Machine Learning Methods for Detection of Epileptic Seizures with Long-Term Wearable Devices

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***Abstract*—The detection of epileptic seizures plays a major role in patient safety and therapy. Although several research projects on mobile seizure detection have already been conducted, there are still no approaches that are able to reliably detect different seizure types in the home environment. The challenge lies in the variety of symptoms of certain seizure types. The present research describes the project EPItect, which aims to detect epileptic seizures with the help of an In-Ear sensor and to set up a networking infrastructure to exchange medical data between relevant actors. We contribute a machine learning framework for the detection of epileptic seizures and exemplify the application using the example of detection of Generalized Tonic-Clonic Seizures using acceleration data from the In-Ear sensor.**

***Keywords*–Epilepsy; Seizures; EPItect; SUDEP; Automated seizure detection; Wearables; IHE; HL7; Accelerometer; Classification; k-NN.**

I. Introduction

Epilepsies are among the most common neurological diseases worldwide. Depending on the degree of severity, affected persons can live a life with great restrictions on their autonomy. Characteristic symptoms are recurring epileptic seizures, which can be very stressful for the affected persons, relatives and carers due to the unpredictability of the time at which seizures occur, as well as the impairment of consciousness and the loss of control over different body functions. Among other things, the mortality of people with epilepsy is increased by a factor of 2-3 due to severe epileptic seizures (e.g., failure of the respiratory center) and seizure consequences (e.g., accidents, suffocation) [1][2]. The early detection of seizures can possibly help to take of appropriate safety measures for the person concerned and to reduce sudden unexpected death in epilepsy (SUDEP). By using technical solutions for better supervision (e.g., video cameras, pulse oximeters) or rooming-in of relatives the SUDEP incidence in an epilepsy center shows a decreasing trend between 1981 and 2016 [3]. In addition to such early detection, an accurate recording of the seizures also helps in the individual planning of the therapy. In order to reduce seizure frequency or, at best, to achieve complete seizure control, a central component of medical treatment is the suppression of seizures by medication. Proper documentation of epileptic seizures by patients or relatives plays an important role in coordinating therapy. The documentation can be done on paper or web-based seizure calendars (e.g., EPI-Vista®) [4]. However, previous studies show that approximately 50% of seizures are not documented and approximately two-thirds of patients provide incorrect data [5][6]. The main reasons for the faulty seizure documentation are, for example, the disturbed perception of one's own seizures, amnesia for seizure or later forgetting of the seizure that has taken place. The seizure documentation by relatives or caregivers is also prone to failure as relatives do not notice symptom-poor epileptic seizures [7].

In this paper we propose and validate a ML Framework using the example of acceleration data of long-term wearable devices. The paper is organized as follows: Section 2 presets a brief literature review about epileptic seizure detection. Section 3 describes the project EPItect including the components of the technical solution. Section 4 describes briefly the data set of the In-Ear sensor employed in our research. This section presets information regarding the methods used in this study. You can find, also, information related to the performance evaluation criteria employed. Section 5 provides the assessment procedures used and the experimental results obtained. Finally, Section 6 describes the conclusion derived from the study and some thoughts with regard to future work.

II. Related Work

Recently, various models have been proposed for the detection of epileptic seizures. Continuous electroencephalographic (EEG) monitoring is the current gold-standard for seizure diagnosis. Algorithms for the automatic detection of EEG-based seizures have been developed in various research projects [8][9]. However, EEG monitoring is expensive, time consuming and needs professional installation and observation. For the detection of epileptic seizures in the home environment mobile sensors are needed. The knowledge about the symptomatology of epileptic seizures can help to select the fittest seizure detection device for each seizure type.

Ulate-Campos et al. [10] literature study showed the effectiveness of various seizure detection devices for certain seizure types. Generalized Tonic-Clonic Seizures (GTCS) produces bilateral, convulsive tonic contraction followed by generalized clonic muscle contractions. They also manifest with a loss of consciousness and marked autonomic distribances. The main findings for GTCS are movements and physiological signals like heart or respiratory rate [10]. By using accelerometry or electromyography, generalized tonic-clonic seizures can usually be easily identified as epileptic seizures based on their characteristic movement patterns and differentiated from everyday movements. To detect motor phenomena, accelerometers (wrist-worn or body-mounted instruments that measure changes in speed or acceleration) and electromyography devices (for example, mounted on the chest, measure electrical muscle activity) are used [11][12].

