INDONESIAN JOURNAL OF LIFE SCIENCES

Volume 5, No. 2, September 2023

RESEARCH ARTICLE

Development of Personalized Long QT Syndrome Detection In Uniform Wavelength Using SciPy

Moses Himawan[1], Muammar Sadrawi[2]*

[1]*Department of Biotechnology, Institut Bio Scientia Internasional Indonesia, Jakarta, Indonesia*

[2]*Department of Bioinformatics, Institut Bio Scientia Internasional Indonesia, Jakarta, Indonesia*

**Corresponding author: muammar.sadrawi@i3l.ac.id*

A B S T R A C T

Long QT syndrome (LQTS) is a type of arrhythmia that manifests itself as the elongation of the QT interval. LQTS is caused due to different disorders in the sodium and potassium channels, which results in reduced activity of the cardiac muscle. To diagnose LQTS, an algorithm is used to detect the elongated QT interval through the detection of the peaks using Python. The current build of the algorithm is able to detect different ECG graphs for their QT interval with more than 70% accuracy. Hhowever, it is not capable of detecting the different components if the graph has too much noise or comprisesif they have irregular wavelengths due to other cardiovascular disease (CVD).

K E Y W O R D S

Arrhythmia, ECG, LQTS, CVD

H I G H L I G H T S

- ❖ Algorithm designed to detect Long QT syndrome.
- ❖ Utilization of SciPy Findpeaks function.
- ❖ Python was able to detect the different peaks.
- ❖ Error rate was below 5% under optimal conditions.Error rate was under 5% in optimal condition.

INTRODUCTION

Electrocardiogram (ECG) is a common tool used to diagnose different cardiovascular diseases (CVDs) such as arrhythmias by recording the heartbeat of patients into a graph (Feather et al., 2020), such as aerobic exercises, and may result in fainting, seizures, or even sudden death (Shah et al., 2019). Early detection can improve the living conditions of people with the disease.

Long QT Syndrome is a hereditary condition, in which most of the sufferers of the disease inherited said disease from their parents (Wallace et al., 2019). 85% of the people who suffered from LQTS received the disease from their parents, with the rest being through de novo mutation. Mutation of the potassium channel (KCN) genes and the sodium channels (SCN) genes, which are responsible for the potassium and sodium channels of the cardiac muscle. Up to 10 different types of LQTS have been discovered and recorded, with three different types being the most commonly diagnosed in patients (Goldenberg et al., 2008). LQT1 results from a slow activation of the potassium channels, which slows down repolarization. Mainly used for visualizing and measuring the heartbeat of a patient, the ECG is a very important tool for monitoring the

health of a person's heart. Using conductive patches attached to the skin, the device can detect slight electrical signals produced when a heart beats (Arquilla et al., 2020). The electrical signals correspond to different stages of a heartbeat, and the intensity of the signals correlates to how the cardiac muscles contract with each beat. By looking at the graph produced by the ECG, a trained physician can see a person's heartbeat and decide whether or not there are abnormalities in the heartbeat (Hampton & Hampton, 2019).

Long QT syndrome (LQTS) is a type of arrhythmia that may occur in a patient. LQTS is a cardiovascular disease (CVD) defined by the elongated time interval between the start of the QRS complex to the end of the end of the T-wave, known as the QT interval. Extension of the QT interval causes reduced heart rate or tachycardia, which reduces a patient's capacity to do strenuous activitiespotassium activity, which reduces the rate of repolarization. LQT3 is a result of reduced sodium flow, which results in a reduced speed of relaxation (Wallace et al., 2019).

To diagnose and determine what type of LQTS a patient is suffering, several factors must be considered. The QT interval is the first aspect that a cardiologist examines. QT interval above 450 ms for males and 480 ms for females is considered abnormal and is used to check if a person has LQTS. T-wave morphology is another sign that is used to diagnose the type of LQTS, as LQT1 has broad T-wave, LQT2 has low and notched T-wave; and LQT3 has long and tall T-waves (Steinberg, 2018). Genetic and clinical history is then collected to truly determine whether or not a person has LQTS. Treatment of LQTS includes beta blockers and cardioverter defibrillators (Steinberg, 2018).

