A Two-Layer Ensemble Method for Detecting Epileptic Seizures Using a Self-Annotation Bracelet With Motor Sensors

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***Abstract*— Using monitoring devices could help avoid injuries and even death. Currently, wearable sensors such as motion sensors and other sensors are used to detect when the patient is having a seizure and alarm their caregivers. However, the development phase of these devices requires labor-intensive work on labeling the collected data, resulting in difficulties in developing wearable monitoring devices. Thus, a more automated auxiliary method of labeling seizure data and a wearable device to detect seizures for daily monitoring use are necessary. We collected data from epileptics outside the hospital with our proposed bracelet. The subjects were asked to press the mark button after they had seizures. We also presented an automatically extraction and annotation of moving segments (EAMS) algorithm to exclude nonmoving segments. Then, we used a two-layer ensemble model (TLEM) using machine learning methods to classify seizures and non-seizure moving segments, which was designed to deal with imbalanced dataset. Then, we build two individual TLEM models separately for the overall (all day and night) seizure detection case and the night seizure detection case, owing to different imbalance of these datasets. The EAMS algorithm exclude 93.9% raw inactive data. The TLEM model achieved 76.84% sensitivity (SEN) and 97.28% accuracy (ACU) for the overall case and achieved 94.57% SEN and 91.37% ACU for the night case. These results indicate that this bracelet can capture seizures efficiently, and our proposed TLEM has higher SEN and ACU than single-layer machine learning models.**

***Index Terms*— Accelerometer (ACM), epilepsy, gyroscope, machine learning, motor sensor, seizure detection, signal processing, wearable device.**

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I. Introduction

According to the World Health Organization's report, there are around 50 million (7‰) epileptics worldwide, based on which the population of epileptics in China would be more than 9 million and is growing at the rate of 400 000 each year [1]. Epileptics are facing plenty of possible risks, including injury, and even sudden unexpected death in epilepsy (SUDEP), with sudden death rate two to four times higher than those who are healthy [2]. They are at risk of random seizures for a long time, even a lifetime.

To date, the pathogenesis of SUDEP is unclear, and SUDEP has many possible related factors. Medication can help about 70% epileptics, but for the remaining 30% [3], it is not effective. Most sudden deaths happened after generalized tonic–clonic seizures (GTCS) [4]. In addition, the risk of SUDEP increases with the frequency of GTCS in patients. The American Academy of Neurology and American Epilepsy Society published "Practice guideline summary: SUDEP incidence rates and risk factors" in 2017, and they announced that the use of monitoring equipment can alarm caregivers to take proper measures, and this could help reduce respiratory dysfunction and hypoxemia [5] of the patient. Epileptic seizures, especially seizures that happened at night, are at serious risk of being missed by their caregivers. Wearable epileptic seizure detection devices could help improve the patients' quality of life and independence, while also providing a means for continuous patient recording treatment evaluation.

Video-electroencephalography monitoring (VEM) is the gold standard for epileptic seizure monitoring [6]. Lahmiri and Shmuel [7] proposed a computer-aided diagnostic tool to help support a decision in clinical applications. They extracted Hurst exponents in different scales and built a K nearest neighbors (KNN) model to automatically detect seizures in electroencephalogram (EEG) signal. Kołodziej *et al.* [8]

developed a seizures and spikes detection algorithm based on the duration and amplitude of the sought spikes. However, an device [7], [8] with wires would be required for VEM, which is uncomfortable for epileptics. Using VEM also requires trained personnel to position the electrodes on the specific area. Consequently, VEM is not a suitable monitoring method for daily care outside the hospital.

Besides the EEG and electrocorticography recording instrumentation and measurements, wearable non-EEG seizure detection systems focus on the use of different sensing modalities or methods, such as accelerometer (ACM) [9]–[14], electromyography (EMG) [15], [16], photoplethysmography (PPG) [17], [18], and electrocardiogram (ECG) [19], [20]. The method or combination of methods most appropriate for seizure detection depends on the type of seizure [21]. For instance, combining ACM and electrodermal activity sensors could not only detect GTCS, but also could quantify the autonomic dysfunction caused by seizures [22].

As a preliminary study, we used an ACM to start our research, because it is the most direct way to detect the severe seizures. There are mainly two kinds of epileptic seizures: convulsive seizures and non-convulsive seizures, of which the first one contributes to most seizure-associated accidents, including injuries, asphyxia, and SUDEP [4]. Movements are the most direct characters of detecting motor seizures, and it is the first choice of all non-EEG seizure detection methods widely used in clinics [23]. ACM sensors mounted on the arms and legs can detect these movements, which are least invasive to patients compared with other non-EEG seizure detection methods [23]. However, there is no single detection device that can detect all kinds of seizures, and most multisensor detection systems include motor sensors to avoid severe convulsive seizures by monitoring abnormal movement events [24].

The normal motor data-collection methods used in these researches [9], [11], [12], [25], [26] are to collect data in a hospital where the patient wears motor-detecting devices and undergoes VEM meanwhile. Although the gold standard for epilepsy monitoring is VEM, it is not suitable for daily monitoring, because the patient would be limited to be equipped with the VEM all day long in the hospital, which means that the collected data only contains the movements that the patient is doing indoors inconspicuous activities. On the other hand, labeling data of seizures according to EEG recordings could be a costly and time-consuming work, and an automatic monitoring data annotation method without medical supervision could help with this situation [27]. Using motor sensors along with video recordings could solve the problem of collecting seizure counts, and this method is more accurate than self-reporting by patients [28] by taking hand-write notes. For patient privacy purposes, another form of electronic recording besides video recording may help to record events, such as adding patient-recorded seizure time to the monitored acceleration (ACC) data in real time. In this research, we illustrate a home-based movement-recording method by adding a mark button (details will be introduced later) on our bracelet. This mark button would help annotate each seizure by the subject during/after having seizures. Such electronic markers, which were recorded in the raw monitoring data, could provide more reliable recordings of seizures' times than patients' handwritten notebooks or mobile phone recordings. We then designed an automatic method to extract the seizure data segments according to these annotations.

Statistical methods and machine learning classification methods have been investigated in the epileptic seizure detection field, with potential clinical applications, such as threshold value method, KNN [10] model, and support vector machine (SVM) model [11]. Cuppens *et al.* [13], Conradsen *et al.* [29], and Luca *et al.* [30] used the threshold value method to classify seizures. They set the threshold value by observing the data. However, this is a labor-intensive method, because it has to set different thresholds for different subjects, and it is not an ideal method to be extended to widely used by all convulsive epileptics. Borujeny *et al.* [10] used the KNN model and artificial neural networks to detect seizures from three patients, which achieved 85% sensitivity (SEN), and the KNN model performed better. They also claimed that if at least 50% of the dataset were seizure samples, the system could detect the seizure more accurately, which illustrated that the KNN model could not deal with this imbalanced dataset seizure detection problem. Kusmakar *et al.* [11] used kernalized SVM to detect convulsive seizures. Although they detected 40 of 46 seizures, a false alarm rate (FAR) of 1.16/24 h occurred, and the system was developed and tested on data collected in a hospital setting. Johansson *et al.* [31] compared the performances of KNN, SVM, and random forest (RF) models, and all models achieved high sensitivities to detect tonic–clonic seizures. SVM and RF had an SEN of 90%, the KNN had 100% SEN, and RF had the lowest false positive (FP) rate, which is owing to the ability of handling imbalanced dataset.