The following sections show some study results using various medical devices and sensors. Sensitivity for the detection

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of clonic, tonic, hypermotoric and generalized tonic-clonic seizures was between $80-90\%$ in several studies [13][14][15]. In [16], Lin et al. developed a small headband for epilepsy patients. The headband is connected to a smartphone and records EEG signals to detect seizures in real-time. Once a seizure is detected, the headband will trigger the apps on the smartphone to locate the patient. Sixteen features indexes (entropy and the powers of 15 frequency bands from 0Hz and 15Hz) were input into the classifier to verify the seizures occurrences. They used the linear classifier called Linear Discriminant Analysis (LDA). The LDA is often used to reduce the dimension by separating the data into different classes and minimizing the data distribution of the same class in the feature space [16]. In another study, Arends et al. [17] employed epileptic nocturnal seizure detection by combining heart rate and movement. The sensor system is a bracelet that was fixed around the upper arm on the side where the seizures were known to start. The algorithm determined the heart rate. Simultaneously, a signal quality index was calculated for each heart rate value. If the signal quality index is $> 80\%$, seizure detection starts. Otherwise, the accelerometer is used to detect seizures. They obtained a signal quality of 94 % for the heart rate and up to 100% for accelerometry. This study demonstrated that it was possible to reliably detect major motor seizures using a combination of heart rate and accelerometer. In [18], an automatic seizure detection algorithm based on EEG, EMG and ECG with an overall detection sensitivity of 86% was developed. The average sensitivity of the developed algorithm depends on the seizure type an the diagnosis. The best result was achieved for the detection of focal seizures evolving to bilateral tonic-clonic. The described work involves small numbers of patients in the evaluation and is predominantly carried out in an experimental environment. A home environment was used in [17]. However, a limitation of seizure detection on nocturnal seizures was made.

The main contribution of this work is the Machine Learning Framework (ML-Framework) for detecting epileptic seizures in experimental and real term environments. Using the example of the acceleration data of the In-Ear sensor, the ML-Framework was initially applied unimodally. Current research is testing the application of multimodal approaches for seizure detection.

III. EPItect

The focus of the project EPItect is to develop a non-invasive sensor system, which reliably detects those bio signals that enable automated detection of epileptic seizures. The sensor is placed in the external auditory canal (similar to a classic hearing aid). The data are made available to selected persons via mobile devices. In this way, the personal environment can also be included if necessary. This specially developed in-the-ear sensor technology and a networking infrastructure based on (inter-)national communication standards (e.g., Integrating the Healthcare Enterprise, Elektronische Fallakte 2.0, HL7 Fast Healthcare Interoperability Resources) are the basis for several IT applications, which are also integrated into the existing medical-nursing processes. In addition, the signals of the In-Ear sensor and the recorded data such as context information about seizures can give scientist much more reliable data to make better diagnosis, because the frequency and severity of seizures can be recorded better. The anonymization and cross-patient aggregation of the data also enables clinical research, for example regarding the drug that reduces the seizures most effectively or different context parameters, which trigger epileptic seizures.

