Performance Evaluation for Compression-Accuracy trade-off using Compressive Sensing for EEG-based Epileptic Seizure Detection in Wireless Tele-monitoring

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Abstract—**Brain is the most important part in the human body controlling muscles and nerves; Electroencephalogram (EEG) signals record brain electric activities. EEG signals capture important information pertinent to different physiological brain states. In this paper, we propose an efficient framework for evaluating the power-accuracy trade-off for EEG-based compressive sensing and classification techniques in the context of epileptic seizure detection in wireless tele-monitoring. The framework incorporates compressive sensing-based energy-efficient compression, and noisy wireless communication channel to study the effect on the application accuracy. Discrete cosine transform (DCT) and compressive sensing are used for EEG signals acquisition and compression. To obtain low-complexity energy-efficient, the best data accuracy with higher compression ratio is sought. A reconstructed algorithm derived from DCT of daubechie's wavelet 6 is used to decompose the EEG signal at different levels. DCT is combined with the best basis function neural networks for EEG signals classification. Extensive experimental work is conducted, utilizing four classification models. The obtained results show an improvement in classification accuracies and an optimal classification rate of about 95% is achieved when using NN classifier at 85% of CR in the case of no SNR value. The satisfying results demonstrate the effect of efficient compression on maximizing the sensor lifetime without affecting the application's accuracy.**

Keywords: *EEG; DCT; wavelet compression; compressive sensing; feature extraction; classification.*

I. INTRODUCTION

Mobile and wireless devices are growing rapidly and are estimated at 5 billion devices world-wide. A critical issue of using such devices is the energy that can be consumed by these devices. These devices are operating on limited power reserves as they are battery-operated, while sensing physical measures. Energy consumption is a major challenge in limiting the mobile device's form factor. Our main motivation is to investigate the energy consumption of mobile nodes at two levels, namely, at the compression level and at the communication level, while keeping the overall classification accuracy at a satisfactory level. Hence, the trade-off between energy consumption at these two levels is studied.

Compressive sensing (CS) [1] is used to reduce the amount of data required to send from transmitter to receiver, hence, has been considered for efficient EEG acquisition and compression in several application contexts [2, 3, 4]. Brain

status information is captured by physiological EEG signals, extensively used for the study of different brain activities. One of these states is the epileptic seizure detection. Epilepsy or epileptic seizure is refers to the one of the most common brain disorders usually caused by brain injury. Approximately, one in every 100 persons is expected to experience a seizure disorder in their life time Iasemidis et al., 2003 [5]. Epilepsy is categorized by the occurrence of multiple episodes of seizures in a row. The diagnosis of epilepsy is clinical, however, the scalp EEG is the most widely accepted test for the diagnosis of epilepsy [6, 7].

In [2, 3], the research work has been focused on the sparse modeling of EEG signals and evaluating the efficiency of CS-based compression in terms of signal reconstruction errors. The work in [4] has tried to estimate the low-power potential of CS for portable EEG systems using datasheet-extracted power consumption figures for the various components. It also estimates the required amount of processing and wireless transmission. Neural Network (NN), Support Victor Machine (SVM), the *k*-nearest neighbor (*k*-NN) and naive Bayes algorithms have been proposed as classification methods [8].

Wang *et al.* [9] have proposed an EEG classification system for epileptic seizure detection. It consists of three main stages, namely, 1) the best basis-based wavelet packet entropy method is used to represent EEG signals by wavelet packet coefficients. 2) *k*-NN classifier with cross validation method in the training stage is used for hierarchical knowledge base (HKB) construction. Lastly, 3) the top-ranked discriminative rules from the HKB used in the testing stage to compute classification accuracy and rejection rate. The method proposed by Weng and Khorasani [10] uses the features which are proposed by Gotman [11] namely, average EEG amplitude, and average EEG duration, coefficient of variation, dominant frequency, and average power spectrum as inputs to an adaptive structured neural network. The method proposed by Pradhan *et al.* [12] uses raw EEG signal as input to a learning vector quantization (LVQ) network. Nigam *et al.* [13] have proposed a new neural network model called LAMSTAR network and two time-domain attributes of EEG, namely, relative spike amplitude and spike rhythmicity. They have been used as inputs for the purpose of epilepsy detection

This paper focuses on the design of an efficient CS-based framework for raw EEG signal acquisition and reconstruction.