People at risk of CVD such as LQTS may utilize personal ECG in order to monitor their heartbeat. Different types of personal-use ECGs are available in the market. The most common model is using a smartwatch's ECG function. The data of the heartbeat collected by the smartwatch is transmitted to the phone through Bluetooth. Smartwatch's ECG, however, is too imprecise to be used for diagnosing different types of arrhythmias. Another common form of ECG is the personal-use ECG using the six-lead system on the torso. The six-lead system gives a better reading and can be hidden under clothing (Beers et al., 2021).

The ECG produces a voltage-time graph, or the ECG graph. A heartbeat is visualized in the graph as a group of waves with 5 distinct parts, the P-wave, the Q-valley, the R-peak, the S-valley, and the T-wave. The P-wave represents the depolarization of the atriums. The QRS complex represents the repolarization of the atriums as it relaxes and the depolarization of the ventricles as it contracts. The T-wave represents the repolarization of the ventricles (Serhani et al., 2020). The graph shows the contractions of the heart, and any abnormalities can be determined by a physician and can be used to determine if the heart is beating correctly or incorrectly.

However, patients may not be able to identify LQTS even if they were wearing an ECG. In order for the patient to diagnose their conditions even with ECG, they need to monitor the graph constantly and need the knowledge of CVD and ECG in order to identify their disease. Another simple algorithm that is produced recently using Python and MATLAB uses a threshold method to identify the Q-point and the T-wave end to calculate the QT interval (Tiwari et al., 2021). However, their research may be flawed, as the QT interval was calculated from the start of the Q-wave and the P-Q junction to the end of the T-wave. As such, this project aims to develop a personalized QT interval detection and measurement system to select patients with regular wavelengths in order to ensure the greatest accuracy in measuring the QT interval.

MATERIAL AND METHODS

Main programming

The main platform the programming was done in is PyCharm. Several Python packages are downloaded into the working system, including SciPy for peak detection and Matplotlib to chart the data, as

well as a basic CSV reading program. Data taken from PhysioNet's QT database was downloaded in 10-second increments and loaded into the system. The data was taken from https://archive.physionet.org/lightwave/. Short intervals of ECG data were used since LQTS is a regular heart irregularity. Subsequently, the QT intervals in each individual heartbeat is uniformly elongated (Moody, 2022).