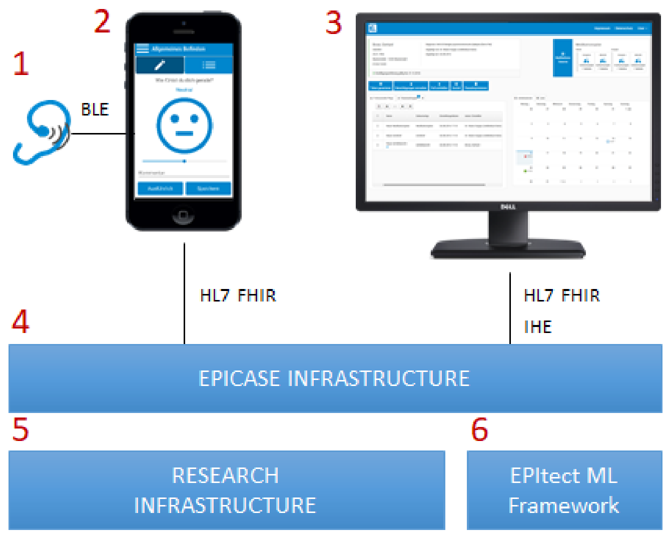

Figure 1. EPItect architecture.

The components of the technological solution are shown in Figure 1: the In-Ear sensor (EPISENS), the mobile application (myEPI), the portal (EPICASE Portal) and the networking infrastructure (EPICASE Infrastructure). EPISENS (1) includes sensors to optimize seizure detection and seizure counting. It sends vital data, raw data and alarm events via Bluetooth Low Energy to the myEPI App. myEPI App (2) is a mobile companion for the patient. The app includes an alarm module. Upon receipt of alarm events, selected persons (e.g., parents or partners of an affected person) should be informed. The patient can use a simple action on the smartphone to confirm the seizure event or classify it as a false alarm. This information is used in the next step to optimize the specificity of the algorithms developed. In the app, the patient also has the opportunity to collect additional data (contextual information on seizure events, mood, medication administration, side effects). He can selectively release data for doctors or relatives. The data is transmitted securely via the EPICASE infrastructure (4) and can be viewed by relevant actors via the EPICASE portal (3). The EPICASE portal is a case based communication portal for patients as well for professional and informal caregivers. It enables exchange of treatment-relevant data (e.g,. medication order, medication administration, seizure documentation, diagnosis). The EPICASE infrastructure connects the IT applications. It is based on international standards and fully complies with data protection and data security requirements. The project EPItect also provides a research infrastructure (5) for pseudonymization, data capturing and integrating and storage of case based generated data. The integrated data is the basis for our machine learning framework (6).

The consortium of the project EPItect coordinated by the epileptologists of the University Hospital Bonn consists of five institutions and two associated partners in Germany: Department of Epileptology at the University Hospital Bonn, Fraunhofer Institute for Software and Systems Technology ISST, Department of Neuropediatrics of the University Kiel (UKSH), the North German Epilepsy Center in Schwentinental-Raisdorf,

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Cosinuss GmbH Munich, the University for Healthcare Professions in Bochum, and the Epilepsy Bundes-Elternverband e.V. [National Epilepsy Parents Network] in Wuppertal.

IV. METHODS

This section first introduces the sensor platform and clinical study. Afterwards an overview of our ML Framework will be given. Then the framework will be applied to the example of acceleration data using the k-NN classification method.

A. Sensor Platform

The sensor system is based on a sensor concept called ”earconnect” which was developed by cosinuss°. The sensor elements are integrated into a silicone screen, which is placed in the ear canal similar to a sports headphone. Behind the pinna sit microcontroller, power supply and the radio connection. There, the analog signals are digitized and then extracted by means of various filters and algorithms, the required vital data. A wearable sensor platform is designed in the EPItect project, which contains 3D accelerometer, PPG, and vital signs (heartrate, temperature). Acceleration data is suitable in order to detect tonic-clonic seizures that are characterized by severe motor symptoms [19]. The entire platform is fixed in the ear at the test subject (see Figure 2).

B. Study

For the evaluation of the technologies, clinical studies are carried out at the participating specialist clinics. The University Hospital Bonn and the Department of Neuropediatrics of the University Kiel have initiated a study with several patients. In the first phase, 170 patients have been recruited to test the biosensors. For these patients, EEG, ECG and In-Ear sensor data were collected over an average period of four days. On the basis of the EEG data, physicians have recorded seizures occurring (period, type of seizure). More than 490 seizures were recorded by January 2019. The data are used to identify relevant biosignals and biosignal patterns and to develop algorithms. Subsequently, the algorithms are validated with test data. This work focuses on tonic-clonic seizures.

