Towards Automatic Pathology Classification for a 24/7 ECG-based Telemonitoring Service

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ABSTRACT

We present work in progress focusing on an extension of a 24/7 monitoring system for persons at cardiac risk, a system that allows patients to move freely in and outside of clinical settings. The system consists of a comprehensive sensor patch, a relay and a monitoring center staffed with clinicians and doctors. Detected anomalies may trigger escalation plans which include activating families, ambulances and clinics. In order for the system to scale up, we demonstrate how anomalies can be automatically detected using machine learning technologies. We describe and evaluate a classifier for detection of Ventricular Extrasystoles. The classifier has been tested on real-world sensor data as well as a standard ECG database and achieves varying recognition rates, depending on many factors. The next steps include an improvement of the detection algorithm, especially its training methods, and introducing the extension into the telemonitoring centre, thus evaluating the user acceptance amongst the cardio experts.

KEYWORDS

ECG monitoring, signal processing, machine learning, RandomForest

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1 INTRODUCTION

Cardiovascular disease (CVD) is the second-most expensive health condition in the western world. In Europe alone, CVD causes 3.9 million deaths which corresponds to over 1.8 million deaths in the European Union (EU). This translates to 45% of all deaths in Europe corresponding to 37% of all deaths in the EU [2].

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Patient's desire to rather stay in their accustomed environment than in the hospital and the costs for the healthcare system accompanied thereby have been driving the development of computational methods in CVD diagnostics, such as prognostic risk scores to predict mortality and re-hospitalization rates in clinical environments, for example [46], [19], or [31]. It has been shown, however, that these models derived from fixed data sets, are often limited in their prediction value on new data [3]. Missing values are a common problem, as they expect certain demographic or medication information to be available, and their statistical background most often means they are concerned with stratifying over larger groups of patients. Therefore, their "reliability at the individual patient level is known to be very poor" [6].

In this paper, we present work in progress extending an innovative telemedical system that monitors individual patients with CVD-related risks. The system not only allows monitored patients to move around freely in their daily environments, but it also increases the degree of attention devoted to each patient. Because of the 24/7 character of the service in combination with living "a normal life", new insights into the field of CVD are possible.

Progression of CVD or the risk for a patient to develop such is reflected in the vital parameters [7]. The electrocardiogram (ECG) yields information about the electric activity of the heart. A normal heart cycle in the ECG is depicted in Figure 3. Origins and conduction pathways of the heart's electric self-stimulation can be approximated from the ECG but also their patterns reveal how critical a deviation from the normal heart cycle is. The ECG indicates life-threatening heart arrhythmias and enables a calculation of risk factors for CVD, such as low heart rate variability [9, 13] and high heart rates [10].

For detection of CVDs, other parameters such as changes in blood pressure [45] or - if the absolute blood pressure is known - cardiac output [47] can be derived from pulse wave measurements. Furthermore, it is important for interpretation of patterns to view vital parameters in connection with the patient's current physical activity, which can be regarded as a vital sign itself [25] and is measured with heat-related sensors, accelerometers or heart rate information [43].

The paper's core contribution is an extension of the existing technical setup. We suggest a machine learning approach for the detection of anomalies in the ECG. The extension supports the cardiac experts in that it automatically signals pathological patterns in the ECG, increasing the accuracy of the complete monitoring system and allowing for scaling up the system. As this stepwise addition is work in progress, we exemplify the approach in a proof of concept, the detection of ventricular extrasystoles (VES).

Figure 1: The electrical signals from the interchangeable electrodes connected to the patch (left picture) are removed from a medical device and powered by a battery pack. After filtering the signals, the communication device (left figure) transmits the data to a file server via GSM/Internet. There, data is stored for further processing. After the necessary calculations and transformations, the information is available for visualisation in a telemonitoring centre (right picture).

