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A faster approach to ECG analysis in emergency situations

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10-06-2020

Contents

1. Introduction

In this Chapter we present our abstract. We then describe how the ECG works and its importance in detecting various heart diseases and anomalies, and then we explore current state of the art ECG taking methodologies and devices.

1.1 Abstract

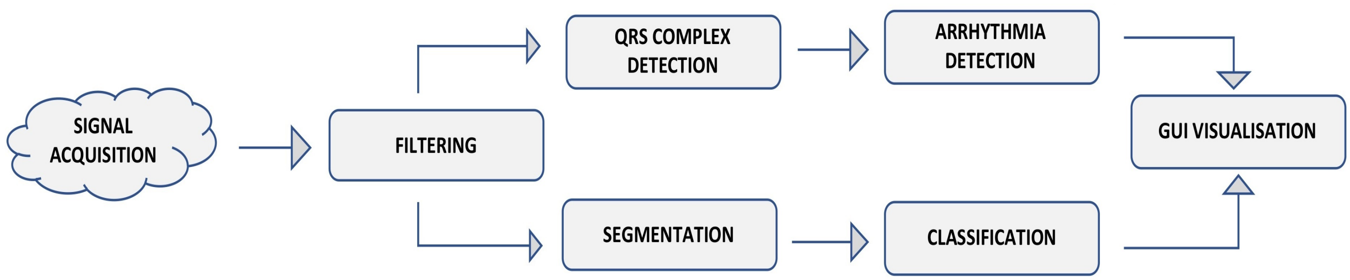

Figure 1.1: Flow chart of the project

Every day, a substantial number of people need to be treated in emergencies and these situations imply a short timeline. Especially concerning heart abnormalities, the time factor is very important. Therefore, we propose a full-stack system for faster and cheaper ECG taking aimed at paramedics, to enhance Emergency Medical Service (EMS) response time. To stick with the golden hour rule, and reduce the cost of the current devices, the system enables the detection and annotation of anomalies during ECG acquisition. Our system, as shown in Fig. 1.1, combines Machine Learning and traditional Signal Processing techniques to analyze ECG tracks, with the future objective of integrating it into a glove-like wearable. Finally, a graphical interface offers a dynamic view of the whole procedure.