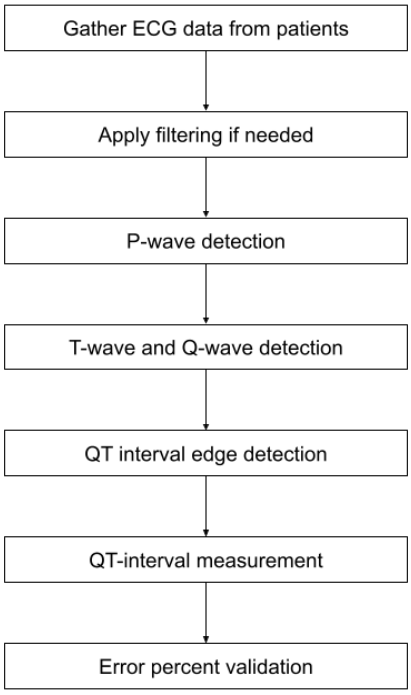

Figure 1. Methodology flowchart

The R-wave was the first wave to be detected, as it allows the algorithm to distinguish single beats due to its standout nature. The main method of finding it was to detect the tallest wave in the complex. By adjusting the minimum height requirement for detection, the algorithm was able to precisely pinpoint the R-waves. By detecting the R-wave, the T-wave was detected by adjusting the height and width of the wave. The T-wave was the second tallest wave and had a wide base compared to other waves like the R-wave and the P-wave. Adjusting the maximum and minimum height detection and the minimum width detection allowed for accurate T-wave detection. Q-wave detection was different from T-wave detection as SciPy was not able to detect valleys. As such, an inverted version of the graph was generated and the position of the Q-wave on the X-axis was detected by detecting the peak based on the inverted graph. Once the position of the Q-wave was detected, the X-axis value was cross-referenced with the numerical data to locate the Y-Axis value of the points, and the graph was annotated accordingly. The QT interval was measured from the start of the Q-wave to the end of the T-wave. This was done with the prominence function, which is a function to compare the height of the highest and lowest points of the wave and the width of the wave. As the lowest points of the waves were on the left or right edge, SciPy detects both sides to do the calculation. By requesting the data for the left edge of the Q-wave and the right edge of the T-wave, the algorithm produced the X-axis position of the left and right edge, which was then compared with the data to pinpoint the height and subsequently annotated into a graph.

A massive challenge in detection was noisy data, which affects the peaks finding function, resulting in a disruption in detection. As such, a filter was added to smooth out the data for better detection. Out of all the filters, a second-order digital forwards and backward filter was used as it preserves the shape of the

wavelengths the best. This is based on the "sosfiltfilt" function of SciPy. The filter was tweaked based on the data to ensure that the Q-wave was not removed by the filter. The filter was only applied when the data's noise peaks interfered with the detection of the Q-waves. The Q-wave can be small and tended to be hard to isolate when the noise of the signal was too extreme.

Validation

To validate the results, the annotation data from SciPy was taken and used to find the error percentage. The edges of the Q-wave and T-waves from the database were taken and using a spreadsheet, the average QT interval length was calculated. The QT interval from the algorithm was requested and used to calculate the error percentage. Error percentage was calculated based on the following formula:

$$\%\, Error = \frac{algorithmic\ result - mean\ database\ interval}{mean\ database\ interval} \times 100\%.$$

If the error was above 30%, the detection parameters was tweaked and the filter magnitude was adjusted to ensure that the results were as close as possible to the database result.

RESULTS

The following graphs show snippets of the graph as produced by the algorithm. The dots represent the apex of the wave while the cross represents the edges of the QT interval. Green for the T-waves and yellow for the Q-waves. The red crosses signify the apex of the R-waves. Three main patients were inspected, named SEL103, Sel114, and SEL117.

Based on the results shown in Table 1, the algorithm was able to detect the QT intervals of patients up to 95% accuracy — Sel114 being the only exception. With this result, under optimal conditions, the algorithm was deemed able to measure the QT interval at a high degree of accuracy. However, under some conditions, the accuracy may drop down significantly.

Table 1. Error rate of the algorithm based on average QT interval.

	Algorithm result (s)	True result (s)	% Error
Sel103	0.398	0.409	4.29%
Sel114	0.565	0.450	26.52%
Sel117	0.468	0.449	4.74%

Sel103 has uniform wavelengths with distinct parts, allowing for easy detection using the algorithm. The data is unfiltered, causing a rough waveform to appear in the graph. However, the distinctive parts allow for identification without filtering. SEL114 has noisy wavelengths, which requires heavy filtering that result in forked Q-waves. Forked Q-waves consequently causes inconsistency in locating the edges of the QT interval, resulting in a higher error rate. It can be inferred that SEL117 is a result of a more irregular wavelength. This highlights the algorithm's capability to identify key parts despite irregular wavelengths under the condition that the wavelength is uniform, as show by the low error percentage.