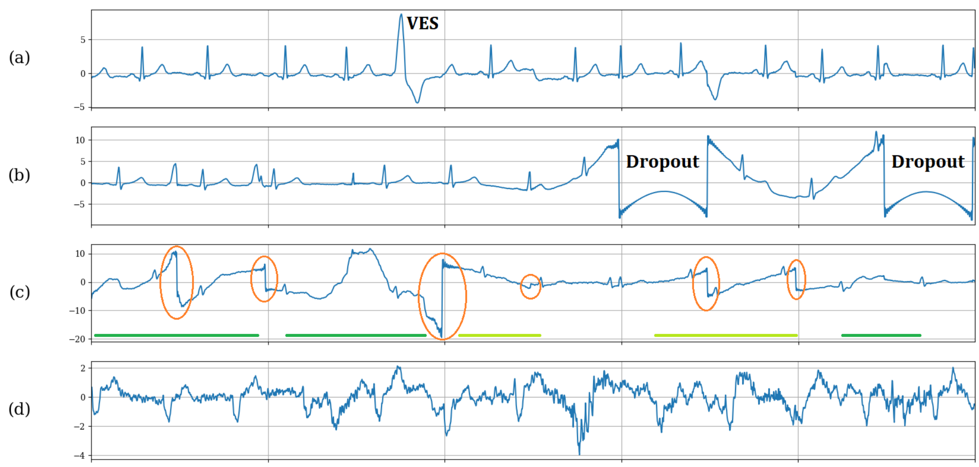

Figure 2: Excerpts from various ECG leads recorded from patients in everyday life with our wearable system: (a) Very clean signal with little to no artifacts, also note the heart beat of VES type, (b) dropouts, which are caused by the recording system internally or by bad skin contact of the ground electrode, (c) an electrode with bad skin contact, resulting in baseline drift and electrode-pop artifacts (orange: electrode-pops, dark green: baseline drift from bad skin contact, light green: filter-induced baseline resulting from artifact flanks), and (d) high frequency noise from electric muscle activity, possibly during body movement or shiver.

2 RELATED WORK

If an ECG reveals several VESs, they will either all originate in the same cell compound of the heart muscle (unifocal) or their exact origin in the tissue will vary (multifocal). VESs may occur in the healthy human without any significance, but in patients with a medical history or if present in certain ECG patterns their morphology indicates cardiac risks and emergencies like ventricular fibrillation or digoxin toxicity [21]. Furthermore, higher risk for stroke [1] and death [4] was reported for patients with frequent VESs.

ECG patterns of the same type of arrhythmia highly vary between- but also within-subject. Furthermore they can be corrupted by artifacts, which especially occur during movements in a stress test or similar situations. Therefore, sparse availability of ECG data poses a significant problem to generalize research findings and algorithms on a certain arrhythmia between-patients.

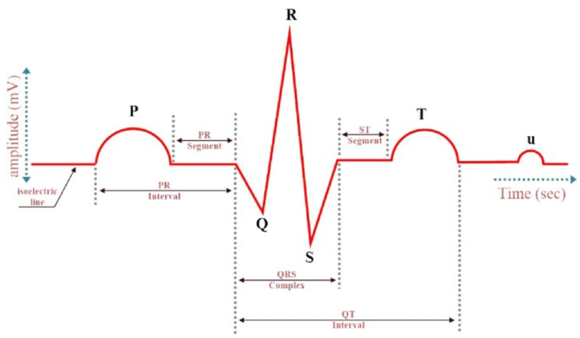

Figure 3: Schematic depiction of the ECG showing a normal heart cycle. The P wave and the heart beat represented by the QRS complex are the impulse for contraction of the atrium and ventricles respectively [12], followed by the T and U wave, which show repolarization of the heart muscle and stimulus conduction system [12, 40].

2.1 Databases

To develop ECG classifiers, either recordings with annotations for every heart beat must be collected from patients, who exhibit the arrhythmia, or a database with public access can be used. In the latter case, the most popular might be the MIT-BIH Arrhythmia database [15, 33], recorded late in the 1970s. This database comprises 30 minutes of 2-channel recordings collected from 48 CVD patients having several kinds of diseases, and its records are fully annotated by two or more independent cardiologists.

The MIT-BIH Arrhythmia database can efficiently be used for validation purposes, but this limited resource is not suitable for a data-driven design of machine learning algorithms. Other approaches are to merge several databases to one bigger corpus [23, 28]. The algorithms must then be able to manage a corpus with imbalanced sets of ECG leads.

2.2 VES Detection

Machine learning methods such as support vector machines, linear discriminant analysis, k-nearest-neighbours, mixture of experts, Bayesian networks, Hidden Markov Models and decision trees are found to be commonly applied in ECG classification tasks [41]. Progress in the field of neural networks in recent years has drawn a lot of attention towards deep learning for ECG classification [41]. Li et al. [23] have reported an accuracy of 0.9943 using convolutional neural networks for detection of VES. Autoencoders also are a type of neural networks and can be used to produce a feature map, which is then classified using softmax regression [48] or a random forest classifier [16].