1.2 Backgroud

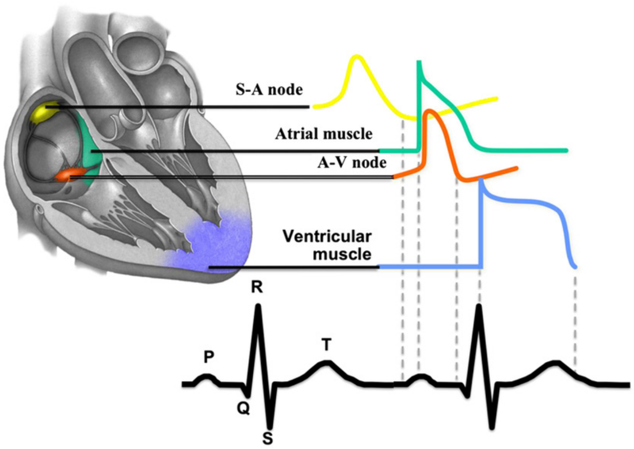

Figure 1.2: Electrical activity of the heart

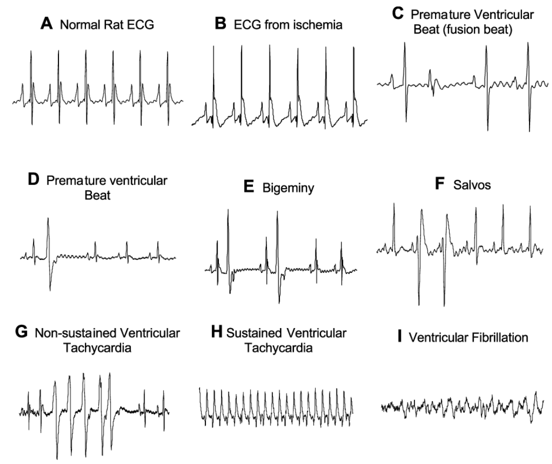

Figure 1.3: Common anomalies revealed in the ECG

Heart Diseases and, in particular, Cardiovascular Diseases (CVDs) are the number one cause of death globally [2]. Among the most common disorders are heart attacks and strokes, which occur when blood is blocked from flowing into the heart or the brain. The concept of "golden hour", first coined by R Adams Cowley [16], applies to such diseases. It refers to the critical time which occurs after an injury or traumatic event has happened in which the likelihood of preventing death through proper care is the highest. Great effort is put into improving intensive and immediate care to lower fatalities. The approach taken in recent years is to have a pre-evaluation of the ST-Elevation Myocardial Infarction (STEMI) [20] patients on-site using electrocardiogram (ECG) monitoring systems, to direct the ambulance to a Hospital where a primary percutaneous coronary intervention [18] (PCI) is available. Interpretation of the ECG requires an understanding of the fundamental structure of the heart and its electrical signals.

The ECG consists of a view of the electrical activity of the human heart taken at 12 different angles. The electrical activity of the heart is a reflection of the contraction of its parts, from the Sino-Atrial node to the ventricular muscle, as shown in Fig. 1.2. A wide range of problems can affect the production and the propagation of the electrical signal, resulting in an offset of parts of the wave or in alterations of its shape. Analysis of the ECG can give precious information for monitoring and detecting abnormal situations, namely rhythm disturbances or arrhythmia, heart block, electrolytes disturbances and intoxication, ischemia and infarction, or structural problems. The main objective is to obtain useful information about the activity of the heart.

ECG signal in emergencies is usually taken using 10 electrodes, providing a view of the heart from 12 different angles [7]. Studies like the one made by Gordon E. Dower [5] have shown that it is possible to obtain the same 12 views of the heart using a reduced number of electrodes with the EASI placement of the electrodes (E, A, and I from the Frank lead system plus S positioned over the upper end of the sternum) [7] [21]. The reduction of the number of leads results in a faster placement of the gel-coated electrodes for the paramedics. Therefore, one of the most relevant challenges in computer science and medicine is how to properly combine the field-specific knowledge to offer a better, more secure, and faster solution. This concept led to the development of several [9] [17] new devices aimed at detecting ECG making use of a reduced number of electrodes, with vast experimentation on the positioning of the sensors, and to the application of computationally intensive methods for signal analysis in the biomedical field. Many of these methods fall under the wide spectrum of Machine Learning, in which statistical methods are used to progressively improve the ability of a computer program to recognize patterns in data [11]. This approach is often used in classification tasks, where data has to be categorized and recognized.

The main contributions of this work can be summarized as follows:

- Development of a model combining Machine Learning and traditional Signal Processing for ECG analysis and anomalies detection.
- Exploration of the reduction of electrodes in emergencies.
- Design of a dynamic interface as a support for medical personnel.

