR intervals are extracted. The anterior RR interval is the time interval between the current and future beats. The RR ratio is the difference between the previous and subsequent RRs. The local RR is calculated as

the average of the current beat's 10 prior RR intervals. To remove interpatient variance, the anterior RR, posterior RR, and local RR have been subtracted from the mean RR interval.

3.5 Classification of ECG Signals Using Neural Networks

To address the objective, the open source, low-code machine learning library PyCaret was used [28], from which two ANN were created to automatically extract possible relationships between various arrhythmias and regular heartbeats. The first ANN was built using [30], `MLPClassifier` function. All hyperparameters were set as default except for the following: `alpha` = $1 \cdot 10^{-5}$, `hidden_layer_sizes` = (10,20,10), `max iter` = 500. The second ANN was built using [31] sequential `Dense Layer`. All hyperparameters were set as default except for the following: `epochs` = 500, `batch_size` = 100, `loss` = categorical_crossentropy, `optimizer` = adam, `metrics` = accuracy. In both cases, given that Rectified learning unit (ReLU) activation function minimizes the model's computational complexity, increases its statistical efficiency and reaches nonlinear capabilities, it was chosen for most of the layers. In comparison to other optimizers, Adam often accelerates the network training process. Details of each model architectures are displayed in Table 2 and Fig. 4.

Table 2. ANN architectures, such that the input consist of eight variables, four hidden layers and the output has size $(k, 1)$ where k = the amount of classes for each supergroup.

Layer Type	Hyperparameter	Keras Dense NN	Sklearn MLP
Input	Size	(8,1)	(8,1)
Hidden	Neurons or Units	10	10
	Activation	ReLU	ReLU
Hidden	Neurons or Units	20	20
	Activation	ReLU	ReLU
Hidden	Neurons or Units	10	10
	Activation	ReLU	ReLU
Dropout	Neurons or Units	10	-
Hidden	Neurons or Units	9	10
	Activation	Softmax	ReLU
Output	Size	$(k, 1)$	$(k, 1)$

4 Results

Our method offers an accuracy rate of up to 99% utilizing machine learning and a simple and easy to understand neural network (ANN) for the same application. Although existing approaches usually anticipate discriminative features,

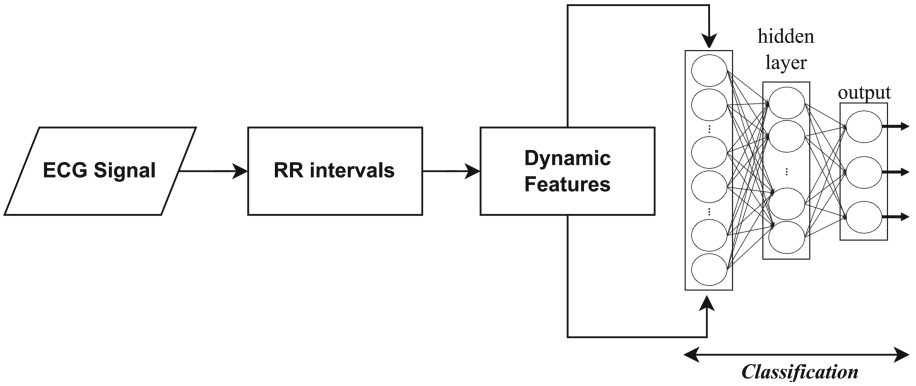


Fig. 4. Artificial neural network classification. Where is appreciated ECG signal, RR intervals, Dynamic Features and ANN Classification with their input, hidden and output layers respectively.

Table 3. ANN performance

Register	Precision	Recall	Fl_score	Error	Accuracy
118	97.64	97.80	97.65	0.020	0.98
124	99.49	99.75	99.62	0.002	1.00
217	98.94	98.94	98.94	0.015	0.99
Overall	98.69	98.83	98.74	0.012	0.99

our method uses ANN and compares with the multilayer perceptron technique, which shows a much better appreciation of the results, moreover, the following Table 3 show the performance of the ANN structure, employing the 8 records of the analog recording F of the MIT-BIH Arrhythmia Database and performing the average of all the records used.

