High Accuracy Epileptic Seizure Detection System Based on Wearable Devices Using Support Vector Machine Classifier

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***Abstract*—This paper aims to develop an efficient and reliable epileptic seizure detection system based on different wearable devices using support vector machine (SVM) classification. The proposed seizure detection system achieves Seizure detection results show that our algorithm achieving an average sensitivity of 100% and an average accuracy 97% with proposed different combining methods for the signals of wearable devices.**

***Keywords*—Epilepsy, seizure, detection, SVM, wearable**

I. Introduction

More than 50 million globally cannot lead a standard life since they suffer from epilepsy. Epilepsy is an abnormality within the Patient's neural that results in unplanned seizures. Epileptic drugs are just successful with 66% of the cases. Surgery is the next available option when drugs fail to cure the epileptic cases. However, not all epileptic cases are eligible for surgery because the epileptogenic zone has to be localized. Surgery at the lobe could yields 60% success rate, while surgeries at the extratemporal lobe yields only 35% success rate. [1]

Several surveys evaluating patients' desirable seizure detection methodologies and reported in [2-5]. All of them are biased to devices with the subsequent characteristics: removable, non-invasive devices with low visibility. In contrast, devices which might require to hold a hat or which might include patch electrodes at the neck, head or face are poorly accepted by patients [3]. Accordingly, the patients' preferences clearly point to non-EEG-based detection devices. These devices may be portable, including wristband, bag, necklace, intelligent clothes or belt systems, or correspond to patch electrodes placed at the chest, the shoulder or the arm [3].

Although major progress has been made within the field of EEG-based seizure detection and prediction using ML, there's much need for improvement within the field of non-EEG wearable devices. Non-invasive wearable devices have great potential to help the management of epilepsy. These devices must have robust signal quality, and patients must be willing to wear them for long periods of their time.

In previous research, the issue of seizure predication and detection were addressed using different approaches like Machine Learning models [6], Deep Learning models [7], statistical models [8], and other approaches [9]. one in all the foremost commonly utilized machine learning methods is Support Vector Machines classifiers which demonstrated effectiveness in previous works.

The paper is organized as follows. Section II provides a background on the evaluated dataset of wearable devises; Section III illustrate proposed seizure detection system. Section IV summarizing the optimum proposed model and compared with other related work in section V. Finally, some conclusions are drawn in section VI.

II. Dataset of Wearable Devices

The dataset evaluated during this work is attained from the Epilepsy Foundation of America - My Seizure Gauge Public Dataset. These data collected by non-invasive wearable biosensors and devices [10], [11] and provides long-term recordings (Between 3-5 days) of epilepsy patients which implies there are more seizures per patient. Recordings from nineteen patients are provided together with seizure times and metadata about the recordings

Data are provided from three devices: Empatica E4, ByteFlies Sensor Dots and Epilog. These devices are recording following signals: Limb accelerometry in three axes (ACCX,ACCY,ACCZ,ACCMAG), Blood volume pulse (BVP), Electrodermal activity (EDA), Heart rate (HR), Temperature (TEMP), Electromyography (EMG), Photoplethysmography (PPG). Summary of each device and corresponding recorded signals is mentioned in table 1. Machine learning algorithm in this paper evaluated on patient "MSEL_01097" which having all recorded signals.

Table 1 - Summary of Wearable devices

Device	***Location***	***Signals***
Empatica E4	Wrist	ACC,BVP,EDA,HR,Temp
ByteFlies Sensor	Variable (patch)	ACC,PPG or EMG
Epilog	Forehead	Single-channel EEG

III. Seizure Detection System

The block diagram of the 4-stage seizure detection system utilized in this work is depicted in Fig 1

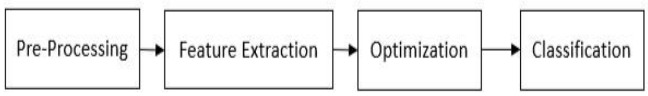

Figure 1 – Block Diagram of Seizure Detection System

A. Data Pre-Processing

During creation of the dataset, Epochs of high-quality, marginal-quality, or poor-quality data were visually identified by reviewers, and reviewer annotations were compared to automated signal quality measures.