DISCUSSION

In the development of the algorithm, one of the biggest issues is non-uniform wavelengths. This is caused by the presence of another CVD that a patient might be suffering from. To illustrate the point,

unusual heartbeats that interfere with the detection program are marked with arrows in Figure 5. The reason that the following heartbeats disrupted the algorithm is because the heartbeats experienced T-wave inversion, where the T-wave of the following waves are inverted, which would cause the detection system to fail as it has not anticipated a valley instead of a hill. Isolated T-wave inversion such as this could be benign or can be very fatal if not tested thoroughly (Finocchiaro et al., 2018). In this patient, a possible CVD that could affect them is myocardial ischemia, as characterized by their inverted and tall T-waves (Li et al., 2021). Many different CVDs such as, ST-elevation myocardial infarction, have been known to affect the T-wave shape by elevating the ST segment of the ECG graph, which blurs the location of the T-wave, resulting in failure of detection (Gibson et al., 2022). A fail safe can be developed to alert the user if the detection failed, as it may be caused by other diseases that the user isn't aware off.

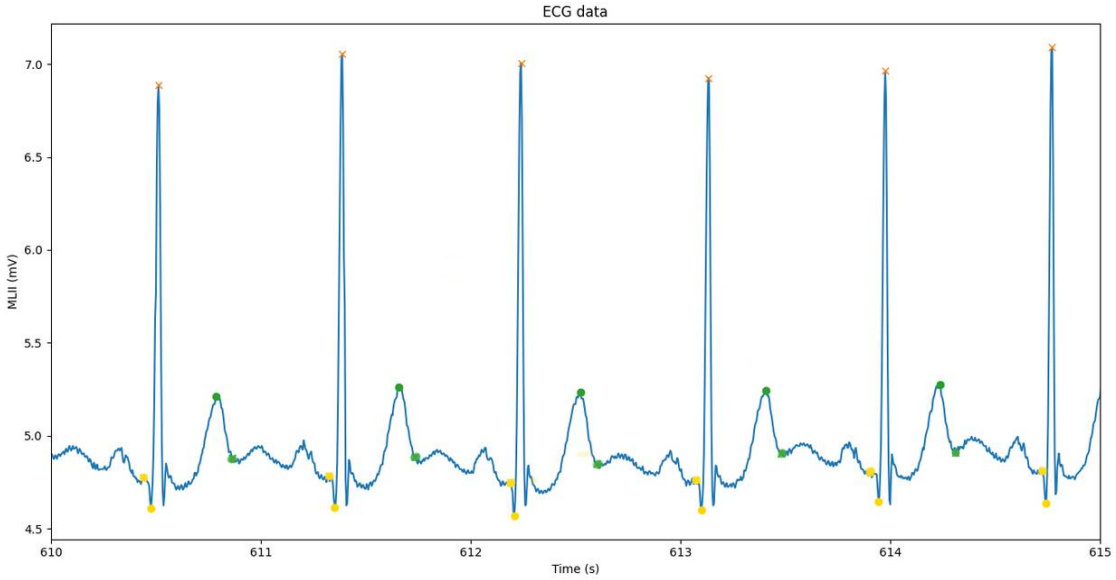

Figure 2. Results for patient SEL103.