However, these mentioned methods are all based upon the assumption that the number of epileptic seizures is in balance with the number of normal movements, which is not the case in practice. Consequently, a technique that can overcome the imbalance of the dataset would be more suitable for seizure detection based on motor data. For instance, RF model's performance on imbalanced data was confirmed in Khoshgoftaar *et al.*'s [32] study. They used ten differently imbalanced datasets to train and test the RF model and other models (KNN, SVM, Naive Bayes, and so on) and compared the performance of these models. The results showed that the RF model had the best performance in accuracy (ACU) when selecting proper the number of trees and features for each tree. RF benefits from randomness in each tree classifier and for its robustness.

In our previous work [33], we have presented a system for detecting and classifying convulsive seizures and normal movements using a single RF model, which could ignore the effects of the imbalanced dataset. Though this system achieved 75.92% SEN for 24-h seizure detection and 88.01% SEN for night seizure detection, it was still not completely trained well due to the lack of enough seizure data.

In this latest study, the main innovations of this work are as follows.

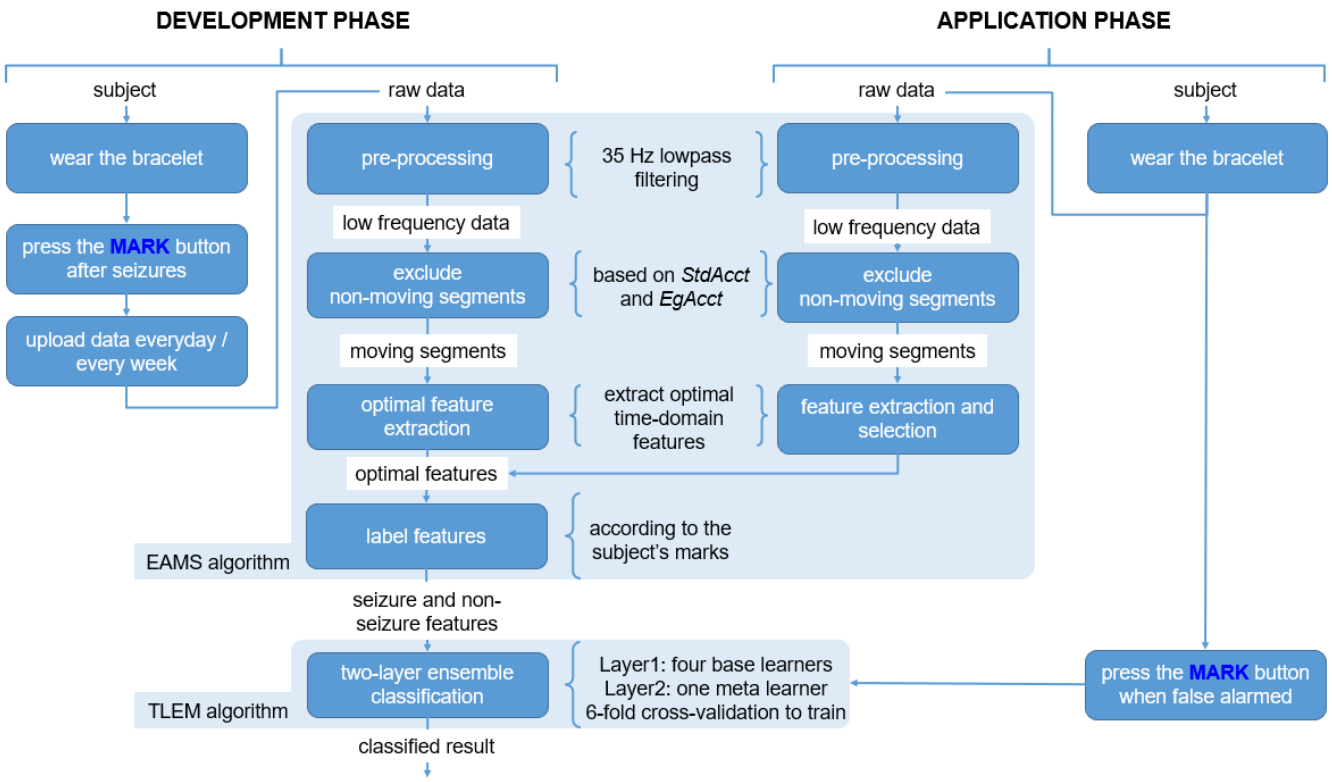

Fig. 1. Protocol of our proposed research, including three main steps: collection of the raw data, extraction and annotation of moving segments (EAMS) algorithm, and a TLEM algorithm using machine learning methods. StdAcct/EgAcct = standard deviation/energy of the total ACC in a time window.

1) Provided a new method making it possible to collect more data from daily life instead of in the hospital, and this is realized by adding a mark button on the device.
2) Designed the EAMS algorithm to increase the efficiency in the preprocessing step by automatically selecting moving segments. The thresholds chosen in the EAMS algorithm also could work on more subjects, because we set them based on human activities, not only specific subjects' seizures included in this manuscript.
3) Presented the two-layer ensemble model (TLEM) algorithm, which is the fusion of four simple and single classifiers, which makes the computing not too complex while increasing the performance.

II. Materials and Methods

Fig. 1 shows the protocol of our proposed research. After we designed the bracelet and collected enough data for our research in Sections II-A and II-B, there are mainly two steps to analyze the data: 1) *EAMS:* thresholding to exclude nonmoving segments and annotating seizure segments, which would be illustrated in Section II-C. 2) *TLEM:* a two-layer approach to classify seizure and non-seizure movements, which would be illustrated in Sections II-D and II-E. In the development phase, the subjects would use the mark button to help annotate seizures. In the application phase in our future study, the MARK button would have two functions; one is to annotate missing seizures by pressing only once after the seizure, and this would help the bracelet recognize the movement before the press as a seizure; the other is to cancel a false alarm by a double press.

Fig. 2. This wireless bracelet has a red mark button. (1) Front panel, the red and green LEDs show the status of the bracelet, that is working/low battery/low storage/charging. (2) Electronics board, including a central processing unit (CPU), an SD card, an ACM sensor, a gyroscope sensor, and a mark button. (3) Chargeable lithium polymer battery, supporting over 24-h work.