The lack of training data puts the use of neural networks for beat classification into question. The mentioned studies trained their classifiers only on the MIT-BIH Arrhythmia database [16, 48] or on multiple databases without resampling them to the same sampling rate [23]. Thus, for these classifiers generalization is problematic considering different VES morphologies between patients and also between ECG leads.

Robust and explainable features of VES are first and foremost ratios of the RR intervals to the surrounding heart beats [8, 14, 35] and QRS or R peak width [8, 35]. A missing P wave before the QRS complex is another important feature to medical experts. Automatic P wave detection yet remains problematic for complex abnormal ECG patterns [26, 27], since it commonly is based on heuristic windowing and thresholding [22, 28] and often algorithms are parameterized on normal ECGs and specific leads [22, 32].

Bayesian models were shown to reach high F1-scores of up to 0.98 in PVC classification [24]. This result must be viewed with respect to the training set. The authors used the MIT-BIH Arrhythmia and split their training and test sets after randomly mixing all input samples. To prevent from overfitting to a patient, the dataset should be separated by recordings.

Classification between several kinds of heart beats, all having abnormal QRS complexes, can be done to some extent training a neural network on the Teager-energy operator, which models the energy the underlying source needs to produce the signal [20]. Simple thresholding of this feature was proven to be useful for classification of VES against normal heart beats [42], but it can be assumed, that the thresholding rather classifies between normal and overall abnormal QRS complexes [20].

Park et al. [37] presented a review of algorithms, which are able to detect the location in the heart tissue, where VESs originated during idiopathic ventricular tachycardia. This form of tachycardia is not an emergency case [5], yet the localization of the VESs reveals the requirements towards signal analysis, also for more severe cases of a present VES. More precisely, due to anatomy, multilead ECG and a feature extraction robust against unrelated alterations of the heart tissue and electrode placement is needed [37].

3 SENSORS

Recordings of biosignals are typically corrupted by artifacts of various technical and physiological origins [11]. Electrode movement or electric activity from other physiological sources such as the muscles impose high demands to the sensors and signal processing to not cause misclassifications.

Artifacts from muscle contractions are commonly reduced by asking the patient to be relaxed and avoid movements. This holds for clinical treatment room settings [11] as well as for wearables such as the *Apple Watch 4* (Apple Inc., Cupertino, USA) [17, 18]. Also, a proper skin contact of the sensor is obligatory for sufficient signal quality. A selection of noisy ECG excerpts recorded with our wearable system is shown in Figure 2.

3.1 State-of-the-Art Technology

Electrodes for measuring surface potentials are placed either applying electrode gel or using dry electrodes. The gel has similar conduction properties as the skin tissue and prevents from air pockets, resulting in low electrode impedance. Drawbacks of the gel are skin irritation in long term measurements and possible allergic reactions from patients, while dry electrodes on the other hand might be perceived more comfortable. Up to date, gel electrodes are commonly preferred over dry electrodes, since they stick to the skin minimizing electrode movement and because of their lower impedance [29].

Increasing interest towards dry electrodes can be observed in recent years, since dry electrodes offer advantages in skin-friendliness

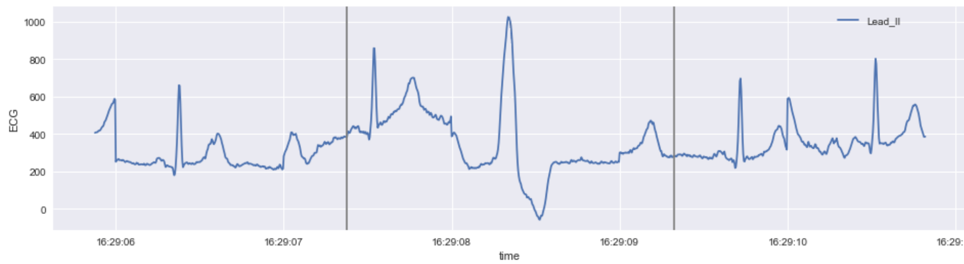

Figure 4: Excerpt of one ECG signal, showing a ventricular extrasystole in lead II. The vertical lines mark the beginning and end timestamps of the area labeled as VES in the training data. The extrasystole itself (here at the center of the annotation) is easily identified by its premature occurrence and deviating shape.