1.3 Releted Work

Figure 1.4: LIFEPAK 12

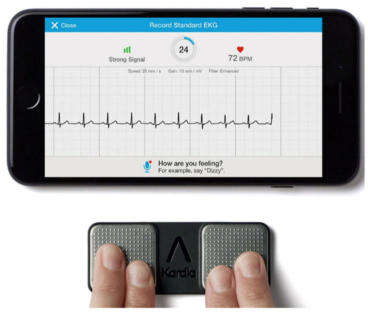

Figure 1.5: KardiaMobile

Figure 1.6: PhysioGlove

Electrical signal acquisitions from the heart were first recorded in 1872 [3]. The state of the art has thus seen a lot of changes over time, regarding both the physical and the analytical part. Initially, the ECG was taken using only three leads [23]. Later on, thanks to the introduction of the precordial and the augmented unipolar limb leads [8] medics were able to obtain the 12-lead ECG which in 1954 was recognized by the American Heart Association as the standard [24]. Looking at Italy, in hospital environments, Cardioline and Nihon Kohden are the go-to for the professional acquisition of 12-leads ECG signal. In pre-hospital environments, especially in emergencies, the choice is limited mainly to the PhysioControl LIFEPAK 12/15 (Fig. 1.4) and the Mortara ELI10. New developments have taken place in the hardware area, mainly regarding portability. Small devices, such as the AliveCor KardiaMobile [9] (Fig. 1.5), allow for self-taking of ECG signal, but they are limited in the number of views obtained. For this reason, they provide just basic diagnoses, such as Atrial Fibrillation [22]. Another solution is the PhysioGlove by Commwell [17] (Fig. 1.6), a reusable 12-lead ECG acquisition system implemented in a glove that is designed to be worn by the patient.

Given the different possibilities of acquisition systems, big steps have been made also in ECG signal analysis, among which is the employment of Machine Learning. Most approaches are based on classical Machine Learning models such as K-Nearest-Neighbors and Decision Forests [12]. Artificial Neural Network (ANN) based solutions have started to emerge. ANNs often perform better and require fewer data preprocessing compared to traditional solutions. For example, Convolutional Neural Networks have been used in ECG analysis to unify feature extraction and data analysis into a single model [13]

2. Methodology And Implementation

In this Chapter we shortly describe the tools we used to build this project and the general structure of the codebase. We then describe in detail the thought process behind every design choice, indicating the solution we adopted.

2.1 Tools

A first version of the project was built using the Matlab framework. While having a wide number of supported tools at the developer's disposal, it lacked flexibility and, more importantly, a Machine Learning framework which is up to date and able to compete with the current state of the art. Furthermore, we felt that having to depend on Mathworks' licence could become a limitation in the future. That's why our choice fell onto the Python language and its plethora of open source libraries and frameworks. We were able to use powerful and documented tools like Numpy and ScyPy for data manipulation, HeartPy for heartbeat analysis, TensorFlow and Keras to develop our Machine Learning models, and Matplotlib for data visualization. Our choice of a GUI framework fell onto Qt and its easy to use tools which, albeit being proprietary, are offered in an LGPL licensed version.

2.2 Project Structure

Usage The main folder of the project contains a Python script used to launch the main program. Dependency installation is handled through the pipenv package tool, which allows for the easy creation of Python virtual environments by defining a Pipfile. The project is publicly available here. Further instruction are in the project's readme file.

Contents The entire project is defined as a Python package called `pynomalous`. Its contents are as follow:

- **gui** contains the main launcher for the graphical interface and contains all widget definitions
- **learning** contains all utility function to generate and train the neural networks and to make predictions
- **miscellaneous** contains helper functions to handle retrival of notes definition and of data files
- **signals** contains all code relative to importing data from Physionet, converting data, create the datasets and analyze the ECG for bradycardia and tachycardia

All main functions are commented using docstrings and integrate with Python's `help` command.

2.3 Dataset selection

The first step to develop our anomaly detection system was to select a dataset to train Machine Learning models. This choice is crucial, as many and diverse samples are needed for a Machine Learning model to generalize on new data, and annotations are needed for training a neural network for a classification task. Our final decision fell onto the St. Petersburg dataset from the PhysioNet database [1]. It is a set composed of 75 12-leads 30 minutes long segments extracted from 32 holter records. The original records were collected from patients undergoing tests for coronary diseases. The annotations in the dataset were produced by an automatic algorithm and then manually corrected, and indicate the type of anomaly and its time signature relative to the ECG. The annotations appearing in the St. Petersburg dataset are normal beat, left bundle branch block beat, right bundle branch block beat, atrial premature beat, supraventricular premature or ectopic beat, premature ventricular contraction and R-on-T premature ventricular contraction.