A. Devices Design

We implemented the bracelet mainly focused on an affordable, lightweight, and wearable solution with improved comforts for patients. As shown in Fig. 2, we designed a bracelet with built-in microelectromechanical systems including a 3-D

ACM and a 3-D gyroscope, and these two sensors are used to capture the subject's motion for seizures detection. This battery-powered embedded electronic system consists of a sensor interface, a power supply module, a secure digital (SD) memory module, and a seizure mark module. The chargeable 800-mA battery could work for more than 24 h. The collected data would be stored in an SD card temporarily, which could store data of more than seven days. We recommended that subjects (or their caregivers) upload the collected data every night before they went to bed if they had seizures that day, and others would upload data every week.

The self-annotation mark button, as shown in Fig. 2, is designed to mark the seizure time by the patient or his/her caregivers. In our future study, this self-annotation button would help improve the ACU and SEN of the detection system by marking the false alarmed normal activity and failed detected seizure event. The 3-D ACM and 3-D gyroscope (ANG) signals were sampled at 100 Hz. The band is made of elastic fabric and could be adjusted to the subject's wrist. The subjects were asked to place this bracelet on their right or left wrist, depending on which side they have the more serious symptom.

B. Data Acquisition

The data collection process was carried out together with each subject's daily life outside the hospital, and we selected patients with GTCS who had been hospitalized for more than a year. Selected patients were trained on how to use the bracelet to collect data at home and how to annotate all seizure events (by pressing the mark button).

In total, 12 patients with convulsive seizures participated were recruited in the hospital for this research, and 7 patients (five males, two females; age among 6–35 years old, median 26 years old) had seizure events (overall 547 times, mean 78.1; at night 314 times, average 44.9) recorded during the data collecting step. The total time of these seven subjects' monitoring was 4152 h (range 120–1344, mean 461.3, median 336).

During the data collection period, all seizure events information (start time, stop time, and symptoms) would be recorded by the subjects through texts or by their caregivers through phone cameras. These self-recordings would only be used to check if the subjects pressed the mark button properly, and if they forgot to press the mark button after a seizure, these recordings would help us find the seizure segment. The quality of all collected data and self-annotated marks was checked by hospital specialists by comparing it with the subjects' records. In this way, we can collect more daily activities, such as brushing teeth, walking around, playing video games, and so on, than the hospital data collection methods. Presumably, the more types of everyday movements we collect, the more practical the bracelet will be.

This data collection method allows collecting data from patients with different daily activities, rather than in hospitals with limited activities. Hospital experts reviewed all the annotations and the moving segments extracted by EAMS. If the patient pressed the button multiple times during/after the seizure, only one mark would be kept and other marks would be removed, while if the subject forgot to press the button, a new mark would be added by the expert. This research was approved by the West China Hospital of Sichuan University Biomedical Research Ethics Committee [No. 2018(590)], and each patient (or his/her caregiver) provided written informed consent.

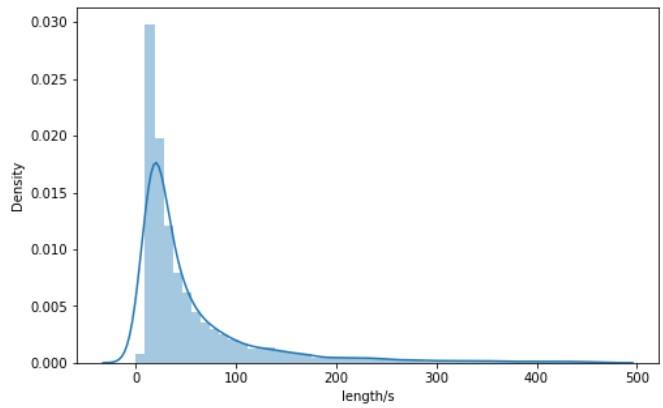

Fig. 3. Distribution of the length of moving segments.

C. Extraction and Annotation of Moving Segments

The original data contained two main categories of data: moving segments (seizures and non-seizure movements) and nonmoving segments. To increase the efficiency of data processing, before the calculation of features, we preprocessed the original data to exclude the segments that do not contain valid information (i.e., no movement) and kept only the moving segments of the patient. Subsequently, moving segments would be further divided into seizure movements and non-seizure movements and labeled properly. The original monitoring data spans over 24 h. Manual detection of moving events is a labor-intensive process. To speed this up, we designed an automated selection method of moving data, followed by a semiautomatic annotation in terms of seizure and non-seizure movements according to the subject's marks, which needs a double check by experts if any abnormal occurs.

The proposed EAMS method has four steps for extraction and three steps for annotation.

As for the extraction phase, first, the raw total ACC data signal ($\text{acct} = (ax^2 + ay^2 + az^2)^{1/2}$) is processed by the eighth-order Butterworth low-pass filter with a cutoff frequency of 35 Hz. It is known that the frequency of the muscular contractions is lower than 20 Hz [23]. Second, a sliding window with a duration of 2 s and an overlap of 1 s between consecutive windows are used to estimate the standard deviation (StdAcct) and short-time energy (EgAcct) of the filtered total ACC signal. The standard deviation StdAcct is calculated by

$$\text{StdAcct}_n = \sqrt{\frac{\sum_i^L \left(\text{acct}_i - \overline{\text{acct}_n}\right)^2}{L}} \tag{1}$$

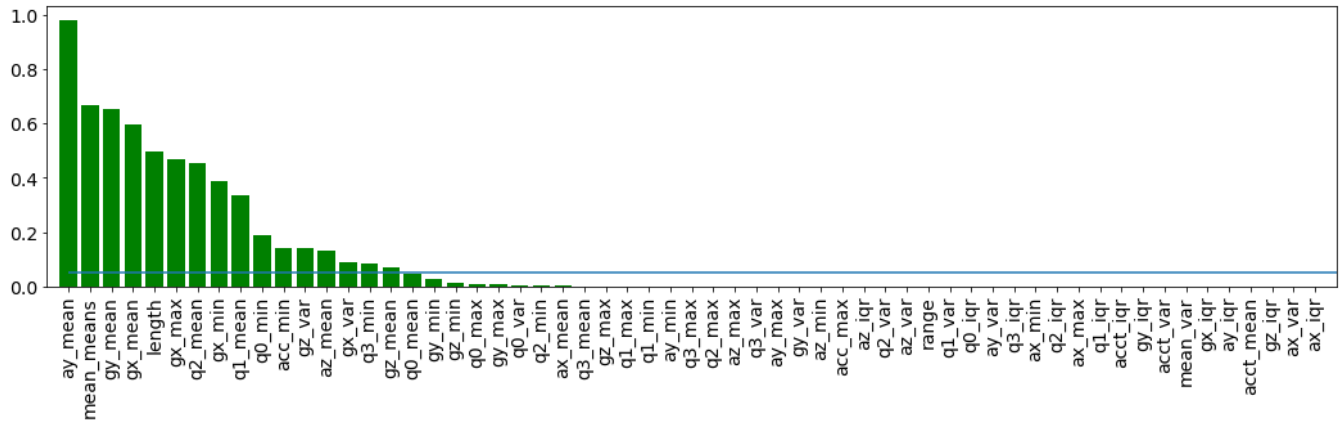

Fig. 4. P values of the extracted features. The blue line shows $P = 0.05$. The features with $P < 0.05$ were kept in this study. The labels of the extracted are named as: (sensor axis)_(feature).