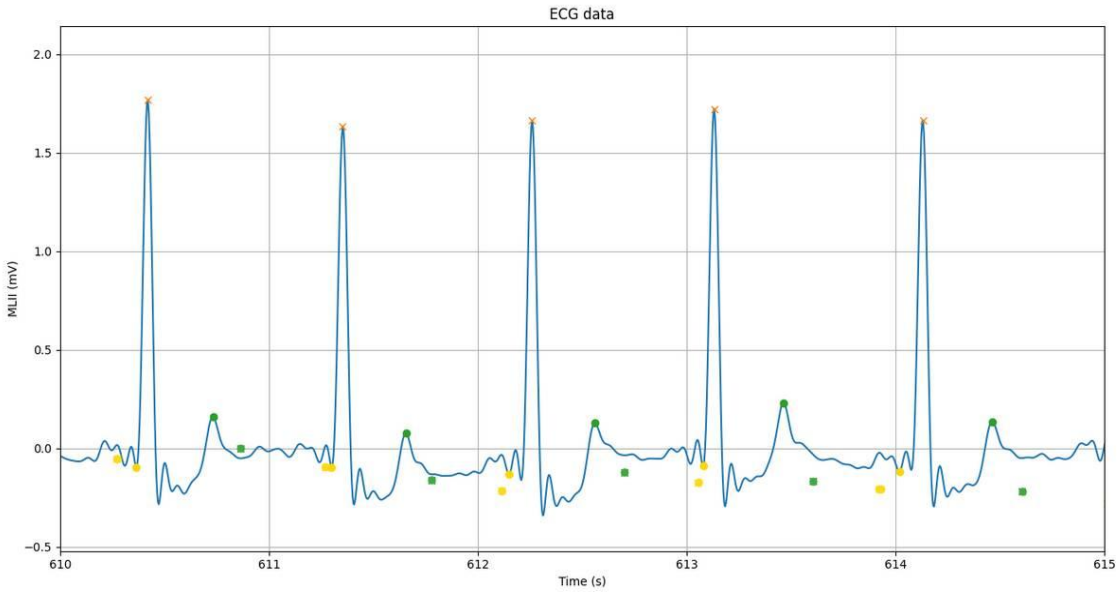

Figure 3. Results for patient SEL114.

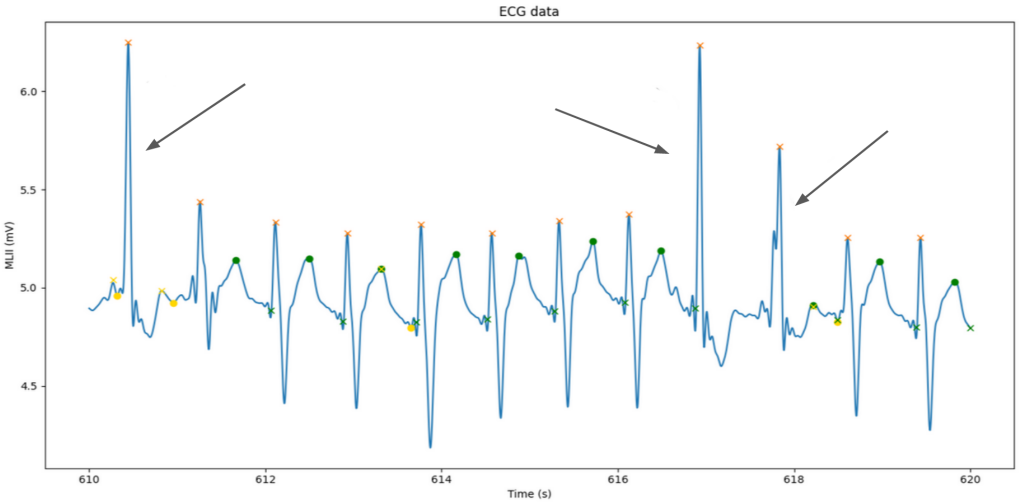

Figure 5. Results for patient SEL101, which is inaccurate due to non-uniform waves. Unusual waves are pointed by arrows