B. Features Extraction

Different features are extracted from wearable devices signals in time domain, frequency domain or time-frequency (Wavelet) domain. Twenty-three linear and non-linear features are implemented, and their corresponding combinations are tested along with SVM, and the best performing combination is obtained. Some of these features are previously recommended in another research in [12], [13]. These features are namely Standard Deviation, Fractal Dimension, Hurst Exponent, Skew, variance, Average Energy, Coastline Feature (Fluctuation Index), Hjorth Mobility Parameters, Mean absolute value, Max absolute value, Min absolute value, root mean square, Permutati spectral power, spectral centroid, variation coefficient, spectral skew, Permutation Entropy, Approximate Entropy, Shannon Entropy, Spectral Entropy, Renyie Entropy, Hjorth Parameters: Complexity and Kurtosis.

The best performing features are found to be Fractal Dimension, Approximate Entropy, root mean square, Shannon Entropy, Standard Deviation, Coastline Feature (Fluctuation Index) and Hjorth Complexity Parameters.

Some signals achieved high sensitivity results. However, Fig 2 showing that one signal is not enough to achieve good results in both sensitivity and accuracy (>95%) and need more optimization of the model which addressed in next sections.

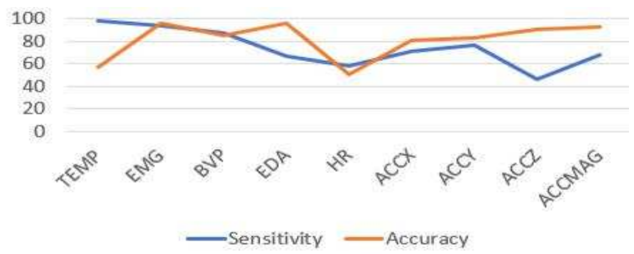

Figure 2- optimum performance results for each signal

C. Classification

Seizure detection is considered a classification problem between two classes, the ictal period when a true seizure happens and the non-ictal period including postictal, pre-ictal and inter-ictal periods. Support vector machine (SVM) is one of the most popular classification techniques. SVM is chosen in binary classification problems as proven excellent accuracy in seizure detection as stated in [14], [13], [15].

D. Performance metrics

Three performance metrics are exploited in this work: sensitivity, specificity, and accuracy. Sensitivity is the ability of a test to correctly identify those with the disease which is also known as true positive rate. Specificity is the ability of the test to correctly identify those without the disease which is also known as true negative. Accuracy refers to how close a sample statistic is to a population parameter

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

E. Model Optimization

To improve performance results, Multiple optimization techniques are performed such as eliminating non useful signals, combining serval signals, and finding the optimized window size.

1) Elimination of redundant signals

There are different signals for Limb accelerometry: ACCX, ACCY, ACCZ, ACCMAG. Fig 2 showing that ACCZ,ACCMAG achieving less sensitivity so compared model combining all signals versus model combining all signals except ACCZ,ACCMAG. Table 2 showing that removing ACCZ,ACCMAG is improving sensitivity so can be eliminated them from the model.

Table 2- Elimination of redundant signals

Signals	***Sensitivity***	***Specificity***	***Accuracy***
All signals	79.166667	94.37751	94.019608
All signals excluding ACCZ,ACCMAG	81.25	92.871486	92.598039

2) Elimination of least contributing signals in sensitivity

Fig 3 shows that EDA,ACCX,ACCY Does not significantly affect the obtained sensitivity Thus can be eliminated to reduce system complexity.

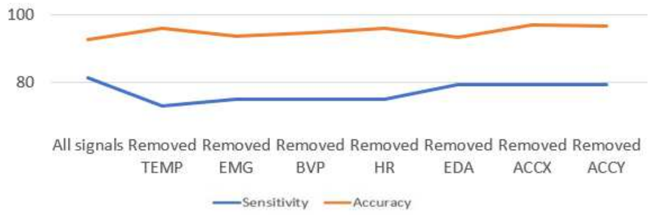

Figure 3 -Elimination of least contributing signals in sensitivity

3) Combining multiple signals based on Majority

In case of combining multiple signals based on Majority, System predicting seizure if number of signals indicating existence of seizure greater than number of signals indicating absence of seizure. Exercised all possible number of signals and combination of signals. Table 3 is summarizing the optimum detected performance results which conclude that combination of TEMP, EMG, ACCY signals achieving the best performance (98% sensitivity, 91% accuracy).