where StdAcct_n represents the standard deviation in the nth window, and L represents the length of data in a sliding window. $L = W_s \times F_s$, where W_s is the window size ($W_s = 2\ s$), F_s is the sampling frequency of the sensor, and $\overline{\text{acct}_n}$ is the average of ACC in the nth window. The short-term average energy EgAcct in the nth window is computed, such that

$$\text{EgAcct}_n = \sum_{i}^{L} (w(L) * \text{acct}(i))^2 \tag{2}$$

where EgAcct_n represents the short-time energy in the nth window, and $w(L)$ is a Hanning window used to smooth the signal before calculating the short-term average energy. The changes in standard deviation and short-time energy illustrate the start and stop of each moving event. Third, two thresholds of StdAcct and EgAcct are used to determine the start and stop times of each moving event. These thresholds (i.e., 0.2 and 15) are selected empirically for each subject to account for the changes in the noise. At last, movement events lasting for less than 15 s are excluded from further analysis. Two adjacent segments with intervals less than 10 s are considered as a whole segment.

As for annotation phase, after identifying all moving segments and excluding inactive data, all automatically selected movement events would be labeled as "seizure" and "non-seizure movement," according to the subject's marks when using the bracelet. First, if the mark was not in a moving segment, the moving segment right before the mark would be annotated as a seizure event. Second, however, some marks could occur during moving segments. If the mark was in the last half of a moving segment, then this moving segment would be annotated as a seizure event. Third, if the mark was in the first half of a moving segment, and it was close (<20 s) to the end of the last moving segment, we would annotate the last moving segment as a seizure event. However, some abnormal could occur, such as two marks appeared in a short time (<5 s), meaning the subject double pressed the mark button, and we would discard the later duplicated mark.

The moving segments range from 15 to 500 s, and the distribution of the length of moving segments is shown in Fig. 3. There are some moving segments lasting for more than 20 s, because two adjacent segments with intervals less than 10 s are considered as a whole seizure segment, which means that we merged such consecutive segments of movements. Those long moving segments usually happen in the daytime.

D. Feature Extraction and Selection

Each moving segment's raw data consist of ten channels, including 3-D ACC (ax, ay, and az), 3-D ANG (gx, gy, and gz), and 4-D quaternion ($q0, q1, q2$, and $q3$). We calculated the total ACC (acct) and regarded it as the 11th channel. The 3-D ACC and 3-D ANG were directly collected from a six-axis motion sensor. The quaternion could also be acquired from the sensor, and it was calculated [34] from the raw signals of the gyroscope by the following equations:

$$\begin{cases} q0^* = q0 + (-q1 * gx - q2 * gy - q3 * gz) * (T/2) \\ q1^* = q1 + (q0 * gx + q2 * gz - q3 * gy) * (T/2) \\ q2^* = q2 + (q0 * gy - q1 * gz + q3 * gx) * (T/2) \\ q3^* = q3 + (q0 * gz + q1 * gy - q2 * gx) * (T/2) \end{cases} \tag{3}$$

where $q0, q1, q2$, and $q3$ are the four components of a 4-D quaternion at time k, and gx, gy, and gz are the 3-D ANG values at time k; then $q0^*, q1^*, q2^*$, and $q3^*$ would be the updated quaternion components at time $k + 1$, and the time window size is T.

Different statistical features have been investigated for classification [10]. We selected a number of time-domain features to describe each event and evaluated these features to select the most useful features to build the classification model. For each dimension of the entire 11-D data ($ax, ay, az, gx, gy, gz, q0, q1, q2, q3$, and acct), we calculated the minimum (min), maximum (max), mean, variance (var), and interquartile range (iqr). In addition, we also included the duration of each movement.

The best features are then selected through a filtering feature selection called analysis of variance. In this method, if a

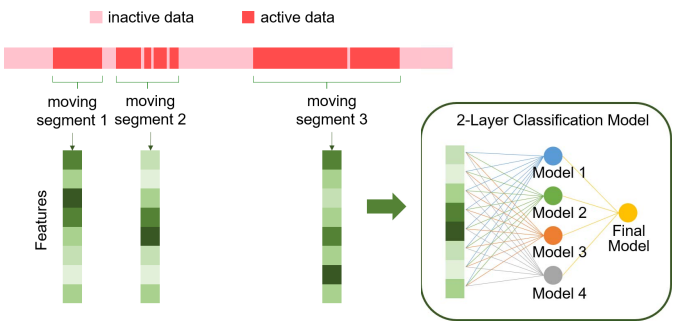

Fig. 5. Extract features from each moving segment and label each feature according to the marks. Next, use these features to train the two-layer ensemble classification.f

TABLE I

PARAMETERS OF THE BASE-LAYER MODELS AND META-LAYER MODEL

Layer	Model	Parameters
Layer1	GBDT	loss = 'deviance', learning_rate = 0.05, n_estimators=100, random_state=2021
Layer1	RF	n_estimators = 100, class_weight = {1:4}, random_state = 2021
Layer1	ET	n_estimators = 100, class_weight = {1:4}, random_state = 2021
Layer1	ADB	n_estimators = 100, random_state=2021
Layer2	LR	C = 2.0, class_weight = {1:4}, max_iter = 100, penalty = 'l1', random_state = 2021, solver = 'liblinear', tol = 0.001

RF = Random Forest, ET = Extra Trees, GBDT = Gradient Boosting Decision Tree, ADA = Adaboost, LR = Logistic Regression.

P value is less than 0.05, we acknowledge that extracted eigenvalues differ significantly between seizure and non-seizure movements. All features with $P < 0.05$ were used for multivariate modeling. At last, we excluded 16 not important features, and kept 43 useful features among all 59 features using Python 3.5 and sklearn module, as shown in Fig. 4. The top five important features in our study are the iqr of ax, var of ax, iqr of gx, mean of acct, and iqr of ay.