Also, the Table 4 compares the performance of the results with other authors who used different classifiers. The records of database recording D were chosen because they have a big variety of data that easily cluster into the superclasses (see Table 1), in addition to the records having a considerable and imbalanced variety compared to the other database recordings of the MIT-BIH Arrhythmia. With machine learning approaches, the ANN methodology is not sophisticated, is of low computing cost and achieves competitive accuracy with earlier studies where more complex and computationally expensive techniques are utilized (see Table 4). One of the key benefits achieved from our technique is related to the grouping by superclasses, which makes our neural network cheap computational cost, non-complex, competitive and achieves an accuracy of up to 99%.

Finally, the comparison of our methodology ANN-based keras dense with sklearn MLP classification method was undertaken, which yielded promising results, despite being a more complicated neural network than the suggested

Table 4. Performance of the results with other authors who used different classifiers.

Author	Year	Method	Accuracy	Reference
Kiranyaz S. et al.	2019	CNN	97.60%	[18]
Zahi X. et al.	2018	CNN	90.00%	[19]
Rangappa V. et al.	2018	KNN	98.40%	[20]
Meshram V. et al.	2017	DNN	98.33%	[21]
Scire A. et al.	2019	FCB	89.10%	[22]
Our method	2022	ANN	99%	

Table 5. Keras Dense NN and sklearn MLP comparison. Where the precision, Recall and F1-score of each class are found

Record	Class	Keras Dense NN			Sklearn MLP		
		Precision	Recall	F1-score	Precision	Recall	F1-score
118	N	0.98	0.99	0.99	0.98	1.00	0.99
	SVEB	0.77	0.61	0.68	0.86	0.64	0.73
	VEB	1.00	0.60	0.75	0.75	0.60	0.67
124	N	1.00	1.00	1.00	1.00	1.00	1.00
	SVEB	0.00	0.00	0.00	0.00	0.00	0.00
	VEB	1.00	1.00	1.00	1.00	1.00	1.00
217	N	0.99	1.00	0.99	0.97	0.99	0.98
	Q	0.99	1.00	1.00	1.00	1.00	1.00
	VEB	0.96	0.92	0.94	0.94	0.92	0.93

one. It can be observed from the Table 5 that, despite adopting a non-complex and cheap computing cost strategy, our method is competitive and produces outstanding results.

5 Discussion and Conclusion

This work classifies distinct forms of cardiac arrhythmias using ANN-based deep learning characteristics. The approach takes advantage of ANN's capability for feature representation, which is a nonlinear dimensionality reduction technique that is frequently utilized in machine learning. Obtaining the signal from the database, signal preprocessing, and signal segmentation are critical for this goal. Additionally, the effect of various strategies utilized for the same aim is examined. Our ANN-based technique can automatically extract discriminative features from data as a representation learning method. QRS segmentation of the signal is required for this purpose, with the peak R serving as a reference point. To validate this capacity, the accuracy score is employed, thereby comparing it with the multilayer perceptron machine learning approach and establishing that the suggested method is better.

To conclude, this study proposes the building of a machine learning technique capable of identifying cardiac arrhythmias. A comparison of the model described in this work to some of the approaches presently available in the literature reveals a good outcome. This model correctly diagnoses several kinds of cardiac arrhythmias using ACC classification, with an accuracy of up to 99%. Additionally, this strategy requires little computing resources. The manner in which this study was conducted enables comparison between multilayer perceptron classification techniques and the suggested approach, which produces promising results with an accuracy comparable to conventional methods.

As a future work, both new characterization (including wavelet transform), and classification approaches will be explored. Also, techniques for adding interpretability as well as lowering computational cost are to be incorporated in further releases of the software.