Table 3 - Combining multiple signals based on Majority

Signals	***Sensitivity***	***Accuracy***
TEMP, EMG	91.6	98.1
TEMP, EMG, ACCY	97.9	90.8
TEMP, EMG, BVP, EDA	93.7	98.2
TEMP, EMG, BVP,ACCX , ACCY	97.9	90.3
TEMP, EMG, BVP, HR EDA, ACCY	79.1	96.7
TEMP, EMG, BVP, HR EDA, ACCX ACCY	81.2	92.5

4) Combining signals based on assumed weights

Combining multiple signals based on assumed weights based on sensitivity results mentioned in Fig. 2 so signals achieving highest results are given higher weights as following: TEMP = 98, EMG = 94, BVP = 88, EDA = 67, HR = 58, ACCX = 71, ACCY = 77, ACCZ = 46, ACCMAG = 68.

System predicting seizure if following condition is satisfied

$$\frac{\sum weights \text{ of signals indicating existence of seizure}}{100 * number\ of\ total\ signals} > 0.5 \qquad (1)$$

Table 4 shows that performance has been improved compared to majority based combining method shown in Table 3 and still the combination of TEMP, EMG, ACCY signals is achieving the best performance (98% sensitivity, 91% accuracy).

Table 4 - Combining signals based on assumed weights

Signals	*Sensitivity*	*Accuracy*
TEMP, EMG	91.6	98.1
TEMP, EMG, ACCY	97.9	90.8
TEMP, EMG, BVP, EDA	93.7	98.2
TEMP, EMG, BVP,ACCX , ACCY	97.9	90.3
TEMP, EMG, BVP, HR EDA, ACCY	79.1	96.7
TEMP, EMG, BVP, HR EDA,ACCX ACCY	81.2	92.5

5) Combining multiple signals based on learnt weights based on machine learning model

Proposing that weights can be extracted using machine learning algorithm. Fig 4 shows the block diagram of this system with added SVM training and classification blocks which was not existing in previous combining systems. Table 5 shows that performance has been improved compared to previous systems shown in Tables 3,4.

Table 5- Combining multiple signals based on learnt weights

Signals	*Sensitivity*	*Accuracy*
TEMP, EMG	97.6	99.6
TEMP, EMG, ACCX	100	96.9
TEMP, EMG, BVP, ACCX	97.6	99.1
TEMP, EMG, BVP, ACCX,ACCY	100	92.5
TEMP, EMG, BVP, HR, EDA, ACCX	83.3	97.4

6) Selecting window length

In previous trials, training/classification window length was assumed as 1 second. Different window sizes for signal segmentation are investigated in order to optimize the performance of seizure detection systems. Window period should be long enough for the lapse to be informative but not too long for it to stay stationary. Similar approach investigated before for EEG signal-based seizure detection in [16].

Fig 5 summarizing performance for using only one signal which showing that 4 sec length is good potential for optimum performance.

Table 6 shows performance comparison between window length 1sec, 4sec of majority based and machine learning weights based combining method. As a conclusion, window with length 4 sec is showing improvement in many signals' scenarios.

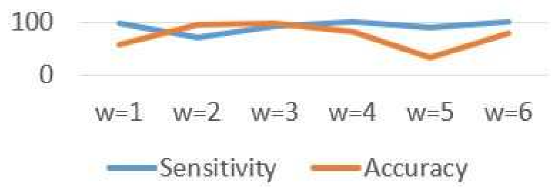

Figure 5 - performance results of different window length

Table 6 - selecting optimum window length

Window size = 1		*Window size = 4*	
Combining based on majority			
Sensitivity	*Accuracy*	*Sensitivity*	*Accuracy*
97.9	90.8	100	95.9
Combining based on machine learning			
100	96.9	100	96.5

IV. Proposed Model

Table 7 shows a summary for the final three proposed models using different signals, window length and signals combining algorithm along with their performance measurements. Hardware complexity implementation of related extracted features can be metric for model selection.