E. Model Estimation and Validation

In this step, we constructed a two-layer stacking ensemble machine learning model, called TLEM, in which Layer1 is the base layer and Layer2 is the meta layer. First, four classifiers on Layer1 were trained individually, and each of them would have a single output (seizure or normal movement). Second, using outputs from the classifiers on Layer1 as the input to Layer2's classifier to make the final prediction to classify these two types of moving segments (seizure movement and non-seizure movement). The framework is shown in the right-hand side of Fig. 5. This ensemble framework could provide advantages such as a reduction in FP rates and better precision, because it would outperform every single model, and overcome the shortcomings of each individual model and improve the final prediction results by adjusting the weights of each base learners according to the performances of each base learner.

Layer1 uses four base learners: RF, extra trees (ETs), gradient boosting decision trees (GBDT), and AdaBoost (ADB). The outputs of Layer 1 would be input to Layer2. Layer2 used logistic regression (LR) as the final classifier. These two-layer model's parameters are shown in Table I. As Layer2 is an LR model, the weights could be learned through model training, which is [0.45, 2.33, 4.12, 6.76] for the four base learners (GBDT, RF, ET, and ADB).

RF consists of a set of decision trees, and voting strategies are used to make final predictions. RF uses the bootstrap method, namely, the resampling technique, to randomly select N samples from N original training samples, and N samples here can be repeated. If we repeat this operation for k times, we will get k new training sets, and each new training set will have N samples. In this study, here are $m_{\text{all}} = 59$ features in each sample, and the maximum number of features that can be used in each leaf is set to m_{try} ($m_{\text{try}} < m_{\text{all}}$). The advantages of the RF classification are that the model can be trained with unbalanced datasets (most of the data are normal movements, and very few are seizures), and the model can be flexibly adjusted as the volume of data increases. ET is similar to RF, and the main differences, which tell ET and RF apart, are that the ET uses all the sample, chooses features randomly, and splits trees randomly. Each tree in ET is grown from the original learning sample instead of bootstrap, which increases the randomness of the model and suppressed overfitting; however, this randomness could lead to larger bias. In this case, its performance is good enough to be a base learner in a two-layer stacking ensemble model. GBDT is an iteration method, which is composed of multiple decision trees, and it uses CART as base learners. GBDT often shows good performance for linear inseparable data. ADB is a method that combines the decision of individual base classifiers. To get better performance, during the iteration process, ADB increases the weights of samples that were classified incorrectly and raises the weights of base classifiers that have a lower error rate. ADB is also a strategy of ensemble learning, which is originally proposed by Freund and Schapire [35]. In general, ADB has shown fast and accurate performance at classifying. Especially, we set the weight of positive samples as four and the negative samples as one, because we assume that false predicted positive events would result in missing seizures, which is not acceptable for a seizure detection model.

We used 70% samples to train our proposed model, which is 7507 normal movements and 370 seizures for the overall model, and 562 normal movements and 222 seizures for the night model. We proposed to establish two separate models to account for the different proportions of normal movements and seizures that occur during the day and at night. For both models' training step, we used a sixfold cross-validation approach to validate the temporary performance. In this step, the training dataset was divided into sixfold for cross validation, and in each iteration, five folds were used to train the classifier, and the remained onefold was used for validation, and the results are shown in Fig. 6.

To avoid overfitting during model training, model validation is necessary. We used a Midscore value to describe the average ACU score of training and validation during the model

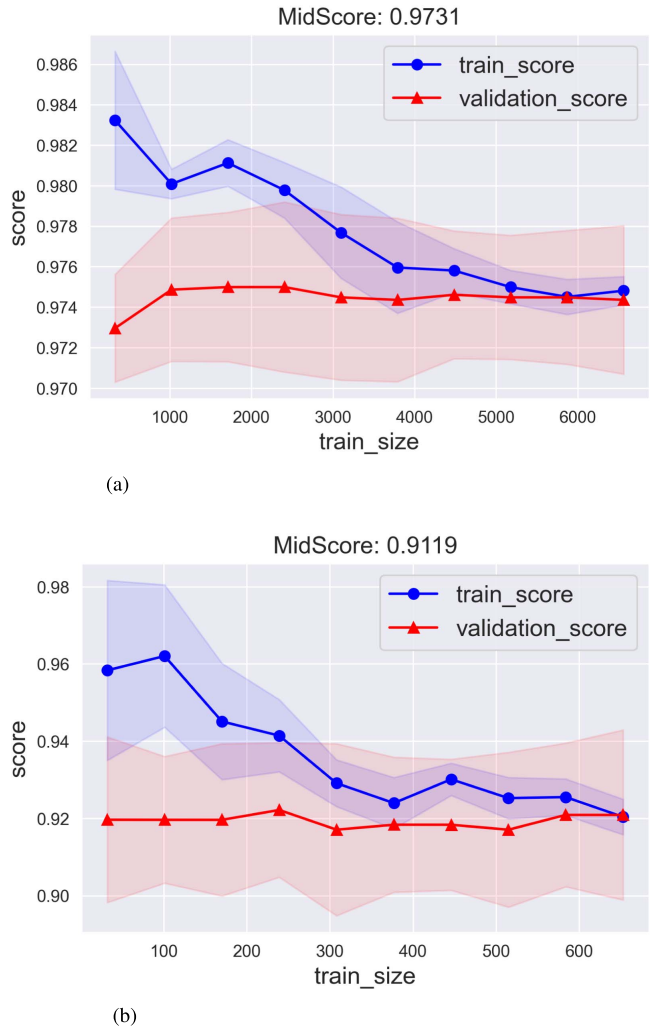

Fig. 6. Learning curves of the proposed TLEM for epileptic seizure detection. The blue line with round dots represents the ACU of training, and the red line with triangles represents the ACU of validation, while the shadow around the line represents the ACU range of the sixfold cross validation. (a) Meta-layer model performance on overall data. (b) Meta-layer model performance on night data.

building step as

$$\text{Midscore} = \frac{\text{mean}_{\text{train}} + \text{std}_{\text{train}}}{\text{mean}_{\text{validation}} - \text{std}_{\text{validation}}} \tag{4}$$

where $\text{mean}_{\text{train}}$ and $\text{mean}_{\text{validation}}$ are the mean ACU of training and validation, respectively, while $\text{std}_{\text{train}}$ and $\text{std}_{\text{validation}}$ are the standard deviation of training and validation ACU scores, respectively. The Midscore reaches 97.31% for the overall model and 91.19% for the night model. Both the overall seizure detection model and the night seizure detection model acquire acceptable training results in this model validation step.

F. Performance Evaluation Metrics

In the abovementioned model validation step, we investigated n-fold cross validation (assume $n = 5/6/10$) to train the model for different cases (overall/night), while the value of n depending on whether the model reaches the best performance on the validation dataset. Having a too small n will reduce the number of events in the training sets, leading to under-training of the model, while having a too big n will likely have too few events in the test set where computing performance metrics will be difficult in case no events are present. We have tried to confirm this using different folds, and the results suggested the use of the current $n = 6$, and the amount of training dataset in this case for the overall model and the night model would be 6000 and 650. To be more specific, Fig. 6 illustrates that the TLEM for overall data and night data reaches the best performance at around 6500 ((5/6) of overall training samples) samples and around 650 ((5/6) of night training samples) samples individually, because the train score curve and the validation score curve match at those number of samples.