Figure 2. The In-Ear sensor ©cosinuss°.

C. ML-Framework

We would argue that the use of a structured experimental approach to the problem of seizure detection is useful to obtain the best possible results with all given data sets. In this section, an intelligent architecture for seizure detection based on the CRISP-DM [20] is presented. Figure 3 gives an overview in the steps of our EPItect ML-Framework. The ML-framework covers both the Experimental Environment and the Real Term Environment.

1) Experimental Environment: The Experimental Environment is used to develop and optimize seizure detection models using controlled conditions for the duration of the study. The main steps are: domain and data understanding, data preprocessing, feature extraction, model selection and evaluation. Domain understanding includes understanding the problem and the goal of the modelling. This means for example the understanding of the symptoms of an epileptic seizure. The understanding is obtained by literature review and by involving neurological experts and also affected persons in the project. A main step is to understand the data, which plays a major role. A detailed analysis of the data and the understanding of the goal would help to avoid later problems. The project integrates a variety of data sources: ECG, EEG, PPG, vital data (heart rate, temperature), seizure labeling and classification, patient meta data (gender, age). The data preparation includes tasks like selecting, cleaning, integrating and formatting data. The data integration and formatting are critical tasks for multimodal approaches. The feature extraction depends on the data and the objective of the model. A feature set can be selected by experts opinion or feature selection algorithms. We test several different feature selection approaches considering their selected classification models. The next step is the modelling process. To select models for the experimentation, a literature review and the identification of similar research activities that have previously been successful are required. Each selected model can be trained on according features and feature sets. A continual evaluation and adjusting of features and models will identify the best model. It is important to preserve the order of the training data for the seizure detection problem, so that upcoming classification are based on previous results. From this we get a new classification model. To evaluate the trained model, one would classify match results into seizure and non-seizure and then determine sensitivity, specificity, positive and negative predictive value. The implementation of a seizure detection system must be valid. The representation is performed using the confusion matrix to estimate the performance of learning algorithms and the generated classifiers. The confusion matrix records the correct and misclassifed features for each class. A comprehensive rating can be obtained from the Receiver-Operating-Characteristic curve. The ROC curve can be used to find the best possible value of a parameter [21] and to assess the trade-off between sensitivity and specificity [22]. The ROC analysis allows the rating of the classifier performance to be independent and complete rather than just accuracy.

2) Real Term Environment: Once a trained model is accepted, it is made available for use (Real Term Environment). For our project, this means deploying the models to mobile devices and sensors. Further training of the models, for example to take into account individual circumstances of the patient, is possible if the mobile devices and sensors provide good computing power and sufficient memory. Unlike the Experimental Environment, the verification of the model is done by the patients' labeling of alarm events which are triggered by the trained model. In order for the trained model to be accepted by the user, it is important that there is no high amount of false alarms. In a survey of patients and care environment (n = 305), we have found that on average a maximum of 2/10 false alarms are accepted. The activities in everyday life (for example: sports, activities that trigger emotional states such as excitement) have a great influence on the signals and possibly on the applicability of the trained model. Further training of the model is therefore an important task and will be addressed in a second study.

D. Seizure Classification

For data analysis, Weka toolkit was used. The Weka toolkit is a machine learning toolbox with many existing algorithms. It also allows to evaluate the algorithms for a particular dataset using cross validation. From the accelerometer data was the three vector component obtained as measurement variables.

1) Data Preprocessing: All observation data that does not involve tonic-clonic seizures are filtered.

2) Feature Extraction: Features were extracted from the raw accelerometer data using a window size of 128 and 50% overlapping between consecutive windows. At a sampling frequency of 50Hz, each window represents 3 seconds. For each measurement variable, the following quantities were derived in time and frequency space: (1) arithmetic mean [23], (2) median [24], (3) variance [23], (4) maximum, minimum and range [23] and (5) skewness and curtosis [25].