[30] and they can be implemented into some wearable technologies like watches more easily. Another trend of sensor research in patient monitoring is the integration into garment. Such textile electrodes may raise the acceptance of wearing sensors for long-term monitoring in everyday life, but also bear the detriment of wearout after a few washings and costly custom-tailoring to every new patient to obtain sufficient electrode-to-skin contact [39, 44].

3.2 Challenges for Wearables in Monitoring

The technical architecture of the presented portable system comes with a number of challenges that need to be addressed. The system is designed to allow the patient to freely move around and live his everyday life during ongoing measurements. Compared to long-term monitoring in hospitals where the patient is in a resting position, the signal quality is poor, particularly we face low signal-to-noise ratio. Artifacts occur due to dropouts in the data transmission. Electromagnetic fields introduce noise at the sensors. This is a reason for hospitals to ban mobile phones from intensive care units [29]. Additionally, movements of the patient lead to artifacts from muscle contractions and electrode movement. Despite this, algorithms have to robustly detect the QRS complex and other waveforms to deliver base data for classification algorithms. This is a non-trivial challenge, for instance, the state-of-art Pan-Tompkins algorithm [36] sometimes adapts to the artifacts and fails in adapting back to the signal in noise-free segments.

3.3 Our 24/7 Monitoring System

The monitoring system is a complex service consisting of a technical system which acquires, transfers and processes relevant signals along with human staff — cardio experts and doctors — who monitor a patient's sensor data.

The technical system is divided into two parts, see Figure 1: a patch with the medical device on the patient's chest and a communication device, essentially a 3G or WiFi communication module, for example a regular smartphone, which can be placed somewhere on the body. The dimensions and energy consumption of the medical device are very small, ensuring continuity of the data for more than 30 hours. The sensor setting within the medical device is based on known and standardised monitoring methods for non-invasive measurement of vital parameters and ECG from the human body surface. The ECG measures the electric activity of the heart and is carried out using standard disposable ECG electrodes. It is followed by a series of common preprocessing steps for denoising the signal, using firmware and software to visualise the signal for the healthcare professionals. All together, the system receives, processes and visualises biosignals from the patient, consisting of:

- ECG - up to 12 Wilson Channels (250 Hz)
- SPO2 (oxygen saturation) - Range 70% to 100%
- Breathing information
- Body temperature - accuracy 0.05 °C
- Trend of systolic and diastolic blood pressure
- Position and activity of the body

In case of anomalies and critical situations, the control centre will invoke an escalation plan that may, for instance, involve contacting relatives, calling an ambulance and preparing hospitals.

4 VES DETECTION

Given their relative distinctiveness in a typical ECG signal, classification of VES serves as a proof of concept for further, more complex pathologies.

4.1 Data

CheckPoint Cardio provided 15 anonymised ECG records with a sampling rate of 250 Hz, spanning 6 to 12 channels each, the shortest comprising just about 30 seconds and the longest almost six hours of data. The recordings were chosen for the occurrence of extrasystoles within them, with no further annotations regarding potential other anomalies. All records are annotated with start and end positions of VES, spanning over one or several heartbeats, as shown in figure 4. The mean duration of these annotations is 1.5 seconds, with about a thousand annotated ranges overall. In total, we detect 60034 heartbeats in the data, of which 1016 are marked as VES, that means about 1.7% of the signal are positive examples.

For additional evaluation, we used data from the MIT-BIH Arrhythmia database [33]. The records in this dataset each contain two 360 Hz channels which may differ from record to record. Two records could not be used: 102 and 104 which had to be left out because they were the only ones not containing a lead II signal used to derive amplitude-related features. For our purposes, the PVC annotation (Premature Ventricular Contraction) served as ground truth marker. Here, annotations are not stored as ranges containing extrasystoles, but single heartbeats are marked as PVC. In total, there are 7124 heartbeats derived as PVC from the used records, out of 105546 detected R peaks, that means about 6.7% of the signal are positive examples.

4.2 Preprocessing

The foremost indicator of a VES is a shortened RR interval in comparison to the normal pulse. Additionally, these premature QRS complexes can differ in size and shape from typical ones, they are usually larger and wider. This knowledge has been implemented for the derivation of meaningful classification features.

We abstract the individual samples to classification instances based on single heartbeats. Our QRS detection algorithm is based on the principles of the Pan-Tompkins algorithm and modified to be more robust against noise. The detector was tested on recordings from the MIT-BIH Noise Stress Test database [15, 34] with signal-to-noise ratios reaching from -6 to 24 dB. Our detector outperformed our basic implementation of the Pan-Tompkins algorithm, as well as QRS detectors from the WFDB package provided via PhysioNet [15, 32], namely ecgpuwave, gqrs, sqrs and wqrs.