To further compare our proposed TLEM with other models, we include ACU, recall/SEN, precision/positive predictive value (PPV), and F_β score. These metrics are computed by

$$\begin{cases} \text{accuracy} = \dfrac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \\ \text{recall} = \dfrac{\text{TP}}{\text{TP} + \text{FN}} \\ \text{precision} = \dfrac{\text{TP}}{\text{TP} + \text{FP}} \\ \text{F}_\beta \text{ score} = \dfrac{(1 + \beta^2) \cdot \text{precision} \cdot \text{recall}}{\beta^2 \cdot \text{precision} + \text{recall}} \end{cases} \tag{5}$$

where TP = true positive, which is the number of correctly classified positive samples; FP = false positive, incorrectly classified negative samples; TN = true negative, correctly classified negative samples, and FN = false negative, incorrectly classified positive samples.

ACU describes how many samples are classified correctly in total, whether the sample is positive or negative. SEN describes the proportion of actually positive samples that are correctly classified as positive. PPV describes the proportion of classified positive samples that are actually positive. F score is also called balanced F score, and it is designed as a harmonic average of precision and recall. F_β score could better describe the model performance even for an imbalanced dataset. In this case, we focused more on the TP rate and FP rate, and FP could cause more severe damage than FP, because FN could lead to ignorance of seizures happening and miss the chance to alarm the patient's caregivers to aid. We set $\beta = 2$, which means the importance of SEN is as twice as PPV, and higher F_β score means better performance.

We trained and tested two individual models separately for overall data and night data and used the abovementioned metrics to evaluate the performance of these trained models.

III. Results

Fig. 7(a) represents an automated detected seizure event, while the start and stop times were automatically detected by the abovementioned algorithm, and the seizure mark was annotated by the patient or his/her caregiver using the red mark button on the bracelet. Fig. 7(b) shows how nonmoving

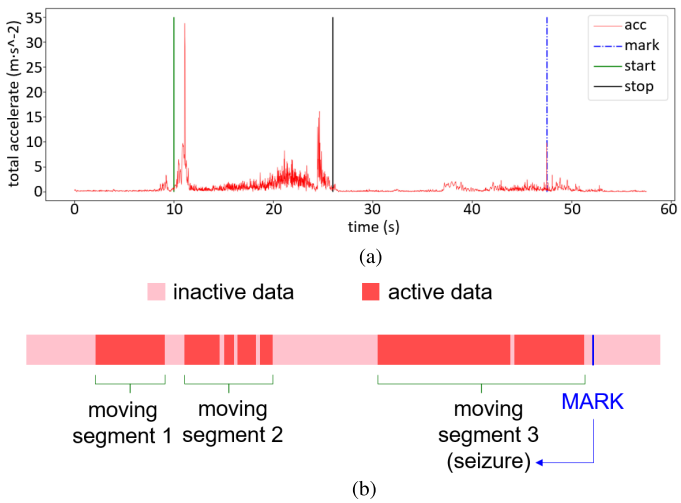

Fig. 7. Moving segment extraction and data annotation. (a) Example of an automatically detected moving segment. The start and stop times of the detected movement are shown in green and black. The blue line showed when the patient or his/her caregiver used the mark button, indicating that this is a seizure event. (b) Nonmoving segments are excluded in this step, and then, moving segments are annotated according to the marks.

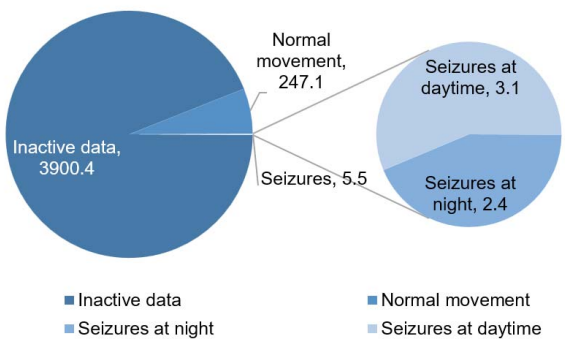

Fig. 8. Hours of recording data, 93.9% of which is nonmoving data, 5.9% is non-seizure moving, and only 0.2% is seizure moving.

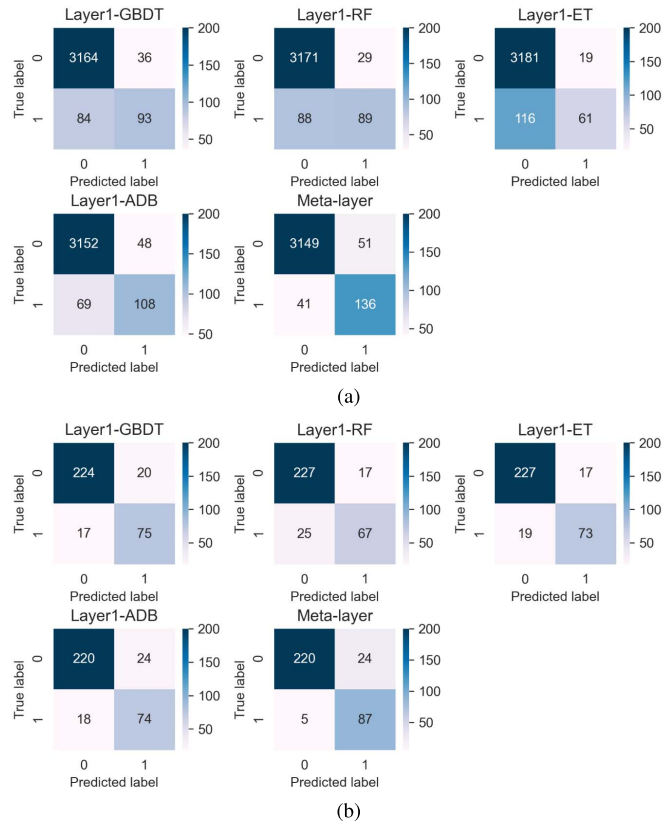

Fig. 9. Confusion matrices of the base-layer classifications and the meta-layer classification. The results are acquired by applying each individual base-layer classification on the test dataset (first to fourth confusion matrix) and applying the ensemble two-layer classification on the test dataset (fifth confusion matrix). Label 1: seizure and label 0: normal movement. (a) Confusion matrix of overall model. (b) Confusion matrix of night model.

segments were excluded, and these nonmoving segments were either totally excluded if it was too long (>10 s), or not excluded if it was a short stop (<10 s) between long time moving segments. The blue line highlighted the time when the subject pressed the mark button. However, there might be several seizures (less than twice in a day) that were not properly annotated, mainly because the patient did not press the mark button in time after the seizure, or there might be some unstable movements before the button is pressed. In these circumstances, the additional movement would be recognized as a seizure, so we would check and remove the incorrect labels and re-label the correct seizure event. In this way, all seizure events and normal movement events are preserved, and data without movement events (inactive data) are excluded. As shown in Fig. 8, we excluded 93.9% inactive data through this automated detection method and annotation method.