Table 7 - Proposed Seizure Detection System

Signals	*Features*	*Window*	*algorithm*	*Sensitivity*	*Accuracy*
EMG, BVP, ACCY	Approximate Entropy root mean square Fluctuation Index	4	assumed weights	100	95.9
TEMP, EMG, ACCX	Fractal Dimension Approximate Entropy Fluctuation Index	1	Machine learning	100	96.9
EMG, BVP, EDA	Approximate Entropy root mean square Shannon Entropy	4	Machine learning	100	96.5

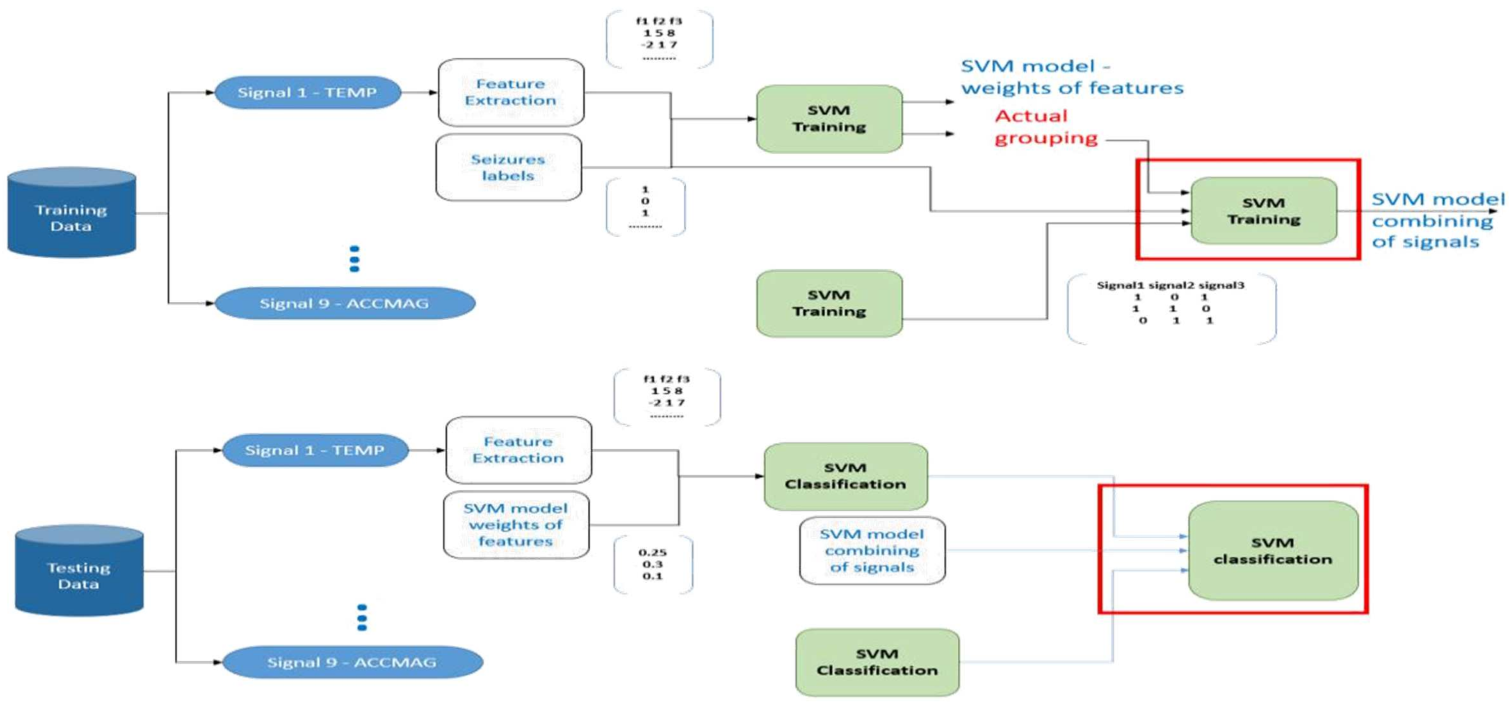

Figure 4- Block diagram of combining signals based on machine learning

V. Comparison with related work

Different pervious research investigated seizure detection using different wearable devices