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References

1. Radha, R., Shahzadi, S.K., Al-Sayah, M.H.: Fluorescent immunoassays for detection and quantification of cardiac troponin I: a short review. Molecules. **26**(16), 4812 (2021). https://doi.org/10.3390/molecules26164812
2. Wongthida, T., Lumkul, L., Patumanond, J., Wongtheptian, W., Piyayotai, D., Phinyo, P.: Development of a clinical risk score for prediction of life-threatening arrhythmia events in patients with ST elevated acute coronary syndrome after primary percutaneous coronary intervention. Int. J. Environ. Res. Public Health **19**(4), 1997 (2022). https://doi.org/10.3390/ijerph19041997
3. Kelley, R.E., Kelley, B.P.: Heart-brain relationship in stroke. Biomedicines. **9**(12), 1835 (2021). https://doi.org/10.3390/biomedicines9121835
4. Shaghiera, A.D., Widiyanti, P., Yusuf, H.: Synthesis and characterization of injectable hydrogels with varying collagen-chitosan-thymosin $\beta 4$ composition for myocardial infarction therapy. J. Func. Biomater. **9**(2), 33 (2018). https://doi.org/10.3390/jfb9020033
5. Patel, P., et al.: Improved blood pressure control to reduce cardiovascular disease morbidity and mortality: the standardized hypertension treatment and prevention project. J. Clin. Hypertens. **18**(12), 1284–1294 (2016). https://doi.org/10.1111/jch.12861
6. Sannino, G., de Pietro, G.: A deep learning approach for ECG-based heartbeat classification for arrhythmia detection. Future Gener. Comput. Syst. **86**, 446–455 (2018). https://doi.org/10.1016/j.future.2018.03.057
7. Vizitiu, A., Nita, C.I., Toev, R.M., Suditu, T., Suciu, C., Itu, L.M.: framework for privacy-preserving wearable health data analysis: proof-of-concept study for atrial fibrillation detection. Appl. Sci. **11**(19), 9049 (2021). https://doi.org/10.3390/app11199049
8. Sraitih, M., Jabrane, Y., el Hassani, A.H.: An automated system for ECG arrhythmia detection using machine learning techniques. J. Clin. Med. **10**(22), 5450 (2021). https://doi.org/10.3390/jcm10225450