In total, we have extracted 10 707 (lasting for 241.6 h) non-seizure moving events and 547 (5.5 h) seizure events, among which 806 non-seizure moving events (5.8 h) and 314 (2.4 h) seizures happened at night.

The results showed that the TLEM model has better performance in ACU, SEN, and F_β score than using one-layer models, which indicated that using our proposed ensemble method could improve the performance. To compare using a single model's performance and our proposed ensemble model's performance, we trained every single model using the same method as we trained the ensemble model. The trained classifiers would make predictions on the testing dataset as well. We used a confusion matrix describe the performances of our proposed TLEM and other single models, as shown in Fig. 9.

We used a total of 30% samples (3200 non-seizure events and 177 seizures) to test the overall seizure detection of the trained two-layer ensemble classification model. At the same time, we used 30% night samples (244 non-seizure events and 92 seizures) for night seizure model.

The test results for overall seizure detection show that a total of 136 out of 177 seizure events (mean SEN 76.84%) seizure events were detected, and 3149 (98.41%) of 3200 non-seizure events were classified correctly with an FAR of 0.98/24 h (51 false alarm from seven patients), and the F_β score reaches 0.7598. At night, the proposed model based on home-collected

TABLE II
PERFORMANCE OF EACH SINGLE CLASSIFIER AND THE PROPOSED TLEM CLASSIFIER

Type	Model	ACU	SEN	PPV	F_β score
Overall	single GBDT	0.9645	0.5254	0.7209	0.5555
	single RF	0.9654	0.5028	0.7542	0.5387
	single ET	0.9600	0.3446	**0.7625**	0.3870
	single ADB	0.9654	0.6102	0.6923	0.6250
	TLEM	**0.9728**	**0.7684**	0.7273	**0.7598**
Night	single GBDT	0.8899	0.8152	0.7895	0.8099
	single RF	0.8750	0.7283	0.7976	0.7412
	single ET	0.8929	0.7935	**0.8111**	0.7970
	single ADB	0.8750	0.8043	0.7551	0.7940
	TLEM	**0.9137**	**0.9457**	0.7838	**0.9082**

RF = Random Forest, ET = Extra Trees, GBDT = Gradient Boosting Decision Tree, ADA = Adaboost, LR = Logistic Regression, ACU = accuracy, SEN = sensitivity, PPV = positive predictive value.

data correctly identified 87 out of 92 night seizure events (mean SEN 94.57%) and 220 out of 244 non-seizure events (90.16%), with an FAR of 0.46/24 h (24 false alarm in seven patients). The F_β score is 0.9082, which further indicated the effectiveness of the night epilepsy detection system.

The F_β score of the night model is much higher than that of the overall model, because movements that happened at night are shorter and less complex than those that happened at the daytime. According to the data we collected in this experiment, normal movements that happened at night only contain turning over in bed, go to the toilet, and other slight moves. Moreover, the ratio of normal movements and seizures at night is 2:1, and the proportion at daytime is 19:1, indicating a more severe imbalance between these two classes at daytime. Thus, those complex normal movements that happened in the daytime, such as brushing teeth and exercising, could be misidentified more often than simple normal movements that happened at night. In the meanwhile, both our proposed TLEM reaches highest F_β score comparing with other single machine learning models.

We compared our two-layer ensemble classification model with other single classifiers as we used in the first layer, and we found that our proposed ensemble model performed better than GBDT, RF, ET, and ADB in most cases, especially for ACU, SEN, and F_β score. It is obvious that for both the overall detection task and night detection task, our proposed two-layer ensemble classification model has kept the best performance.

IV. DISCUSSION

In this work, we designed a data collection method and device used in the home, and the practicality of this method was investigated and proved. Our proposed automated algorithm EAMS could exclude nonmoving segments efficiently while reducing the calculation quantity and accelerating the operation efficiency in the following classify step. For the exclusion step, the thresholds were derived based on the observation of our subjects, and it is detecting whether a human being is moving or not. These thresholds are not describing the typical seizures that our subjects are having, but the normal daily movements and seizure-related movements, therefore, we assume these thresholds could also be efficient in the application phase, which would be further validated in our future study. However, there are several misannotations during the marking step, which is mainly because the subjects forgot to press the button after the seizure, or an exanimation happened after the seizure. This situation happened less than once a day, so such this will not cause a lot of errors of annotation. In this case, we would recheck the data according to the subject's dairy recordings and relabel that moving segment as a seizure event. On the other hand, if duplicated marks happened in a short time (<5 s), we would remove the later mark manually.

The subjects included in this study are having convulsive seizures lasting for 15 s, so we only kept segments lasting for no less than 15 s in this manuscript, but this threshold could be changed if we include different types of seizures in our further study.

As shown in Fig. 4, we found that the iqrs of the 3-D ACM, the 3-D gyroscopes, and the quaternions showed great importance in this study, which means the ACC and angular velocities that change in a large range during a period could indicate a possible seizure in some way. When the subject was having a seizure, his/her movement would change both in the linear aspect and the rotational aspect. Moreover, the variances of the 3-D ACM are also important in this study, while the variances of the 3-D gyros showed less importance. The variance reflects the mean degree of data dispersion, so this result indicates that seizures could lead to random changes in the linear motion, but not in the rotational motion. The mean values of each axis (of the ACM and the gyroscope) are not significant to the detection. When the subject was having seizures, the movement would result in changes of both directions of an axis. Then, the minimum value would change to a lower value (negative), and the maximum would also change to a higher value (positive); therefore, the mean value only changed slightly not too obvious. However, the mean value of the total ACC (positive) is informative, which is because the total ACC ignores the direction of moving and only considers the ACC magnitude.

We proposed a TLEM approach to classify imbalanced datasets of normal movement events and seizure events. Moreover, different types of normal movements were involved in this study. Compared with the previous experiments [9]–[13], this dataset collecting procedure was mainly carried outside the hospital account for the "real world" scenario. Our proposed detecting method brings this study closer to a real-life scenario for daily monitoring purposes. In this study, features were extracted from each entire moving segment. However, exploring other extraction methods, such as using sliding window to extract features, will be interesting in the future study, and this might be able to increase the feature density, and this could be possibly a potential benefit for the future study.