Individual heartbeats make up the classification instances, with every detected R peak regarded as the focal point of a beat spanning a fixed amount of time (600 ms to the left and 500 ms to the right). Ground truth is derived from the annotations. In case of VES ranges, a heartbeat is a positive instance if most of its samples lie within the range annotated as VES. In case of single samples marked as PVC, a heartbeat is a positive instance if it contains the sample marked as PVC near the detected R peak.

After some experiments, the number of features could be reduced by eliminating redundant or useless information. Candidates have been identified by studying which features the classifiers found useful and which ones correlate with each other and/or the target variable.

Amplitude-based Features As the value ranges even of the same ECG channel between different datasets can differ, working with absolute values proves difficult when using the amplitude of the signal as a feature. We thus derive local relative values in order to detect heartbeats of deviating size. From each instance, lead II's relation between its maximum amplitude and mean amplitude is derived as feature AMPMAX, as well as MAXFROMMEAN, the largest difference in either direction between any sample and the heartbeat's mean amplitude. These values target the property of VES to show a shape different to that of regular QRS complexes.

R-peak-based Features From each heartbeat, first its RRD is computed, its R peak's distance to the previous R peak in seconds, and used to derive further features, namely the relation of the heartbeat's RRD to the RRD mean over the record and to the previous heartbeat's RRD. These features aim to identify shortened RR intervals in comparison to a regular pulse.

4.3 Classification

For classification, a RandomForestClassifier as provided by the scikit-learn package [38] is trained on the derived features. We use 75 estimators and leave the remaining options at the default values.

A Random Forest offers the advantage that its inner workings can be inspected and understood quite easily, for example it can provide information about which features are most important for its classification decision. This is helpful when selecting features, but also to explain what the model is looking for in the data, satisfying the recent demand of explainable AI, especially in medical contexts.

Unsurprisingly, the most useful features identified by the classifier rely on the RRD, confirming the expectation that extrasystoles are most easily identified by a shortened RR distance.

4.4 Evaluation

For evaluation, a custom leave-one-record-out technique has been implemented in which the classifier is trained on all but one records in one database and tested on the remaining one each time. This is done to ensure that a classifier trained on a collection of records can be used to detect VES even in data from a previously unseen record. For each of the experiments, a confusion matrix and further evaluation metrics are derived. In the end, these findings are combined into a complete report. Additionally, a cross-test between both databases has been performed, training on all records of one and testing on all of the other. The confusion matrices for all experiments are shown in figure 5.

The evaluation results vary strongly between different databases and even records. The best results are achieved when training on the MIT-BIH Arrhythmia data and applying the classifier to the CheckPoint Cardio data, with almost no misclassifications. The opposite, however, using a classifier trained on CheckPoint Cardio data on the MIT-BIH Arrhythmia, yields far less success with a good amount of the instances classified as normal when they are in truth VES and only very few correct detections. Training and testing on different records from the same dataset yields different results depending on the record, the figure shows the averaged results.

On a closer inspection, the reasons for this become clear: Not only can VES differ in their properties from record to record, but also individually - regardless of noise and artifacts, extrasystoles come in many different shapes which often deviate from the prototypical form (see 6).

Another problem both in training and evaluation are annotations and their different formats. When deriving a heartbeat-based ground truth from ranges, the surrounding beats are often by definition marked as extrasystoles as well, leading to confusing training data for the classifier and wrong information used in the evaluation phase. While more training examples can counter this effect in training, it becomes a problem when detecting extrasystoles in unseen data, leading to false negatives. Also, as the annotations are created by manual work they are not guaranteed to be correct in the first place. Some of the false positives show, on closer inspection, all signs of VES without having been annotated as such (see 7). To optimize and evaluate the true performance of a classifier, a unification and correction of the annotations will be done in the future.

5 DISCUSSION AND FUTURE WORK

We have presented ongoing work in extending a human-staffed remote 24/7 monitoring system for persons suffering from cardiovascular diseases, a system that has been up and running for several years. The system promises a higher degree of monitoring than what is possible even in clinical settings.