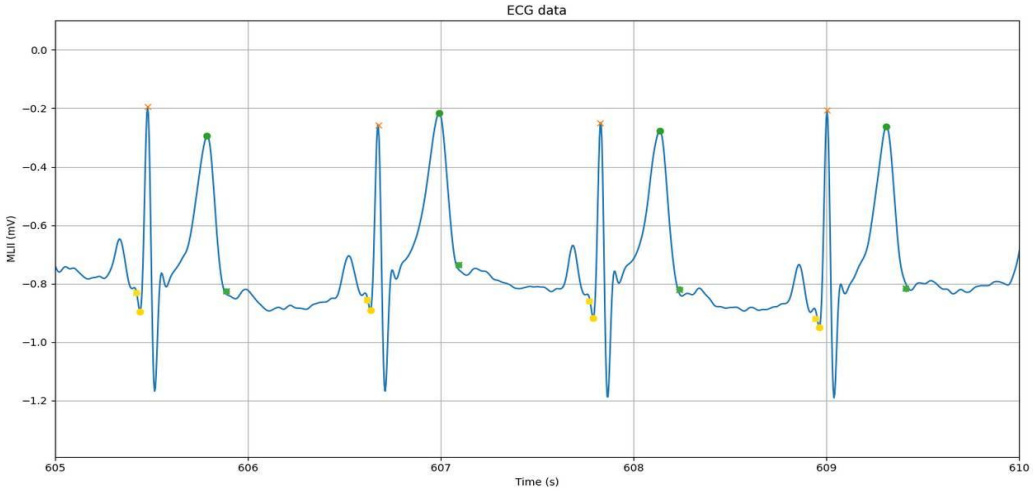

Figure 4. Results for patient SEL117.

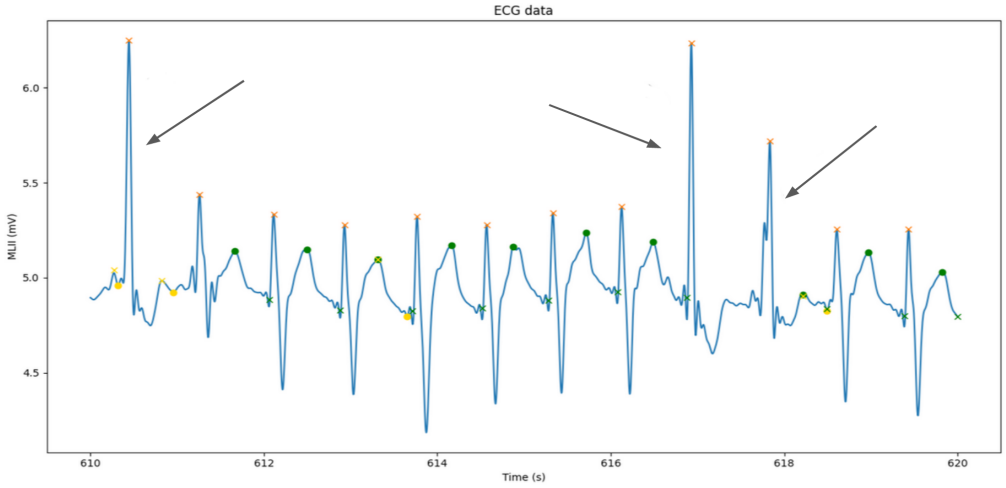

Figure 5. Results for patient SEL101, which is inaccurate due to non-uniform waves. Unusual waves are pointed by arrows.

In addition to irregular heartbeats, the filtering can introduce new issues into the detection algorithm. Figure 6 displays the raw data graph (red line) and filtered data (green line). The filter used is the lowpass butterworth's filter, utilizing a second-order applied forwards from the beginning of the dataset to the end and backwards from the end of the dataset to the start. Butterworth filter uses a certain limit and attenuates frequency higher than the limit to smooth out the graph (Mahata et al., 2018). SciPy could be used in this context to apply the filter and adjust it based on the amount of noise (Virtanen et al., 2019). While the use of a butterworth filter is done based on the paper from Ming et al. (2017), the application was not ideal. As seen from the graph, the location of the Q-wave peak, shown as dots on Figure 6, has shifted, introducing inaccuracies into the detection and measurement algorithm. As such, adjustments to the filtering system can be made in the future.

