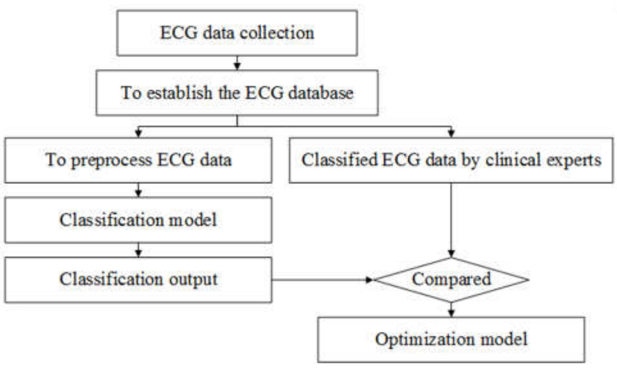
MOL2NET, International Conference Series on Multidisciplinary Sciences

Signal Analysis of Heart Rate Variability and Applications on the Diagnosis of Cardiovascular Diseases

Shoujing Wang [a,b], *Bairong Shen*[a], *Cesar Martin* [b].

[a] *Institutes for Systems Genetics, Frontiers Science Center for Disease-Related Molecular Network, West China Hospital, Sichuan University, Chengdu, Sichuan, China.*
[b] *University of the Basque Country UPV/EHU, Bilbao, Biscay, Spain*
Corresponding Author: Bairong Shen, bairong.shen@scu.edu.cn.
Cesar Martin, cesar.martin@ehu.eus.

Graphical Abstract



Abstract.

The electrocardiogram (ECG) is a fundamental tool in daily clinical medicine practice, recording millions of ECGs annually. Computer-assisted interpretation is becoming more and more important in clinical ECG processing and interpretation, serving as a crucial adjunct to physician interpretation in many clinical settings. But the existing commercial ECG interpretation algorithms still show substantial rates of misdiagnosis, and there is still a lack of comprehensive evaluation of computer-aided interpretation. We recommend using an ensemble method to process and classify clinical ECGs for providing accuracy and increasing rhythm classes.

Cardiovascular disease is the general term for heart or vascular disease. As the number one cause of death, it has a wide range of epidemiological effects. With the aging of the world population, it is estimated that by 2030, the number of deaths due to cardiovascular diseases will increase to 22.2 million each year [1]*, and the global direct medical costs caused by cardiovascular diseases may reach US$20 trillion* [2]*. Nearly 300,000 lives in the United States and 700,000 lives in Europe are lost because of sudden cardiac death (SCD) each year* [3, 4]*. Approximately 5-37 out of 1000,000 young people die from SCD* [5]*. By 2030, it is estimated that deaths related to coronary artery disease (CAD) will increase by 37% in emerging countries* [6]*.*

The electrocardiogram (ECG) is a fundamental tool in daily clinical medicine practice, recording millions of ECGs annually [7]*. The ECG is pivotal for diagnosing a wide spectrum of abnormalities from arrhythmias to acute coronary syndrome* [8]*. The Computer-aided interpretation was first attempted in the 1950s. Computer-assisted interpretation is becoming more and more important in clinical ECG* *processing and interpretation, serving as a crucial adjunct to physician interpretation in many clinical settings* [9, 10]*. Although the ECG algorithm continues to improve, the existing commercial ECG interpretation algorithms still show substantial rates of misdiagnosis* [11-13]*. Many previous works have focused on single aspect of the ECG processing pipeline, such as noise reduction, feature extraction, detecting only a handful of heartbeat types or rhythm diagnoses* [14-18]*. As to whether it can be used to analyze raw ECG data to classify various diagnoses, there is still a lack of comprehensive evaluation of computer-aided interpretation.*

In future research, we recommend using an ensemble method to process and classify clinical ECGs for providing accuracy and increasing rhythm classes. First, in machine learning, we recommend ensembling method combines many base estimators to improve the robustness and generalization ability of the overall model. Second, we will construct a large ECG dataset，which came from patients and classified them by clinical experts.