The trade-off between sensor power consumption and the classification accuracy are addressed in the paper. In the same ti ne, the major components of research in this area including physiological sensing and data preprocessing, noisy wireless communication, feature extraction, and classification accuracy of the epileptic seizure application are also been considered. The proposed framework compresses the raw EEG data, transmits it over the wireless channel, showing the effect of channel impairments on the compression requirements to achieve target application accuracies. The proposed system h s four phases:

1) Sampling of the original EEG signals by DCT method with best basis for feature extraction for compression, and then sent over wireless channel,

2) Reconstructing the down-sampled signal using inverse DCT,

3) Cross-validation, training stage together with one of these NN, SVM, k-NN and Bayesian classifiers was used for hierarchical knowledge base construction. During each validation process, the obtained optimal values with the best classification accuracies as the discriminative rules were stored and re-organized and

4) Testing stage, to categorize a new sample into either epileptic or normal class, classifiers are using discriminative rules from HKB was used to calculate the similarity between the new sample and the corresponding training process samples, respectively.

The remainder of this paper is structured as follows. In Section II, materials and methods which include description of EEG data, compressive sensing, and discrete cosine transform. Section III, describes our proposed system model which includes the feature extraction, and classification data analysis. Results and discussions are illustrated in Section IV. P per is concluded and presented at Section V.

II. MATERIALS AND METHODS

A. EEG data description

The data was originated from Andrzejak et al. [14] EEG archive of pre-surgical diagnosis and composed for the study to differentiate healthy subjects and epilepsy disease suffering subjects. In this work, EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. The data is for five sets indicated A–E, each one holding 100 single channel EEG segments of 23.6-sec duration. Sets A and B both of them were relaxed in an awake situation with eyes open and eyes closed, respectively. Segments of sets A and B are taken from surface EEG recordings which were carried out using a standardized electrode placement scheme on five healthy volunteers. Segments in set C from the hippocampal formation of the opposite hemisphere of the brain, and those in set D were recorded from within the epileptogenic zone. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity.

Segments here were selected from all recording sites presenting ictal activity. All EEG signals were recorded with the same 128- channel amplifier system, [neglecting electrodes that having strong eye movement artifacts (A and B) or pathological activity (C, D, and E)]. The data was written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. AbdulJalil et al. [15] proposed an evidence theory-based approach for epileptic seizure detection using time domain features and several classifiers. Each classifier is considered an independent information source, and hence has its own view of the current brain state. These local views are then combined using the Dempster's rule of combination. The proposed approach achieved an overall 89.5% classification accuracy. The objective in [16] was to differentiate recordings from set A healthy volunteers with eyes open, set C from the hippocampal formation of the opposite hemisphere of the brain, and set E epilepsy patient during epileptic seizures. The experimental results show that on the proposed method they could be able to achieve significant improvements. In this research, data sets A, C, and E are used as measure of interest. Figure 1 illustrated he ideal raw EEGs signals of sets A, C, and E.
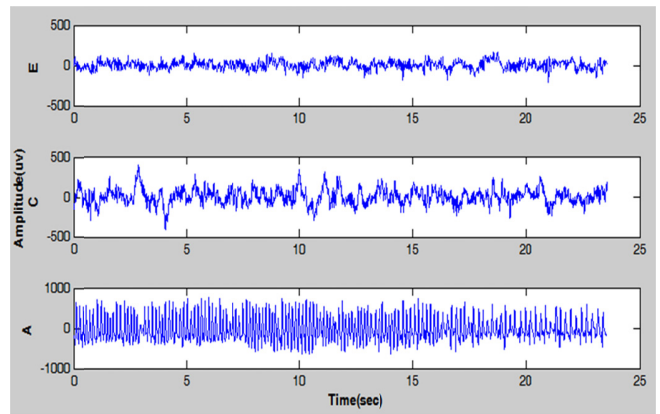

Fig. 1: Example of three different classes of EEG signals taken from different subjects