The experimental results show that our proposed two-layer ensemble method could effectively characterize epileptic overall and night seizures with the accuracies of 97.28% and 91.37%, and the SEN values of 76.84% and 94.57%, respectively. Missed seizures might be caused by small amplitudes. As the proportions of seizures are different during the day and at night, it is necessary to establish a separate night seizure

TABLE III
COMPARISON OF OUR PROPOSED APPROACH WITH OTHER SINGLE-SENSOR-BASED SEIZURE DETECTION SYSTEM

Study	Our approach	Kusmakar *et al.* [11]	Beniczky *et al.* [15]	Kramer *et al.* [25]	Lockman *et al.* [26]	Borujeny *et al.* [10]	Nijsen *et al.* [14]
sensors	1 ACM + 1 ANG	1 ACM	1 ACM	1 ACM	1 ACM	3 ACMs	5 ACMs
classifier	TLEM	SVDD	threshold	threshold	threshold	KNN	FLDA
# seizure patients	7	20	20	15	6	3	36
Recording time	4152h	5576h	4878h	1692h	–	–	–
# seizures	547(O) 314(N)	46	39	22	8	60	153
SEN	76.84%(O) 94.57%(N)	86.95%	89.70%	91.00%	88.00%	85.00 %	80.00 %
FAR	0.98/24 h(O) 0.46/24 h(N)	1.16/24 h	0.2/24 h	0.11/24 h	–	–	–

ACM = accelerometer, ANG = angular, SVDD = support vector data description, FLDA = . Fisher's linear discriminant analysis, O = proposed overall model, N = proposed night model

detection model. We set the weight of seizure samples to four that of the normal movement samples, and increasing the weight of the seizure samples will lead to a higher TP rate and, unfortunately, a higher FP rate.

As shown in Table II and Fig. 9, compared with the single-layer classification model, first, our designed ensemble classification model has an SEN of 76.84%, which raised by at most 55.15% performance of single classification for overall model, and has an SEN of 94.57%, which raised by at most 22.99% performance of single classification for night model. The performance of simply using single classifiers is not as good as our proposed method, which had a low fusion complexity and reached a better performance. There were only five seizures failed to be detected due to the subject's arm, which wore the bracelet was held by themselves and could not move freely. This illustrates that this two-layer ensemble classification model could detect more seizure events while still keep a low FAR.

As shown in Table III, compared with other studies, we collected more seizure events in a free-living home environment compared with the study of, for example, Nijsen *et al.* [14] conducted in a hospital with only 153 seizures included, while other mentioned studies have even fewer recordings. In other words, our study is expected to provide more convincing results as trained and tested on a larger dataset with more data modalities. However, this could also lead to lower SEN in the daytime, because more daily activities are included in the dataset. The SEN of our approach in the nighttime is the highest among all studies (to the best of the authors' knowledge), and the SEN in daytime would be lower, because many other daily activities (for example, doing sports or house working) were included in the dataset. This would lead to increasing chance of challenges in distinguishing seizure movements from all other daily movements. We consider having a relatively low SEN could be acceptable (when we took care of the tradeoff between FAR and SEN), because, as consistently observed that SUDEP happens more during the night and the very early morning than the daytime [36]. Nevertheless, future work should focus on the challenge of classifying seizure movements and movements caused by other daily activities.

One limitation of this study is that only convulsive seizures can be detected by motor sensors, because some seizures are not clearly visible in the ACM and ANG signals. Besides one single type of epileptic seizure detection, the classification of seizure types is more challenging due to the limited number of multiple types of seizure data and subjects. The measurement of the EMG and other signals might be useful to include more types of seizures. EMG does not measure any movement directly, but it illustrates muscle tones in tonic contractions, so using both ACM and EMG sensors could include tonic seizure type [16] into our proposed seizure detection system. Besides wearable devices, non-contact sensors allow the subject to be free from wearing any device while still under detection, and our group has designed a radar-based respiratory rate and heart rate detection device [37] to use at night while the subject was sleep, aiming to avoid night SUDEP. Moreover, this night radar was designed as a non-contact method, which means the subject does not have to wear any device while sleeping. In our future study, we would use this non-contact radar to detect seizures at night. And in our further study, we would use wearable PPG, EMG, and ECG monitoring devices to promote more types of seizures, such as non-convulsive seizures. The first version of our proposed device has only motor sensors, and the heart rate will be integrated in the future, and we do plan to conduct a study integrating heart rate data. The use of heart rate combining with motor data (e.g., ACMs) can boost the detection performance [38].

Another limitation of this study is that most of the subjects had different numbers of seizures including some having only a few seizures. Therefore, "leave patients out" approach would cause clear limitation in model training, which might likely lead to biasing the model to patients dominating the number of seizures. In the real application to adopt our model, we could potentially ask the users to press buttons to mark their seizures in an early phase, and those marked data can be used to train a model using our proposed algorithm. Nevertheless, we should include more patients with more seizure events in the future to develop a "patient-independent" algorithm, where no data from the same patient were used for both training and testing.

V. CONCLUSION

In this study, we designed a bracelet with motor sensors to help to monitor epileptics at home, which helps save labor costs. The self-annotation mark button could help improve

the efficiency of labeling data. To extend, this mark button could be used to improve the ACU of the detecting algorithm. This proposed device is capable of detecting convulsive type seizures lasting for over 15 s.

We proposed two main algorithms in this study; one is the automatic active data selection method, namely, EAMS algorithm, and the other is the two-layer ensemble classification method, namely, TLEM algorithm. The proposed selection method helps to discard over 90% inactive data to speed up the following data analyzing and classifying step. We also found the proper amount for the proposed model to get the best performance. The proposed classification method is trained well on 6000 samples and 650 samples for overall and night models individually, and it is validated on collected data from patients using the bracelets we designed. The proposed two-layer classification is capable to deal with the imbalanced dataset while combining the first-layer base learners' benefits and reaching an improved performance. The model detected 136 (76.83%) of 177 seizures in total, in which 87 (94.57%) of 92 night seizures are recognized. Compared with single classification models, the proposed two-layer ensemble classification model shows the feasibility of automated detection of convulsive seizures. Both overall and night model have reached the best performance based on the proposed approach with the size of the dataset with 6500 and 650 samples individually.

In conclusion, the results suggest that this study can be used for the automated seizure detection based on home-collection methods with ACM and ANG data and is expected to contribute to a complete wearable multisensor seizure detection system.

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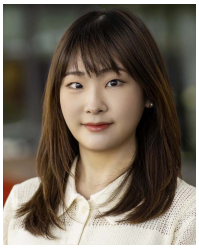

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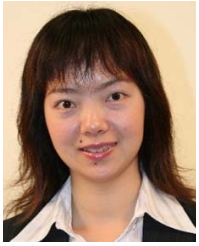

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