Keywords: *Electrocardiogram; Cardiovascular Diseases;classification.*

References

1. Mutyambizi, C., Chola, L., Groot, W., Pavlova, M., et al. (2017). The extent and determinants of diabetes and cardiovascular disease comorbidity in South Africa - results from the South African National Health and Nutrition Examination Survey (SANHANES-1). *BMC Public Health, 17*(1), 745.
2. Bloom, D., Cafiero, E., Jané-Llopis, E., et al. (2012). The Global Economic Burden of Noncommunicable Diseases. *IDEAS Working Paper Series from RePEc,* IDEAS Working Paper Series from RePEc, 2012.
3. Lloyd-Jones, D., Adams, R., Brown, T., et al. (2010). Heart disease and stroke statistics--2010 update: A report from the American Heart Association. *Circulation, 121*(7), E46-E215.
4. Pagidipati, N., & Gaziano, T. (2013). Estimating deaths from cardiovascular disease: A review of global methodologies of mortality measurement. *Circulation, 127*(6), 749-756.
5. Sessa, F, Anna, V, Messina, G, et al. (2018). Heart rate variability as predictive factor for sudden cardiac death. *Aging-Us, 10*(2), 166-177.
6. Acharya, U., Fujita, R., Sudarshan, H., et al. (2017). Application of empirical mode decomposition (EMD) for automated identification of congestive heart failure using heart rate signals. *Neural Computing and Applications, 28*(10), 3073-3094.
7. Holst, H., Ohlsson, M., Peterson, C., Edenbrandt, L. (1999). A confident decision support system for interpreting electrocardiograms. *Clin. Physiol.* 19, 410–418.
8. Schlant, R., Adolph, Dimarco, et al. (1992). Guidelines for electrocardiography. A report of the American College of Cardiology/American Heart Association Task Force on Assessment of Diagnostic and Therapeutic Cardiovascular Procedures (Committee on Electrocardiography). *Circulation, 85*(3), 1221-128.
9. Rautaharju, P. (2016). Eyewitness to history: Landmarks in the development of computerized electrocardiography. *Journal of Electrocardiology, 49*(1), 1-6.
10. Schläpfer, Jürg, Wellens, Hein J., (2017). Computer-Interpreted Electrocardiograms Benefits and Limitations. *Journal of the American College of Cardiology, 70*(9), 1183-1192.

11. Shah, A., & Rubin, S. (2007). Errors in the computerized electrocardiogram interpretation of cardiac rhythm. *Journal of Electrocardiology, 40*(5), 385-390.
12. Poon, K., Okin, P., & Kligfield, P. (2005). Diagnostic performance of a computer-based ECG rhythm algorithm. *Journal of Electrocardiology, 38*(3), 235-238.
13. Hannun, A., Rajpurkar, P., Haghpanahi, M., et al. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature Medicine, 25*(1), 65-69.
14. Ochoa, A., Mena, L., & Felix, V. (2017). Noise-Tolerant Neural Network Approach for Electrocardiogram Signal Classification. *Proceedings of the International Conference on Compute and Data Analysis, 130280*, 277-282.
15. Pourbabaee, B. J., Khorasani, K., & Roshtkhari, M. (2018). Deep Convolutional Neural Networks and Learning ECG Features for Screening Paroxysmal Atrial Fibrillation Patients. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 48*(12), 2095-2104.
16. Acharya, U. Rajendra, Oh, Shu Lih, et al. (2017). A deep convolutional neural network model to classify heartbeats. *Computers in Biology and Medicine, 89*, 389-396.
17. Al Rahhal, M. M. et al. Deep learning approach for active classification of electrocardiogram signals. Inf. Sci. (NY) 345, 340–354 (2016).
18. Rahhal, M., Bazi, Y., Alhichri, H., et al. (2016). Deep learning approach for active classification of electrocardiogram signals. *Information Sciences, 345*, 340-354.