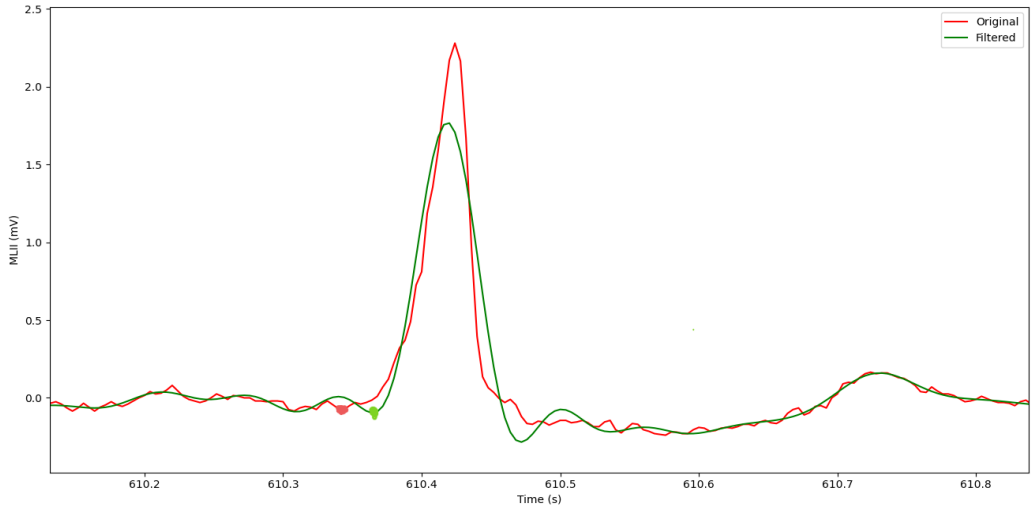

Figure 6. Comparison between filtered data and non-filtered data. Q-waves are represented by dots in each respective color.

In the future, an automated system can be used to detect whether or not an irregular system was detected and the algorithm was able to detect another type of CVD not associated with LQTS. in addition, further development can be made for automated adjustment of the system to allow for automation between patients.

CONCLUSION

In conclusion, the algorithm utilizes peak detection as a method to find the different waves needed to calculate the QT interval. The algorithm is able to identify the start and end of the QT interval with relative accuracy in ideal scenarios. Several main limitations of the algorithm include irregular waveforms due other CVD and the filtering system introducing inaccuracies. In the future, a study may be done to incorporate detention systems with other the algorithm to assist in diagnosing irregular patterns in the ECG graph.

REFERENCES

Arquilla, K., Webb, A., & Anderson, A. P. (2020). Textile Electrocardiogram (ECG) electrodes for wearable health monitoring. Sensors, 20(4), 1013. https://doi.org/10.3390/s20041013

Beers, L., van Adrichem, L. P., Himmelreich, J. C. L., Karregat, E. P. M., de Jong, J. S. S. G., Postema, P. G., de Groot, J. R., Lucassen, W. A. M., & Harskamp, R. E. (2021). Manual QT interval measurement with a smartphone-operated

single-lead ECG versus 12-lead ECG: a within-patient diagnostic validation study in primary care. BMJ Open, 11(11), e055072. https://doi.org/10.1136/bmjopen-2021-055072

Birnbaum, Y., Rankinen, J., Jneid, H., Atar, D., & Nikus, K. (2022). The Role of ECG in the Diagnosis and Risk Stratification of Acute Coronary Syndromes: an Old but Indispensable Tool. Current Cardiology Reports, 24(2), 109–118. https://doi.org/10.1007/s11886-021-01628-7

Cardiovascular diseases. (2019, June 11). Cardiovascular diseases. https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1

Feather, A., Randall, D., & Waterhouse, M. (2020). Kumar and Clark's Clinical Medicine E-Book (10th ed.). Elsevier.