2.4 Data preparation

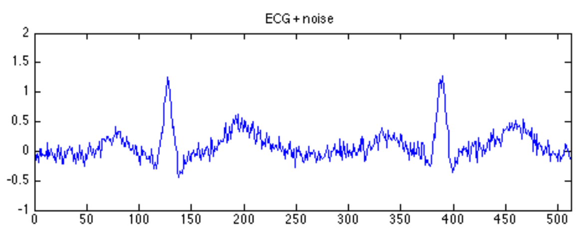

Figure 2.1: Unfiltered ECG signal

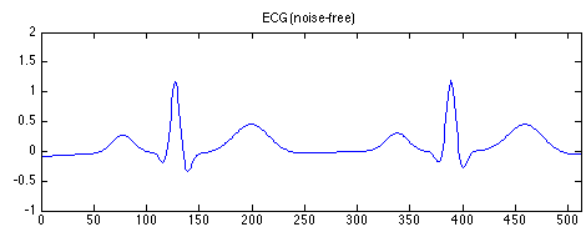

Figure 2.2: Processed ECG signal

Data Filtering The reference unfiltered dataset has two main problems: baseline shift, caused by involuntary movements of the patient, and high-frequency noise, which accompanies every electrical measurement. These issues were solved using a bandpass filter, which removed both the low-frequency baseline shift and the high-frequency noise, retaining only the meaningful part of the data. The SciPy package offers a convenient way of building finite filters designed using the window method by specifying the filter's size and the cutoff frequency. The filter was then applied on the signals with a convolution operation.

Data Segmentation We wanted to identify the category of disturbance present in short segments of signal. One method to achieve this is to construct a multi-classification network which, however, requires the classes to be mutually exclusive. Since more anomalies can show up in the same segment, we decided to develop a solution based on training a binary classifier for each class. We extracted 2 second long ECG samples from the raw data, labeling each with the anomalies it contained, including a special label in case of normal heartbeat. We then composed the segments into our datasets, one for each anomaly. Every dataset was thus composed of *"ill"* samples, each made of the segments containing a specific anomaly, and *"sane"* samples, each made of segments which did not contain any trace of the specific anomaly, but that could contain all other anomalies together with normal beats. This allows the single binary classifier to recognize the presence of a generic anomaly as well as the specific type of anomaly. If classes are not balanced Machine Learning models tend to just learn to recognize every sample as the most common class. This problem falls in the category known as overfitting. We solved it by undersampling the most common class in every dataset. The different availability of anomalies in the St. Petersburg dataset reflected in the size of the dataset for each anomaly. The biggest dataset was the one related to Premature Ventricular Contraction with 12800 samples, followed by the Atrial Premature Beat dataset with 3600 samples. Every dataset was split into training, validation, and testing using a 70-15-15 ratio. The data was imported into Python using Physionet's wfdb-python package, which allows for easy conversion between the dataset's format and Python data objects. All datasets are saved as numpy arrays for easy retrival and manipulation.