B. Compressive Sensing

An N-dimensional EEG signals x is considered to illustrate the CS compression and reconstruction. Assume that this signal is represented by a projection on to a different bases set Ψ:

$$x = \sum_{i=1}^{N} x_{0_i} \Psi_i \quad \text{or} \quad x = \Psi x_0 \quad (1)$$

where x_0 is N*1 bases function vector and Ψ is N*N bases matrix. The sparse vector x_0 can be calculated from the inner product of x and Ψ:

$$x_{0i} = <x, \Psi_i> \quad (2)$$

The basis (Ψ) can be Gabor, Fourier, or Discrete Cosine Transform (DCT), Mexican hat, Linear Spline, Cubic Spline, Linear B-spline, and Cubic B-spline basis. In compressive sensing, Ψ is chosen such that x_0 is sparse. The vector x_0 is k-

sparse if it has k non-zero entries and the remaining ($ -k$) entries are all zeros. In addition to the projection above, it is assumed that x can be related to another signal y:

$$y = \Phi x \qquad (3)$$

where Φ is a measurement matrix (also called sensing matrix) of dimensions $M*N$ and y is the compressively sensed version of x. Matrix y has dimensions $M*1$ and if $M < N$ data compression is achieved. It can be shown that this technique is possible if Φ and Ψ are incoherent. To satisfy this condition, Φ is chosen as a random matrix. The Compression Ratio (CR) is then defined as:

$$CR = \left(1 - \frac{M}{N}\right) * 100 \qquad (4)$$

where x is the original signal, and x_r is the reconstructed signal. Given a compressed measurement y at the receiver, the sparse signal x_0 can be reconstructed.

C. DCT algorithm

Discrete cosine transform (DCT) in particular is a Fourier-related transform like the discrete Fourier transform (DFT), however, it is using only real numbers, and low computational complexity. In order to obtain the signal $x(n)$ in the DCT domain, that will lead to the definition of the $(N + 1)$x(N+1) DCT transform matrix, whose elements are given by:

$$[C]_{mn} = \sqrt{\frac{2}{N}} \left\{ k_m k_n COS\left(\frac{mn\pi}{N}\right)\right\}, m, n = 0, 1, \dots, N \qquad (5)$$

$$k_i = 1 \qquad \text{for } i \neq 0 \text{ or N}$$
$$= 1/\sqrt{2} \qquad \text{for } i = 0 \text{ or N}.$$

This matrix is unitary and when it is applied to a data vector x of length $N + 1$, it produces a vector X_c, $X_c = [C] * x$ whose elements are given by,

$$X_c(m) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N} k_m k_n COS\left(\frac{mn\pi}{N}\right) x(n) \qquad (6)$$

III. SYSTEM MODEL

A. System Model

The system model consists of two main parts, the transmitter and receiver. The transmitter has 4096 raw electroencephalography (EEG) represented by (x), and uses CS technique to down-sample the data based on the compression ratio (CR). The CS bases that can be used are Wavelet families include Haar, Daubechies, Symlets, Coiflets, Biorthogonal, Reverse biorthogonal and discrete approximation of Meyer wavelet. In this paper we opted to using DCT and basis ψ for different quantities of M, to get the compressed data $\hat{x}$ that will be transmitted over the noiseless channel (i.e., Radio Frequency (RF) or Bluetooth). On the other hand, transmitting the same data on noisy wireless channel, we added an Additive White Gaussian Noise (AWGN) to enforce SNR with 1dB, 5dB and 10dB values.

While the receiver, which receives the compressed signal M size, reconstruct back the EEG data using inverse DCT (iDCT) and basis pursuit to get the x_r. The iDCT reconstruction algorithm is for the DCT or an optimization problem with certain constraints is solved for the CS [17, 18, 19]. For example, the following is given a compressed measurement y at the receiver, the signal x can be reconstructed by solving one of the following optimization problems.

$$\text{Min} \parallel x_0 \parallel_2 \text{ Subject to } y_i = < \Phi_i, \Psi x0_i > \qquad (7)$$