Finocchiaro, G., Papadakis, M., Dhutia, H., Zaidi, A., Malhotra, A., Fabi, E., Cappelletto, C., Brook, J., Papatheodorou, E., Ensam, B., Miles, C., Bastiaenen, R., Attard, V., Homfray, T., Sharma, R., Tome, M., Carr-White, G., Merlo, M., Behr, E. R., . . . Sharma, S. (2018). Electrocardiographic differentiation between 'benign T-wave inversion' and arrhythmogenic right ventricular cardiomyopathy. *Europace*, *21*(2), 332–338. https://doi.org/10.1093/europace/euy179

Gibson, C. M., Mehta, S., Ceschim, M., Frauenfelder, A., Vieira, D., Botelho, R., Fernández, F., Villagran, C., Niklitschek, S., Matheus, C., Pinto, G., Vallenilla, I., Lopez, C., Acosta, M. I., Munguia, A., Fitzgerald, C., Mazzini, J., Pisana, L., & Quintero, S. (2022). Evolution of single-lead ECG for STEMI detection using a deep learning approach. *International Journal of Cardiology*, *346*, 47–52. https://doi.org/10.1016/j.ijcard.2021.11.039

Hampton, J., & Hampton, J. (2019). *The ECG Made Easy E-Book*. Elsevier Health Sciences.

Li, R., Zhao, X., Gong, Y., Zhang, J., Dong, R., & Xia, L. (2021). A new method for detecting myocardial ischemia based on ECG T-Wave Area curve (TWAC). *Frontiers in Physiology*, *12*. https://doi.org/10.3389/fphys.2021.660232

Mahata, S., Saha, S. K., Kar, R., & Mandal, D. (2018). Optimal design of fractional order low pass Butterworth filter with accurate magnitude response. *Digital Signal Processing*, *72*, 96–114. https://doi.org/10.1016/j.dsp.2017.10.001

Ming, L., Hao, H., Xiong, P., Lin, F., Hou, Z., & Liu, X. (2017). Constructing a guided filter by exploiting the Butterworth filter for ECG signal enhancement. *Journal of Medical and Biological Engineering*, *38*(6), 980–992. https://doi.org/10.1007/s40846-017-0350-1

Moody, G. B. (2022). PhysioNet. In Encyclopedia of Computational Neuroscience (pp. 2806-2808). New York, NY: Springer New York.

Serhani, M. A., Kassabi, H. T. E., Ismail, H., & Navaz, A. N. (2020). ECG Monitoring Systems: review, architecture, processes, and key challenges. *Sensors*, *20*(6), 1796. https://doi.org/10.3390/s20061796

Shah, S. R., Park, K., & Alweis, R. (2019). Long QT Syndrome: A Comprehensive review of the literature and Current evidence. *Current Problems in Cardiology*, *44*(3), 92–106. https://doi.org/10.1016/j.cpcardiol.2018.04.002

Steinberg, C. (2018). Diagnosis and clinical management of long-QT syndrome. *Current Opinion in Cardiology*, *33*(1), 31–41. https://doi.org/10.1097/hco.0000000000000465

Tiwari, A. K. (2021). Automatic detection of Q-T interval in ECG using MATLAB Tool.. https://doi.org/10.21203/rs.3.rs-970625/v1

Trappe, H. J. (2018). EKG-Befunde: Tipps und Tricks zur richtigen Diagnose. Herz, 43(2), 177–194. https://doi.org/10.1007/s00059-018-4684-4

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., . . . Vázquez-Baeza, Y. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature Methods, 17(3), 261–272. https://doi.org/10.1038/s41592-019-0686-2

Virtanen, P., Gommers, R., Burovski, E., Oliphant, T. E., Cournapeau, D., Weckesser, W., Alexbrc, Peterson, P., Mayorov, N., Van Der Walt, S., Wilson, J., Laxalde, D., Brett, M., Millman, J., Nelson, A., Haberland, M., Eric-Jones, Polat, I., Larson, E. B., . . . Vanderplas, J. (2019). scipy/scipy: SciPy 1.2.1. *ui.adsabs.harvard.edu*. https://doi.org/10.5281/zenodo.2560881

Wallace, E., Howard, L., Liu, M., O'Brien, T., Ward, D., Shen, S., & Prendiville, T. (2019). Long QT Syndrome: genetics and future perspective. *Pediatric Cardiology*, *40*(7), 1419–1430. https://doi.org/10.1007/s00246-019-02151-x