3) Classification: For our intended goal of embedded system classification we focused on classifiers that could be implemented in computationally efficient manner. There are a large set of classifiers. Our choice was to classify the data with the k-NN algorithm. The k-NN is an instance-based classifier based on majority voting of its neighbors: The k-NN algorithm finds a close group of k objects in the training dataset with the target object in the training data and predicts the class of closest objects to the target object [26].

4) Evaluation Metrics: The results can be evaluate by sensitivity (SEN), specificity (SPE), positive (PPV) and negative predictive value (NPV):

$$\mathrm{SEN} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \qquad \mathrm{SPE} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{1}$$

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \qquad \mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FN}} \tag{2}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, false negatives, respectively [27].

5) Computation time and memory requirements: Computational time and memory requirements are essential for the decision if an algorithm is suitable for a particular purpose. The software cannot work efficiently if they are too high.

V. Results

The experimental results of the k-NN algorithm with different k values of $\{1, 2, 3, 5, 10\}$ are summarized in Table 1. With $k = 1$ with the full feature set a sensitivity 65.1% is obtained. It has been shown that the k-NN algorithm has the potential to recognize tonic-clonic seizures. While some seizures are well classified, distinguishing different types of seizures is more challenging and leads to lower classification performance. With the reduced sensor set, classification performance worsens as expected. The number of detected seizures are quite low. For a better classification performance it is required to combine different sensors to get a higher classification rate.

TABLE I. k-NN ALGORITHM RESULTS.

k	*sens [%]*
1	65.1
2	52.4
3	60.6
5	54.4
10	45.9

Specific memory and runtime tests must be performed to determine if k-NN is possible on the EPItect sensor.

VI. Conclusion and Future Work

With the use of acceleration data we detect tonic-clonic seizures with a sensitivity of 65.1% for $k = 1$ and 60.6% ($k = 3$). Following improvements will increase the classification performance: With a reduced feature set, classification performance worsens as expected. Using more features can improve the seizure detection. For this reason, many more features should be generated. From the large amount of features, feature selection methods can be used to reduce the optimal number of features to avoid the “curse of dimensionality” [28]. Die length of the clonic-tonic seizures vary from one to another. The fixed window size can be the reason for the misclassification. Therefore, the window size should be adjusted dynamically.

The optimization of the developed model is continued using the following steps feature extraction, model selection, classification and evaluation of the ML Frameworks to obtain a better trained model.

A. Combination of bio signals

In summary, the studies to date, despite their rather good sensitivity, do not yet show sufficient specificity for the correct recognition of non-epileptic events in order to make meaningful use of these methods for automated seizure counting. In addition, seizures with dominant motor phenomena were predominantly investigated. Given the variety of seizure symptoms, multimodal synchronous measurement and analysis of various body signals (e.g., simultaneous measurement of heart rate, skin resistance, and acceleration of limb movements) appears to be most promising to achieve high sensitivity and specificity in seizure detection.

Our current work addresses the implementation of multimodal approaches using the ML Framework. An important task is the combination of different data sources (e.g., ECG and PPG) for the development of models. We use PPG and ECG data to determine the pulse transit time and evaluate whether the pulse transit time has an impact on the model for the detection of epileptic seizures. The PTT is related to the blood pressure. It describes the time that a pulse wave needs to arrive [29]. The time of the heart contraction and the beginning of the pulse waves are needed to determine the blood pressure. In future work, we will analyze the PTT-data to identify epileptic seizures.

B. Clinical study under everyday conditions

In a subsequent clinical study (from January 2019), the technological solutions will be tested for everyday suitability. For this, 30 affected children and adolescents and 30 affected adults each receive an ear sensor and the mobile companion solution for one week each. The informal carers of the patient (e.g., parents), as well as the professional nurses received access to the EPICASE portal and can participate in the data exchange process. The study addresses the following subgoals.