2.5 Machine Learning

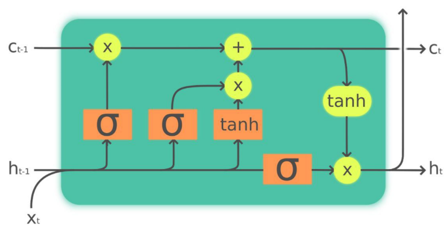

Figure 2.3: LSTM cell

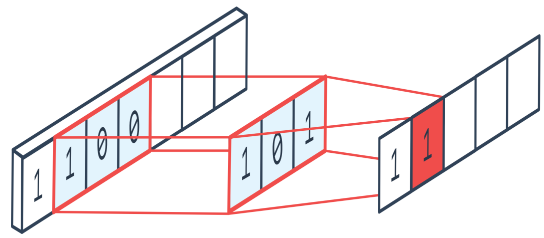

Figure 2.4: 1D convolution

We evaluated several different neural network architectures for our project. Because of the approach we chose to perform multi-classification analysis of data, we had to train a distinct neural network to distinguish between the presence or absence of every single anomaly. Our first choice fell onto Short-Term Memory (LSTM) [10]. Such architecture is particularly well suited for processing sequences of data [6], and ECG signals in particular [4] [19]. The architecture of the neural network we developed makes use of the LSTM architecture to analyze and extract information from the sequences of readings that make up the ECG segments. The output of the LSTM layers is passed to a dense network, which reduces its dimensions to two and makes possible the classification through a softmax function. The structure of the network is made up of three consecutive LSTM layers with 32 hidden neurons, followed by two fully connected layers of size 16 and 2. While the LSTM layers are fed the entire sequence, only the last activation is passed to the fully connected layers. Every neural network was trained on its dedicated training set using the ADAM policy for 10 epochs with a batch size of 128 and using the accuracy as minimization criteria. At inference time the ECG segment is analyzed by all neural networks. We created our RNNs using various MATLAB libraries (Parallel, Signal Processing, Deep Learning). For our second successful attempt we migrated to open source platforms, in particular Python and Google's TensorFlow which, compared to Matlab's integrated solution, offers a wider range of neural network layer architectures and provides greater flexibility in combining those into Machine Learning models. Convolutional neural network are the state of the art for a wide number of tasks. Their main application is in the analysis of 2D images [14], although it has proven itself capable of performing 1D signal analysis as well, and in particular it has already been successfully used for the analysis of ECG signals [15]. The architecture is composed of three Conv1D layers, each followed by max pooling and a ReLU activation function and two dense layer. A softmax function is used to convert the final 2 activations into probability values. Each network was trained for 10 epochs with batch size 32, using the rmsprop optimizer and using the categorical cross entropy as loss function. Training was done on an NVIDIA GTX 1050Ti GPU for hardware acceleration.

2.6 Signal Analysis

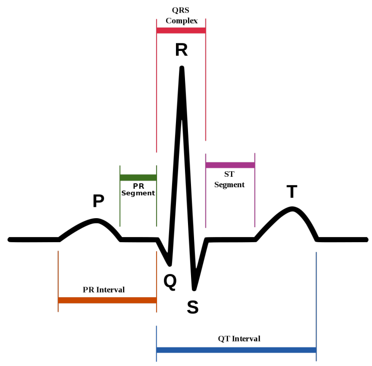

Figure 2.5: Naming of the different parts composing an ECG beat

As can be seen in Fig. 1.1, signal processing is the approach we chose to detect QRS Complex positions, Tachycardia and Bradycardia. Signal processing is used to identify specific points in the wave, called QRS complexes, that are associated with each beat Fig. 2.5. The algorithm detects R peaks and then calculates the average BPM using the distance between them. It takes as input the first derivation of a 12 lead ECG signal and transforms it into a binary signals, indicating the presence or the absence of an R peak. Then the algorithm counts the number of R peaks in the interval that it is analyzing (n_p) and calculates the distance between the first and the last peak (d_p). The algorithm calculates the BPM trend using the formula:

$$BPM = 60 \cdot \frac{f_s \cdot n_p}{d_p}$$

where f_s is the sampling rate. Using the output of this algorithm we were able to detect Tachycardia and Bradycardia by considering both the age of the patient and the trend of the BPM value. Our algorithm detects Tachycardia and Bradycardia following the guidelines from the U.S. National Library of Medicine.

2.7 GUI

Figure 2.6: Default interface

Figure 2.7: Anomalies plot

The final part of our system is the GUI, which was designed to be easy to use and to display the results obtained using our solution to doctors and other users. To develop it we used Qt tools for a clean and simple interface. Qt is a widely used cross-platform framework which offers tools and libraries to create rich graphical user interfaces. GUI development in Qt revolves around the creation of standalone widget that can be composed in more complex structures. QtDesigner is a WYSIWYG tool that can aid the creation of interfaces which easily integrates with user defined widgets and helps speed up GUI development. The idea behind our GUI was to have a main page where the user could see a general ECG trend of the whole measurement and have a clear vision of anomalies found in the track. A second page (accessible by clicking on the buttons of the anomalies) was used to display only the samples found to contain anomalies. Although functional, we decided to show the resulting GUI of the Matlab implementation as it resulted in cleaner design in Figures 2.6 and 2.7. An operating example of the most significant components of our interface is visible in Fig. 2.6, where you can see four panels that graphically shows the progress of the ECG where anomalies were found and 10 buttons that take on different colors depending on the frequency of detection of the specific anomaly within the track.