Using a trick of basis Pursuit, finds the vector x_0 with the lowest L2 norm that satisfies the observations made. For N-dimensional EEG signal x:

$$x = \Psi \alpha \qquad (8)$$

where Ψ is the wavelet family basis and α is the wavelet both are domain coefficients. At the receiver side, once we detect α, iDCT will be utilized to reconstruct it back into the original signal. Figure 1 showed the model of compressed sensing EEG-based epileptic seizure.
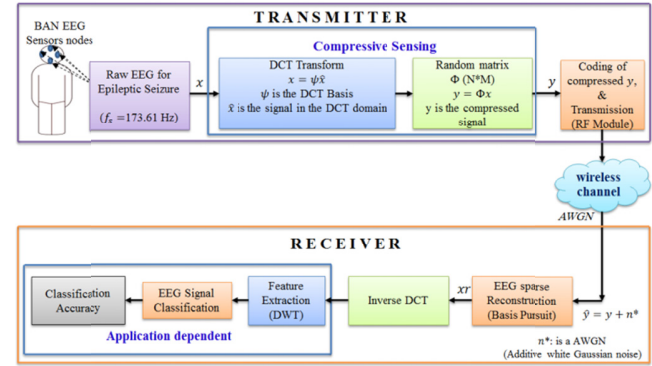

Figure 2: Compressed Sensing EEG-Based Epileptic Seizure Framework.

B. Feature extraction

EEG Feature Extraction plays a significant role in diagnosing most of the brain diseases. After reconstructing the original signal x_r, we implement feature extraction technique to using DWT to obtain a set of features to be used for epileptic seizure detection. Recently, numerous research and techniques have been developed for analyzing the EEG signal. Discrete wavelet transform (DWT) is an excellent candidate for feature extraction from such data since the EEG is time-varying and space-varying non-stationary signal [9].

DWT, like the Fourier transform, is a localized linear decomposition of the signal with different basis function, which is translated and scaled in time [21]. DWT has a key advantage over Fourier transform [20, 21, 22, 23] that, it captures both frequency and time location information. Different families of DWT can be used like Haar, Daubechies, and symlets, Coiflets, Biorthogonal, Reverse biorthogonal and discrete approximation of Meyer wavelet.

Wavelet series expansion for $f(x)$, where $f(x) \in L^2(R)$ $L^2(R)$ relative to wavelet $\psi(x)$ and scaling function $\varphi(x)$

$$f(x) = \sum_k c_{j0}(k)\varphi_{j0,k}(x) + \sum_{j=j_0}^{\infty} \sum_k d_j(k)\psi_{j,k}(x) \quad (9)$$

c_{j0} is the approximation coefficients. It uses scaling function to provide an approximation of $f(x)$ at scale j_0 [it is exact at $f(x) \in V_{j_0}$] where j_0 is an arbitrary starting scale. The approximation coefficients c_{j0} can be calculated as:

$$c_{j_0}(k) = \langle f(x), \varphi_{jo,k}(x) \rangle \quad (10)$$

In the second sum a finer resolution is added to the approximation to provide increasing details and $d_j(k)$ called details coefficients and it can be calculated as:

$$d_j(k) = \langle f(x), \psi_{j,k}(x) \rangle \quad (11)$$

The aforementioned set of wavelet families can be applied for the feature extraction purpose. To obtain maximum classification accuracy, Daubechies 6 with 7 levels of decomposition is utilized [24]. Classical statistics (maximum, minimum, mean and standard deviation) are obtained from each wavelet subband and combined together to devise the feature vector, which in turn used in the classification process.

C. Data Classification

Our previous survey in [25] shows that EEG detection and classification plays an essential role to the timely diagnosis and analyzes potentially fatal and chronic diseases proactively in clinical as well as various life settings. In this research, therefore, using the Rapidminer software tool [26] we implemented several classifiers to measure the classification accuracy of such EEG data. Since our concern is the trade-off between algorithm complexity and classification accuracy of the obtained features, any classifier model can be used in the classification process. NN, SVM, *k*-NN and Bays classifiers were used to classify the classification accuracy according to the compression ratio (CR). For more details about the comparison between NN, SVM, *k*-NN and Bays which are used in this research as different supervised learning techniques please refer to [27].

