

Efficient Epileptic Seizure Type Classification Using Hyperdimensional Computing

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Abstract—Precise seizure identification plays a vital role in understanding cortical connectivity and informing treatment decisions. Yet, the manual diagnostic methods for epileptic seizures are both labor-intensive and highly specialized. In this study, we propose a Hyperdimensional Computing (HDC) classifier for accurate and efficient multi-type seizure classification. Despite previous seizure analysis efforts using HDC being limited to binary detection (seizure or no seizure), our work breaks new ground by utilizing HDC to classify seizures into multiple distinct types. HDC offers significant advantages, such as lower memory requirements, a reduced hardware footprint for wearable devices, and decreased computational complexity. Due to these attributes, HDC can be an alternative to traditional machine learning methods, making it a practical and efficient solution, particularly in resource-limited scenarios or applications involving wearable devices. We evaluated the proposed technique on the latest version of TUH EEG Seizure Corpus (TUSZ) dataset and the evaluation result demonstrate noteworthy performance, achieving a weighted F1 score of 94.6%. This outcome is in line with, or even exceeds, the performance achieved by the state-of-the-art traditional machine learning methods.

Keywords—EEG, Seizure classification, HD computing

I. INTRODUCTION

Hyperdimensional (HD) computing, a recent machine learning paradigm inspired by neuroscience, has attracted significant attention across various domains and applications. Examples include text classification [1], language recognition [2], speech recognition [3] and gesture recognition [4]. Additionally, it is employed for detecting epileptic seizures from EEG [5]. HD computing stands out for its exceptional efficiency, boasting reduced energy and memory demands. This makes it particularly appealing for integration into wearable devices [6], [7], and a compelling alternative to traditional machine learning methods. Currently, there is a notable increase in research dedicated to wearable devices for monitoring patients' disorders. Notably, one area of focus is epilepsy monitoring, with a specific emphasis on real-time seizure detection, seizure prediction, and the classification of specific seizure types.

Epilepsy is widely recognized as one of the most common neurological disorders, impacting around 50 million individuals globally. This condition affects a considerable portion of the world's population [8]. Seizures present in varied forms, each demanding a distinct treatment approach. To start treating them correctly, it's important to identify the specific seizure type. Accurately identifying seizure types is crucial for selecting the right treatment plan. Classifying seizure types is challenging due to various factors. Some seizures share similar clinical and electroencephalography (EEG) patterns, making it difficult

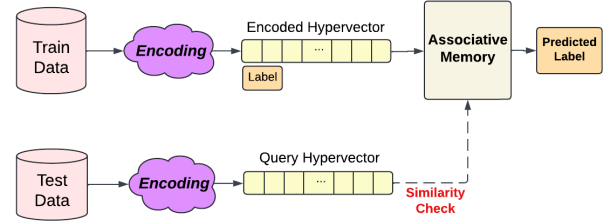


Fig. 1: Overview of the basic classification process with HDC

for experienced neurologists to visually distinguish them. Additionally, certain cases require extended monitoring, such as video-EEG monitoring lasting for days, demanding significant effort and time from neurologists for manual analysis [9].

The state-of-the-art machine learning-based seizure type classifications pose challenges due to their excessive complexity in terms of computing memory and hardware requirements. Consequently, they are not practical candidates for implementing efficient low-power wearable devices. In contrast to conventional machine learning classifications, HD computing for classification offers reduced computational complexity, resulting in lower energy consumption, minimal memory requirements, and a smaller hardware footprint. In our research, we present a lightweight efficient approach for detecting various types of seizures through HD single-pass (one epoch) learning. To the best of our knowledge, our work represents the first implementation of multi-type epileptic seizure classification using hyperdimensional computing. This approach stands out as a significantly less complex alternative compared to conventional machine learning methods while achieving comparable performance to state-of-the-art research.