3. Experimental Results

Table 3.1: Table of accuracy results

Anomaly	Accuracy
Premature Ventricular Contraction	0.996
Atrial Premature Beat	0.958
Fusion of Ventricular and Normal Beat	0.885
Supraventricular Escape Beat	0.767
Nodal (Junctional) Escape Beat	0.983

Our signal analysis software uses two simultaneous approaches: Machine Learning and Signal Processing. Regarding the performance of the neural network, we obtained varying results. We managed to improve them through filtering the data, improving the segmentation algorithm, and experimenting with different Neural Network structures, in particular the switch from a Recurrent Neural Network to a Convolutional Neural Network. The final results come from the evaluation of the performance of the predictive models on the respective test datasets. We believe that the performance of the Machine Learning model is strictly related to the availability of data regarding the specific anomalies, as all of the metrics we used showed the same descending trend as the number of available samples decreased. We observed clear signs of over-fitting in the machines trained to recognize anomalies that were not present in large quantities (<1000 samples) in the data-set. Table 3.1 shows the results in terms of accuracy of the 3 most common anomalies in the dataset, detected with a Machine Learning approach. The levels of sensitivity and specificity reached above 95% for the most common anomalies, progressively lowering as the availability of data decreased. We observed 99,8% accuracy in detecting tachycardia and bradycardia, in line with the traditional state of the art signal analysis methods. Those two approaches are then combined in a simple-to-use interface (GUI visualization).

4. Conclusions

With this work, we have given first proof that a fast and dynamic approach in ECG taking is possible. The proposed solution will increase the comfort and ease of use for paramedics. It will be a cheaper alternative to commercially available products as it can analyze an ECG trace taken in a short time detecting a significant number of anomalies. Ideally, our future developments will focus on developing a glove which fully supports EASI placement that, in combination with our analysis system, will form a complete product and then obtaining a bigger and richer dataset to work with. Finally, creating a custom loss function for the neural network to give more weight to false negatives and less on false positives.

Our work was also accepted as a full contributed paper for the annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).

5. Special Thanks

We would like to thank Eleonora D'Arnese and Marco D. Santambrogio for their continuous support to this project.

Bibliography

[1] St petersburg incart 12-lead arrhythmia database. https://physionet.org/content/incartdb/1.0.0/. Accessed: 2020-06-10.

[2] World health organization - cardiovascular diseases (cvds). https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds). Accessed: 2020-01-13.

[3] RM Birse and Knowlden PE. Muirhead, alexander (1848–1920), electrical engineer. *Interactive Factory*, 2004.

[4] Sucheta Chauhan and Lovekesh Vig. Anomaly detection in ecg time signals via deep long short-term memory networks. In *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, pages 1–7. IEEE, 2015.

[5] Gordon E Dower, Andrew Yakush, Sami B Nazzal, Roy V Jutzy, and Cynthia E Ruiz. Deriving the 12-lead electrocardiogram from four (easi) electrodes. *Journal of electrocardiology*, 21:S182–S187, 1988.

[6] A Graves M Liwicki S Fernandez, R Bertolami H Bunke, and J Schmiduber. A novel connectionist system for improved unconstrained handwriting recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(5), 2009.

[7] Francis M Fesmire, Robert F Percy, Jim B Bardoner, David R Wharton, and Frank B Calhoun. Usefulness of automated serial 12-lead ecg monitoring during the initial emergency department evaluation of patients with chest pain. *Annals of emergency medicine*, 31(1):3–11, 1998.