IV. RESULTS AND DISCUSSION

We used simulation model that Matlab with RapidMiner tool to conduct performance evaluation for the complexity-accuracy trade-off study. Compressive sensing technique has been implemented using Matlab, with DCT basis method to down-sample the *N* raw EEG data samples to *M* measurements, composing the transmitted data *y*. Wireless channel effect is then incorporated through applying AWGN noise with different SNRs to evaluate the effect of physical layer channel impairments. We used a range of SNRs from 1 to 10 dB, and we checked it against the noiseless channel case. Finally, feature extraction, and classification using the NN, SVM, *k*-NN and Bayes classifiers were performed, using

RapidMiner to evaluate the classification accuracy as a function of CR. For each CR value, we conduct 20 simulations with different values of the random measurement matrix, and evaluate the average to enhance the confidence of the obtained results. First, regarding the execution time for each feature file, we observe that, on the average, NN takes around 2.65 minutes, SVM takes one second, while both of *k*-NN and Bayes times is less than a second. Most of the classifiers parameters were configured to the default values. NN, training cycles are 500, learning rate is 0.3. SVM type was nu-support vector classification (nu-SVC), cache size is 80 megabyte. *k*-NN type is radial, *k* settings to 10. Eventually, Bayes used Laplace correction to avoid high potential impact zero, default: true.

Figure 3 illustrates the classification accuracy against CR in the case of the noiseless wireless channel, using the four classifiers. Figure 3 also shows the results for NN, SVM, *k*-NN, and Bayesian classifier accuracy for noiseless wireless channel. The results show that accuracy decreases logarithmically with the increase of CR. We can divide the results into three main regions, at CR = 75%, and 85% respectively. While accuracy remains stable above 90% for all classifiers in the first region, NN, and Bayesian seems to have significant accuracy of about 5%. The decay in accuracy seems to be reasonable in the second region, showing NN making the lead in high compression values, and then it starts to decay exponentially in the third region for all classifiers. While NN consistently outperforms the other three classifiers in all regions, the high classification time and complexity of implementation makes it prohibitive in real time wireless tele-monitoring applications.
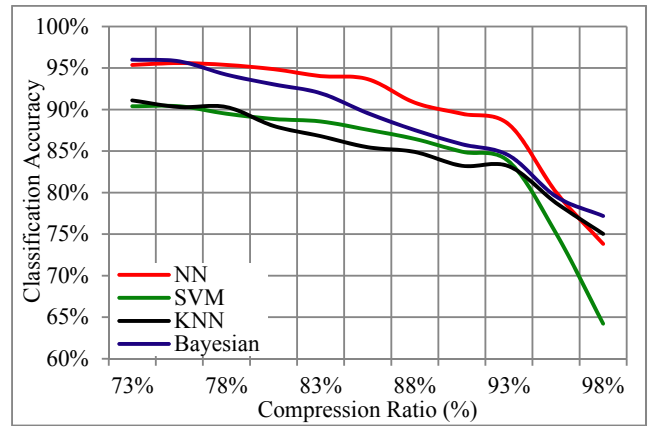

Figure 3: Classification accuracy against CR for noiseless wireless channel

Figure 3 illustrates the classification accuracy against CR in the case of the noiseless wireless channel, using the NN, SVM, *k*-NN and Bayes classifiers.

Hence, the following figures show the results of classification accuracy against CR, after adding the effect of

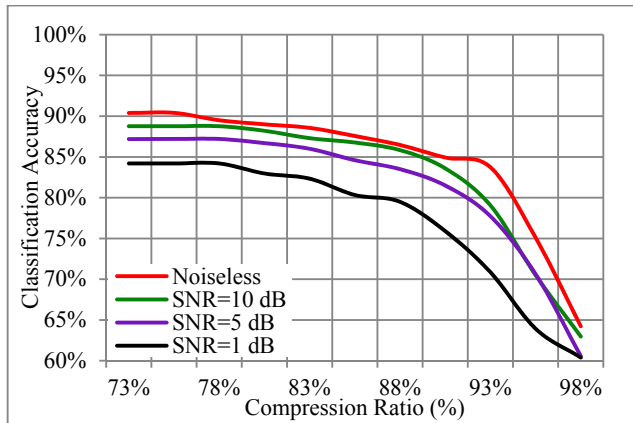physical channel impairments for SVM, *k*-NN, and Bayes classifiers.