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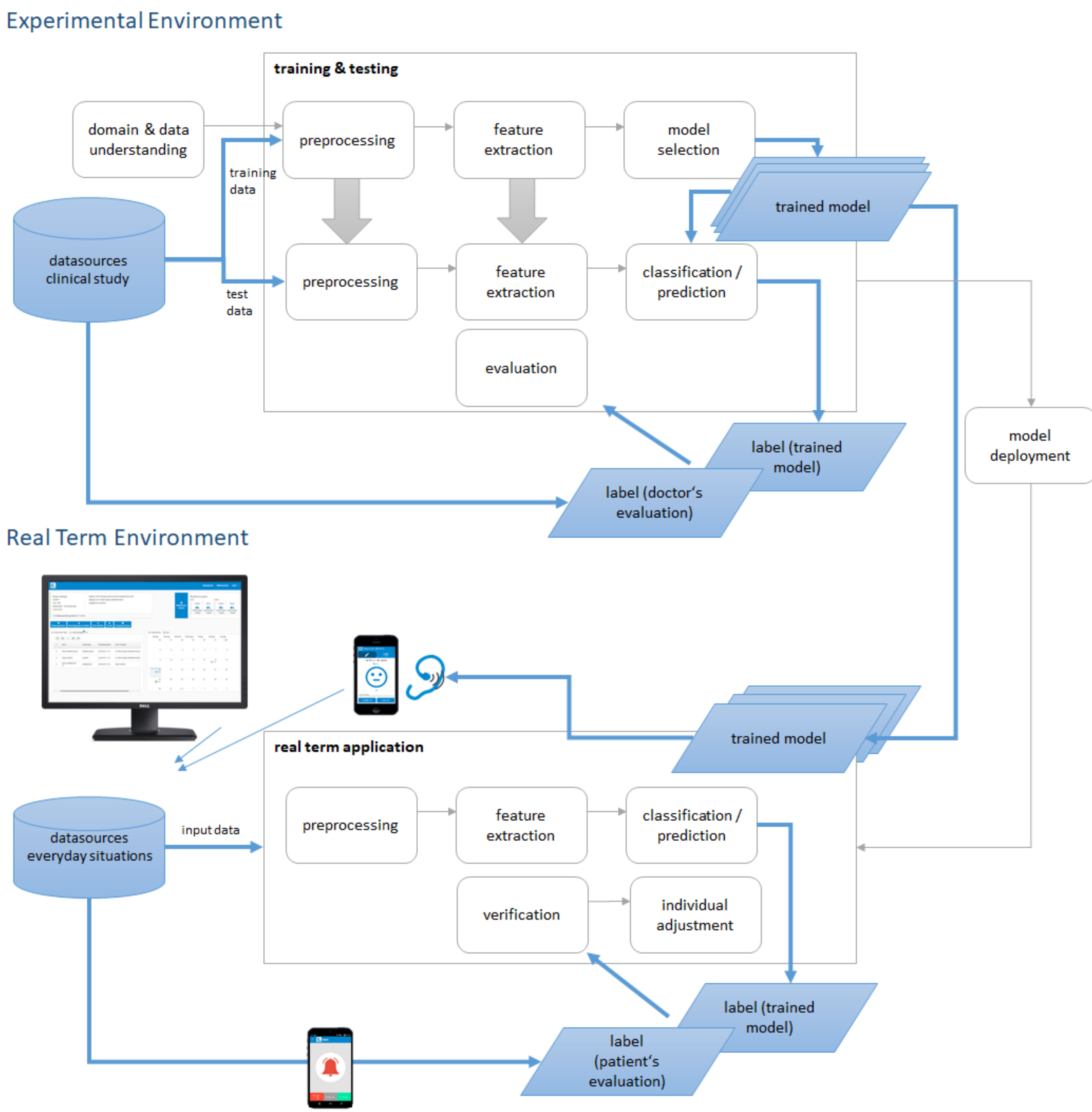

Figure 3. The ML-Framework.

1) Validation of the algorithms in everyday situations: It is to be examined whether the developed algorithms are applicable to everyday situations. Since the data was collected during the first phase while lying down or sitting, it is to be expected that the algorithm must be adjusted iteratively.

2) Effects of the technologies: The aim is to examine the impact of all technologies (sensor, app, portal) on automated and manual seizure records, quality of life and care processes.

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