[8] Emanuel Goldberger. A simple, indifferent, electrocardiographic electrode of zero potential and a technique of obtaining augmented, unipolar,extremity leads. *American Heart Journal*, 23(4):438–492, 1942.

[9] Julian PJ Halcox, Kathie Wareham, Antonia Cardew, Mark Gilmore, James P Barry, Ceri Phillips, and Michael B Gravenor. Assessment of remote heart rhythm sampling using the alivecor heart monitor to screen for atrial fibrillation: the rehearse-af study. *Circulation*, 136(19):1784–1794, 2017.

[10] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[11] Nir Kalkstein, Yaron Kinar, Michael Na'aman, Nir Neumark, and Pini Akiva. Using machine learning to detect problems in ecg data collection. In *2011 Computing in Cardiology*, pages 437–440. IEEE, 2011.

[12] Nir Kalkstein, Yaron Kinar, Michael Na'aman, Nir Neumark, and Pini Akiva. Using machine learning to detect problems in ecg data collection. In *2011 Computing in Cardiology*, pages 437–440. IEEE, 2011.

[13] Serkan Kiranyaz, Turker Ince, and Moncef Gabbouj. Real-time patient-specific ecg classification by 1-d convolutional neural networks. *IEEE Transactions on Biomedical Engineering*, 63(3):664–675, 2015.

[14] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

[15] D. Li, J. Zhang, Q. Zhang, and X. Wei. Classification of ecg signals based on 1d convolution neural network. In *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)*, pages 1–6, 2017.

[16] Wendalyn K Little. Golden hour or golden opportunity: Early management of pediatric trauma. *Clinical Pediatric Emergency Medicine*, 11(1):4–9, 2010.

[17] Alan Naditz. Commwell physioglove. *Telemedicine and e-Health*, 15(5):490–491, 2009.

[18] Brahmajee K Nallamothu, Elizabeth H Bradley, and Harlan M Krumholz. Time to treatment in primary percutaneous coronary intervention. *New England Journal of Medicine*, 357(16):1631–1638, 2007.

[19] Shu Lih Oh, Eddie YK Ng, Ru San Tan, and U Rajendra Acharya. Automated diagnosis of arrhythmia using combination of cnn and lstm techniques with variable length heart beats. *Computers in biology and medicine*, 102:278–287, 2018.

[20] Ph Gabriel Steg, Stefan K James, and Bernard J Gersh. 2012 esc stemi guidelines and reperfusion therapy: Evidence-based recommendations, ensuring optimal patient management. *Heart*, 99(16):1156–1157, 2013.

[21] Gabriele Wehr, Ron J Peters, Khalifé Khalifé, Adrian P Banning, Volker Kuehlkamp, Anthony F Rickards, and Udo Sechtem. A vector-based, 5-electrode, 12-lead monitoring ecg (easi) is equivalent to conventional 12-lead ecg for diagnosis of acute coronary syndromes. *Journal of electrocardiology*, 39(1):22–28, 2006.

[22] Jonathan Williams, Keith Pearce, Ivan Benett, J Williams, M Manchester, K Pearce, and I Benett. The effectiveness of a mobile ecg device in identifying af: sensitivity, specificity and predictive value. *Br J Cardiol*, 22(2):70–72, 2015.

[23] Frank N Wilson, Franklin D Johnston, Francis F Rosenbaum, and Paul S Barker. On einthoven's triangle, the theory of unipolar electrocardiographic leads, and the interpretation of the precordial electrocardiogram. 1946.

[24] Frank N Wilson, CHARLES E KOSSMANN, GEORGE E BURCH, EMANUEL GOLDBERGER, ASHTON GRAYBIEL, HANS H HECHT, FRANKLIN D JOHNSTON, EUGENE LEPESCHKIN, and GORDON B MYERS. Recommendations for standardization of electrocardiographic and vectorcardiographic leads. *Circulation*, 10(4):564–573, 1954.