In [18], Author used wrist-worn, wireless accelerometer sensor for detecting generalized tonic–clonic seizures (GTCS). Seventy-three patients were monitored for mean 67 hours with thirty-nine GTCS. The device detected 35 seizures. The mean of the sensitivity calculated for each patient was 91%.

In [19], Author used wearable accelerometer device (Epi-Care) for clinical validation of seizure detection. Seventy-one patients had been using the device and the median sensitivity of seizure detection is 90% and false alarm rate 0.1/d.

In [20], Author validated a seizure detection algorithm based on heart rate variability (HRV) using patient-specific cutoff values. Electrocardiography (ECG) was recorded using a wearable device ePatch which placed by the staff on the lower left ribs. Total 19 patients were recruited at the Danish Epilepsy Centre, Dianalund, and at Aarhus University Hospital, Denmark.. Seizures of 5 patients were detected with sensitivity 0%, 1 patient with sensitivity 25%, 1 patient with sensitivity 33%, 1 patient with sensitivity 50%, 1 patient with sensitivity 66%, 10 patient with sensitivity 100% .

In [21], Author proposed automated real-time detection of tonic-clonic seizures using a wearable EMG device. The sensitivity of the wearable device was 93.8%

In [22], Author proposed automated detection of epileptic seizures using wearable devices. Quantitative surface electromyography (EMG) changes are characterized by a dynamic evolution of low and high-frequency signal components. Algorithms targeting increase in high frequency EMG signals. The accuracy of wearable EMG devices with high sensitivity (76%-100%).

Table I summarizing comparison between results of previous research and our proposed model.

Table 8 - Comparison with Related Work

Signals	***[18]***	***[19]***	***[20]***	***[21]***	***[22]***	***Our work***
EMG				93.8 %	76,9,100	94
HR			0,25,33, 50,66,100			71
EGG						
ACC	91	90				83
Combined signals						100

VI. Conclusion

Wearable devices satisfy needs and preferences of seizure patients and this paper proved that they have great potential to be used in high accuracy epileptic seizure detection system. Although using one signal is not sufficient for high performance detection system, We proposed different combining methods which lead to achieving desired both sensitivity and accuracy.

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References

[1]P. Boon, T. Vandekerckhove, E. Achten, E. Thiery, L. Goossens, V. K, D. M, G. Van Hoey, B. Vanrumste, B. Legros and e. al., "Epilepsy surgery in Belgium, the experience in gent," Acta Neurologica Belgica, no. 99, p. 256, 1999.

[2]Bruno E, Simblett S, Lang A, Biondi A, Odoi C, Schulze- Bonhage A, et al. Wearable technology in epilepsy: the views of patients, caregivers, and healthcare professionals. Epilepsy Behav 2018;85:141–9.

[3]Hoppe C, Feldmann M, Blachut B, Surges R, Elger CE, Helmstaedter C. Novel techniques for automated seizure registration: patients' wants and needs. Epilepsy Behavior 2015;52:1–7.

[4]Janse SA, Dumanis SB, Huwig T, Hyman S, Fureman BE, Bridges JFP. Patient and caregiver preferences for the potential benefits and risks of a seizure forecasting device: a best-worst scaling. Epilepsy Behav 2019;96:183–91.

[5]Tovar Quiroga DF, Britton JW, Wirrell EC. Patient and caregiver view on seizure detection devices: a survey study. Seizure 2016;41:179–81.

[6]I. Alaa, N. Ahmed, M. Nader, A. Magdy, M. Ibrahim, M. Khalil, M. H.Zakhari, and H. Mostafa, "Seizure Prediction & Segmentation Merge Yielding a Boosted Low Power Model", IEEE International Conference on Microelectronics (ICM 2019).