9. Vargas-muñoz, A.M., Chamorro-sangoquiza, D.C., Umaquinga-criollo, A.C.: Diseño de un prototipo de bajo coste computacional para detección de arritmias cardiacas, pp. 470–480 (2020)
10. Rodríguez-Sotelo, J.L., Peluffo-Ordoñez, D., Cuesta-Frau, D., Castellanos-Domínguez, G.: Unsupervised feature relevance analysis applied to improve ECG heartbeat clustering. Comput. Methods Programs Biomed. **108**(1), 250–261 (2012). https://doi.org/10.1016/J.CMPB.2012.04.007
11. Sansone, M., Fusco, R., Pepino, A., Sansone, C: Electrocardiogram pattern recognition and analysis based on artificial neural networks and support vector machines: a review (2013). http://www.sciencedirect.com/
12. Tripathy, S., Singh, R.: Convolutional neural network: an overview and application in image classification. In: Poonia, R.C., Singh, V., Singh Jat, D., Diván, M.J., Khan, M.S. (eds.) Proceedings of Third International Conference on Sustainable Computing. AISC, vol. 1404, pp. 145–153. Springer, Singapore (2022). https://doi.org/10.1007/978-981-16-4538-9_15
13. Wang, J., Yang, Y., Mao, J., Huang, Z., Huang, C, Xu, W.: CNN-RNN: a unified framework for multi-label image classification (2016)
14. Ghorbanian, P., Ghaffari, A., Jalali, A., Nataraj, C.: Heart arrhythmia detection using continuous wavelet transform and principal component analysis with neural network classifier. Comput. Cardiol. **2010**, 669–672 (2010)
15. Moody, G.B., Mark, R.G.: The impact of the MIT-BIH arrhythmia database. IEEE Eng. Med. Biol. Mag. **20**(3), 45–50 (2001). https://doi.org/10.1109/51.932724
16. Ramkumar, M, Ganesh Babu, C., Vinoth Kumar, K., Hepsiba, D., Manjunathan, A., Sarath Kumar, R.: ECG cardiac arrhythmias classification using DWT, ICA and MLP neural networks. J. Phys. Conf. Ser. **1831**(1), 012015 (2021). https://doi.org/10.1088/1742-6596/1831/1/012015
17. Sheta, A., et al.: Diagnosis of obstructive sleep apnea from ECG signals using machine learning and deep learning classifiers. Appl. Sci. **11**(14), 6622 (2021). https://doi.org/10.3390/app11146622
18. Kiranyaz, S., Ince, T., Abdeljaber, O., Avci, O., Gabbouj, M.: 1-D convolutional neural networks for signal processing applications. In: ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, May 2019, vol. 2019, pp. 8360–8364 (2019). https://doi.org/10.1109/ICASSP.2019.8682194
19. Zhai, X., Tin, C.: Automated ECG classification using dual heartbeat coupling based on convolutional neural network. IEEE Access **6**, 27465–27472 (2018). https://doi.org/10.1109/ACCESS.2018.2833841
20. Rangappa, V.G., Prasad, S.V.A.V., Agarwal, A.: Classification of cardiac arrhythmia stages using hybrid features extraction with K-nearest neighbour classifier of ECG signals. Int. J. Intell. Eng. Syst. **11**(6), 21–32 (2018). https://doi.org/10.22266/IJIES2018.1231.03
21. Nanjundegowda, R., Meshram, V.A.: Arrhythmia detection based on hybrid features of T-wave in Electrocardiogram. Int. J. Intell. Eng. Syst. **11**(1), 153–162 (2018). https://doi.org/10.22266/ijies2018.0228.16
22. Scirè, A, Tropeano, F., Anagnostopoulos, A., Chatzigiannakis, I.: Fog-computing-based heartbeat detection and arrhythmia classification using machine learning. Algorithms. 12(2), 32 (2019). https://doi.org/10.3390/a12020032
23. Luz, E.J.S., Schwartz, W.R., Cámara-Chávez, G., Menotti, D.: ECG-based heartbeat classification for arrhythmia detection: a survey. Comput. Methods Progr. Biomed. **127**, 144–164 (2016). https://doi.org/10.1016/j.cmpb.2015.12.008

24. Patro, K.K., Kumar, P.R.: De-noising of ECG raw signal by cascaded window based digital filters configuration. In: 2015 IEEE Power, Communication and Information Technology Conference, PCITC 2015 - Proceedings, March 2016, pp. 120–124 (2016). https://doi.org/10.1109/PCITC.2015.7438145
25. Blanco-Velasco, M., Weng, B., Barner, K.E.: ECG signal denoising and baseline wander correction based on the empirical mode decomposition. Comput. Biol. Med. **38**(1), 1–13 (2008). https://doi.org/10.1016/j.compbiomed.2007.06.003
26. Pinto, J.R., Cardoso, J.S., Lourenço, A., Carreiras, C.: Towards a continuous biometric system based on ECG signals acquired on the steering wheel. Sensors **17**(10), 2228 (2017). https://doi.org/10.3390/s17102228
27. Lourenço, A., Silva, H., Leite, P., Lourenço, R., Fred, A.: Real time electrocardiogram segmentation for finger based ECG biometrics. In: BIOSIGNALS 2012 - Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing, pp. 49–54 (2012). https://doi.org/10.5220/0003777300490054
28. Ali, M.: PyCaret: an open source, low-code machine learning library in Python, PyCaret version 1.0.0, April 2020. https://www.pycaret.org
29. Oweis, R., Oweis, R.J., Al-Tabbaa, B.O.: QRS detection and heart rate variability analysis: a survey. Biomed. Sci. Eng. **2**(1), 13–34 (2014). https://doi.org/10.12691/bse-2-1-3
30. Pedregosa, F., et al.: Scikit-learn: machine learning in Python. J. Mach. Learn. Res. **12**, 2825–2830 (2011)
31. Chollet, F.: Keras: the python deep learning library. Astrophys. Source Code Libr. ASCL-1806 (2018)