Fig. 4: Classification accuracy for noisy wireless channel using SVM classifier.
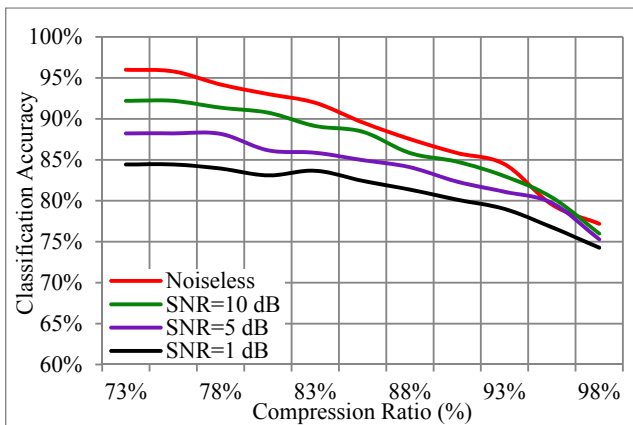

Fig. 5: Classification accuracy for noisy wireless channel using Bayes classifier.
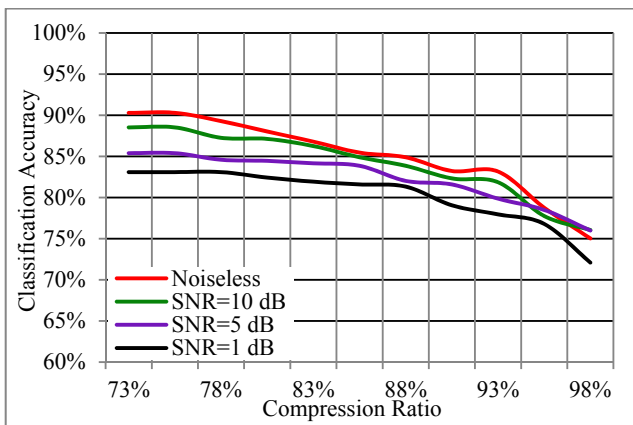

Fig. 6: Classification accuracy for noisy wireless channel using *k*-NN classifier.

Figure 4 shows that the accuracy decreases consistently, while the exponential decay starts earlier with the increase of channel noise. For example, the exponential decay start at CR~90% for the noiseless channel, while it starts at CR=85% when SNR=1dB.

Figure 5 shows a slightly different behavior for Bayesian classifier. While the classification accuracy starts to decay linearly after CR=75%, the effect of noisy communication is more evident, causing the decrease of more than 10% when SNR=10dB.

Eventually, Figure 6 shows steady decrease against both CR, and SNR, nominating *k*-NN to be the best tolerable classifier to wireless channel noise, and changes in CR.

Figure 3-6 show the best compression ratio is at 85%. Also, the NN classifier is more accurate and gives a better accuracy at 95%. Bayes is less complex and uses only Laplace correction. However, SVM and *k*-NN give less accuracy than NN and Bayes. This is mainly because these classifier models use different classification strategies. For example, the Bayes classifier assumes that the features of the input pattern are independent. In the case of neural networks, the dependency relationship can be learned from data. For the k-NN and SVM models, the default parameters were used. Optimized parameters may lead to better classification; this can be investigated for future work.

V. CONCLUSION

In this work, we developed an efficient framework for evaluating the trade-off between complexity and accuracy for a compressive sensing in wireless tele-monitoring used for EEG-based Epileptic Seizure Detection application. For the wireless EEG tele-monitoring system, low-complexity of energy-efficient compression paradigms can be achieved through utilizing the iDCT method for data reconstruction. The proposed system model uses data set A, data set C, and data set E of the EEG-based epileptic seizure application to measure the data classification accuracy. We have also investigated the impact of the wireless channel characteristics on the transmission of the compressed EEG signal, showing the effect of wireless channel impairments. The results revealed that NN with a better accuracy at 95% outperforms the other three classifiers, namely SVM, *k*-NN, and Bayes. However, the implementation complexity, and classification latency makes NN prohibitive for real-time tele-monitoring applications. The results show that *k*-NN is the most stable classifier as it tolerates to the imperfection of data due to channel noise, and high compression values. The accomplished results are basis for deriving an analytical model of compression at the transmitter, which can be used to adapt and predict the classifier performance when the transmitter changes compression to respond to potential wireless channel degradation.

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