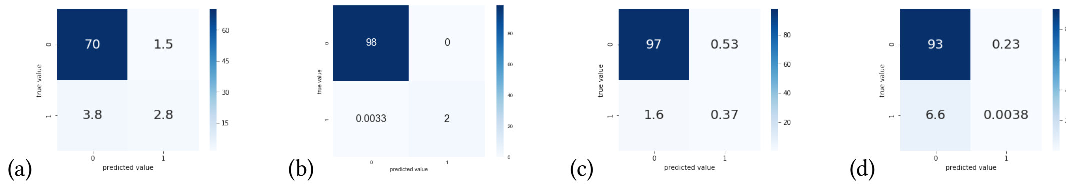

Figure 5: Confusion matrices for all four major experiments. (a) Averaged results of training on all but one record from the MIT-BIH Arrhythmia, testing on the remaining, (b) results of a classifier trained on the MIT-BIH Arrhythmia, testing on the CheckPoint Cardio set, (c) averaged results of training on all but one record from the CheckPoint Cardio set, testing on the remaining and (d) results of a classifier trained on the CheckPoint Cardio set, tested on the MIT-BIH Arrhythmia.

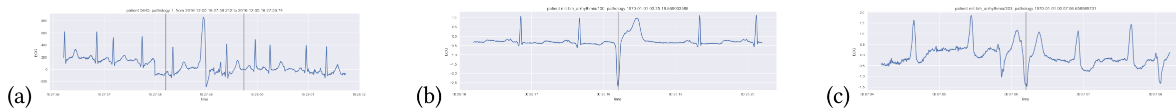

Figure 6: Examples of atypical extrasystoles. (1) "VES"-annotated range centered between two normal heartbeats, (2) PVC with negative peak and (3) unclear behavior.

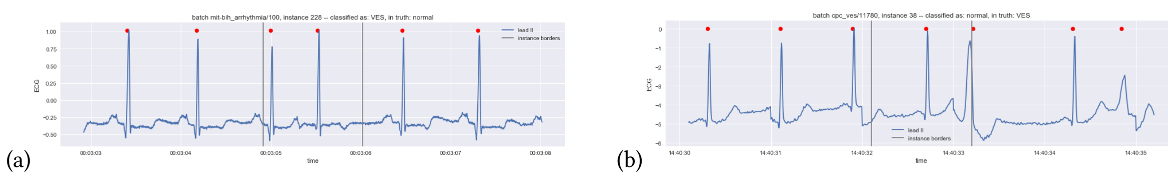

Figure 7: Examples of problematic annotations. (1) Instance classified as VES but annotated as normal (due to an annotation error) and (2) instance classified as normal but annotated as VES (due to the next one being a VES and the range of the annotation overlapping).

However, there remains a major challenge: even with the technical setting, the monitoring personnel misses anomalies in particular. Our extension targets exactly this: introducing an automatic classification layer in the technical architecture that supports personnel by highlighting anomalies, thus steering their attention to relevant parts of the signal. This extension simultaneously addresses scalability: a cardiac expert can theoretically monitor a more patients simultaneously. The combination of sensor data, human monitoring and a detection layer in between has the potential to become a very powerful monitoring service that in the future will save lives and increase quality of life for persons at cardiac risk.

As a proof of concept, we have presented an automatic detection method for ventricular extrasystoles developed and tested on real-world data. Data recorded from wearables is challenging in that it contains a lot of artifacts normally not present in clinical settings where patients typically are laying still. Another major problem is the individuality of biosignals, leading to cross-database and even cross-record classification problems for pathologies deviating from the prototypical shape.

The first improvement will concern the annotations, so that optimal training and reliable evaluation become possible on the available data. This might require a manual overhaul of the whole dataset, checking each annotation for correctness and adding potentially missed extrasystoles, for which a custom annotation tool is being created.

In the future, we will address improvements on the detection of ECG waveforms, especially tackling issues of detection sensibility and robustness against noise peaks. Clearly, this is a key factor not only for the improvement of VES detection, but any anomaly detection in general. VES are a less complex anomaly both when it comes to detection as well as their consequences: extrasystoles are typically not an emergency case. However, in addressing more critical conditions, the whole modus operandi in the telemonitoring centre has to be adapted accordingly.

In order for the classifiers to become more robust, they need to be trained on much more data, getting used to the various shapes of the pathology to detect. To test on a bigger noise-corrupted corpus, the automatic detection has to be introduced into the telemonitoring centre and evaluated under working conditions. We expect that the introduction of the automatic classification will lead to adaptation of the working instructions. The current situation has been based on the assumption that the cardiac experts are solely responsible for the detection of the anomalies.

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