[7]Khan H, Marcuse L, Fields M, Swann K, Yener B. Focal onset seizure prediction using convolutional networks. IEEE Trans Biomed Eng 2018.

[8]Myers MH, Padmanabha A, Hossain G, de Jongh Curry AL, Blaha CD. Seizure prediction and detection via phase and amplitude lock values. Front Human Neurosci 2016.

[9]Zandi AS, Tafreshi R, Javidan M, Dumont GA. Predicting epileptic seizures in scalp EEG based on a variational Bayesian Gaussian mixture model of zerocrossing intervals. IEEE Trans Biomed Eng 2013.

[10]Kuhlmann, L., Karoly, P., Freestone, D.R., et al., (2018) Epilepsyecosystem.org: Crowd-Sourcing Reproducible Seizure Prediction with Long-Term Human Intracranial EEG, Brain, awy210, https://doi.org/10.1093/brain/awy210

[11]Nasseri, M, Nurse, E, Glasstetter, M, et al. Signal quality and patient experience with wearable devices for epilepsy management. Epilepsia. 2020; 00: 1– 11. https://doi.org/10.1111/epi.16527.

[12]M. A. Elgammal et al., "Linear and nonlinear feature extraction for neural seizure detection," in Proc. IEEE 61st Int. Midwest Symp. Circuits Syst.,2018, pp. 795–798.

[13]H. Elhosary, M. H. Zakhari, M. A. Elgammal, M. A. Abd El Ghany, K. N. Salama and H. Mostafa, "Low-Power Hardware Implementation of a Support Vector Machine Training and Classification for Neural Seizure Detection," in IEEE Transactions on Biomedical Circuits and Systems, vol. 13, no. 6, pp. 1324-1337, Dec. 2019, doi: 10.1109/TBCAS.2019.2947044.

[14]Y. Liu, W. Zhou, Q. Yuan, and S. Chen, "Automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 6, pp. 749–755, Nov. 2012.

[15]M. A. Elgammal, H. Mostafa, K. N. Salama and A. Nader Mohieldin, "A Comparison of Artificial Neural Network(ANN) and Support Vector Machine(SVM) Classifiers for Neural Seizure Detection," 2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS), Dallas, TX, USA, 2019, pp. 646-649, doi: 10.1109/MWSCAS.2019.8884989.

[16]A. Alzahy, M. Elgammal, H. Mohammed and H. Mostafa, "Optimal EEG Window Size for Neural Seizure Detection," 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST), 2019, pp. 1-4, doi: 10.1109/MOCAST.2019.8741714.

[17]Beniczky, Sándora,b; Jeppesen, Jespera Non-electroencephalography-based seizure detection, Current Opinion in Neurology: April 2019 - Volume 32 - Issue 2 - p 198-204 doi: 10.1097/WCO.0000000000000658

[18]Beniczky S, Polster T, Kjaer TW, Hjalgrim H. Detection of generalized tonic–clonic seizures by a wireless wrist accelerometer: a prospective, multicenter study. Epilepsia 2013; 54:e58–e61.

[19]Meritam P, Ryvlin P, Beniczky S. User-based evaluation of applicability and usability of a wearable accelerometer device for detecting bilateral tonic–clonic seizures: a field study. Epilepsia 2018;

[20] Jeppesen J, Fuglsang-Frederiksen A, Johansen P. et al. Seizure detection using heart rate variability: A prospective validation study. Epilepsia 2020; 61 (Suppl 1): S41-S46 DOI: 10.1111/epi.16511.

[21]Automated real-time detection of tonic-clonic seizures using a wearable EMG device Sándor Beniczky, Isa Conradsen, Oliver Henning, Martin Fabricius, Peter Wolf Neurology Jan 2018, 90 (5) e428-e434; DOI: 10.1212/WNL.0000000000004893

[22] Beniczky S, Conradsen I, Wolf P. Detection of convulsive seizures using surface electromyography. Epilepsia 2018;59:23–29