Autonomous Medical Monitoring and Diagnostics

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CSEM has developed a platform that evaluates how data mining and machine learning can pave the way towards autonomous medical monitoring and diagnostics. Even though the original conception was oriented towards space applications, CSEM's autonomous diagnosis platform can play an important role in many remote locations where telecommunications systems are not reliable.

Global plans for exploratory missions aim at extending the distances travelled by humans well beyond low-Earth orbit and establishing permanent bases on the surface of the Moon and Mars [1].This will inevitably lead to an increase of mission duration, radiation intensity, and degree of confinement and isolation to which the crews will be exposed. In this extended context, the astronauts should have the means to collect medical/physiological data in order to understand whether their health conditions are within nominal levels. The astronauts should be informed about possible diagnoses and should receive practical recommendations about treatment options in order to deal with medical issues with limited or no interaction with the Earth. The mentioned scenario is possible if and only if the astronauts and medical crewmembers have access to an autonomous medical monitoring system with embedded diagnostic algorithms.

The systems developed today very often target one type of arrhythmia detection. [2] The results obtained from these studies are highly comparable with the outcome of the CSEM platform. In addition, the CSEM platform detects several types of cardiac arrhythmias simultaneously.

Figutre 1 briefly describes the evaluation platform developed by CSEM. The general working principle of this pipeline can be explained as follows. It starts out with a selection of available medical databases, depending on the medical use case considered and the validation mode. All selected signals and associated annotated anomalies obtained from the databases (ground truth) are loaded into the algorithm pipeline. The "feature extraction & alignment" block is in charge of extracting generic and signal-specific features from the signals and thereafter aligning them with annotated anomalies used to train several "anomaly detection" models. These models (e.g. k-NN, SVM) aim at classifying the values of the features extracted as either "normal" or "abnormal". When at least one abnormal feature value is encountered, an anomaly is said to be detected. Being able to classify which type of anomaly has been detected based on which types of features have been classified as abnormal is the task of the "anomaly classification" models. Moreover, some models (anomaly detection and classification models) will perform both tasks jointly (anomaly detection and classification). The trained "anomaly detection", "anomaly classification", and "anomaly detection and classification" models are then applied to new data (validation dataset) during the validation phase of the algorithm pipeline (lower row of the block diagram) in the "apply trained models" block. Lastly, the performance of the models in terms of detection and classification performance is assessed in the "performance evaluation" block.

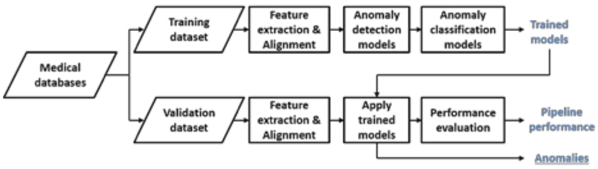

Figure 1: Overview of the developed evaluation platform.

Table 1 shows some of the results based on the MIT-BIH arrhythmia database (47 subjects). These results were obtained by using various models for the detection of a particular type of anomaly, in this case cardiac arrhythmias. Each individual heartbeat was classified by the anomaly detection models as either normal (sinus rhythms) or abnormal (cardiac arrhythmias). Comparing the detected anomalies to the ground truth (annotated anomalies from the databases), sensitivity and specificity scores were computed to assess their performance. The harmonic mean of sensitivity and specificity was also computed as a global performance measure.

Table 1: Performance scores from the normal (sinus rhythms) versus abnormal (cardiac arrhythmias) classification.

Classification Scores	k-NN	SVM Linear	SVM Nonlinear
Sensitivity	87%	89%	90%
Specificity	76%	95%	90%
Harmonic mean	81%	92%	90%

While Table 1 illustrates the results of the normal versus abnormal separation (anomaly detection), Table 2 shows the performance of the models for anomaly classification. The CSEM pipeline manages to classify the normal beats with an accuracy of 94% when using SVM Linear. The atrial fibrillation classification work best with k-NN (78%), while the highest classification score for premature ventricular contraction was obtained with SVM Nonlinear (78%).

Table 2: Classification scores of the different cardiac rhythms. PVC = Premature Ventricular Contraction, AF = Atrial Fibrillation.

Cardiac rhythms	k-NN	SVM Linear	SVM Nonlinear
Sinus rhythms	74%	94%	83%
PVC	66%	76%	78%
AF	78%	72%	71%

With the results obtained so far, the CSEM autonomous diagnosis platform demonstrates a promising capacity to be extended to other signals and pathologies.

[1] International Space Exploration Coordination Group, the Global Exploration Roadmap, 2013.

[2] P. Ziegler, J. Koehler, R. Mehra, Comparison of continuous versus intermittent monitoring of atrial arrhythmias, Heart Rhythm, 3(12) (2006) 1445–52.