II. BACKGROUND ON HD COMPUTING

HD computing employs high-dimensional vectors instead of traditional computing elements like Booleans and integer numbers. These HD vectors typically have thousands of dimensions and are composed of pseudo-random components that are independently and identically distributed. These ultra-wide vectors introduce redundancy against noise, and are, therefore, inherently robust. The primary properties of hypervectors are (1) Almost orthogonality between any randomly chosen pair of vectors, and (2) A vector formed by summing other vectors is highly likely to be more similar to its component vectors than to any other randomly selected HD vector [10].

These hypervectors are generally categorized into two types: binary and non-binary. For this work, we employ binary vectors

TABLE I: (TUSZ) dataset seizure types and descriptions

Label	Seizure Type	Description
SEIZ	Seizure	Basic annotation for seizures.
FNSZ	Focal non-specific seizure	Seizures occurring in a specific focality.
GNSZ	Generalized non-specific seizure	Seizures occurring throughout the entirety of the brain.
SPSZ	Simple partial seizure	Brief seizures begin in one part of the brain where the patient is fully aware.
CPSZ	Complex partial seizure	Similar to simple partial seizures but with impaired awareness.
ABSZ	Absence seizure	Sudden and brief seizures involving a lapse in attention. Commonly found in children and usually last under 5 s.
TNSZ	Tonic seizure	Seizures involving stiffening of muscles. Commonly, albeit not always linked with tonic-clonic seizures.
TCSZ	Tonic-clonic seizure	This seizure type is often linked with violent muscle contractions and loss of consciousness.
MYSZ	Myoclonic seizure	A seizure occurring with brief involuntary twitching.

with components set to either 0 or 1. This selection minimizes memory requirements and facilitates simpler operations [11].

In HD computing with binary hypervectors, the primary operations include bit-wise addition, multiplication, and permutation. Addition, also known as bundling, is performed bit-wise, denoted as $A + B$. The resulting vector is maximally similar to the original vectors. The multiplication of two HD vectors, known as binding and represented as $A * B$, yields a third vector that is dissimilar (approximately orthogonal) to the original two. This operation is specifically designed for information association, such as assigning values to variables. Permutation is a unary operation that shuffles the hypervector, generating a dissimilar hypervector from the input. This operation facilitates the assignment of specific orders to hypervectors within the hyperspace. To assess the similarity between two binary vectors, one effective approach is to employ Hamming distance as the similarity metric. Normalized hamming distance of two vectors A and B with the length of bitstream equal to D can be calculated by Equation (1):

$$Ham(A, B) = \frac{1}{D} \sum_{i=1}^D 1_{A(i) \neq B(i)} \quad (1)$$

If the Hamming distance of two hypervectors is close to 0, they are defined as similar. In the case of two orthogonal HD vectors the hamming distance is equal to 0.5 and if two HD vectors are opposed, the similarity is 1. As illustrated in Figure 1, a basic HDC classifier learns hypervectors corresponding to different classes during training. In the testing phase, hypervectors generated from test data (query hypervectors) are compared with class hypervectors stored in the associative memory. An associative search is then conducted to predict the most probable class for a given query hypervector [12].

III. HDC MULTI-TYPE SEIZURE CLASSIFICATION FRAMEWORK

A. EEG Dataset

In this study, to ensure a robust comparison with state-of-the-art machine learning classifications, we employed the TUSZ, the only open-source EEG dataset that contains annotations of multiple seizure types. The TUSZ dataset stands out as the most extensive publicly accessible collection of EEG recordings [13]. The TUSZ dataset comprises 30,000+ clinical scalp EEG recordings gathered since 2002. These recordings originate from diverse medical settings. The raw

EEG signals consist of multi-channel recordings, with the number of channels varying between 20 and 128, and the frequency of the samples ranges from 250 to 1024 Hz. Table I illustrates various types of seizures and their corresponding descriptions. Epileptic seizures are categorized into: focal non-specific seizure (FNSZ), generalized non-specific seizure (GNSZ), simple partial seizure (SPSZ), complex partial seizure (CPSZ), absence seizure (ABSZ), tonic seizure (TNSZ), tonic-clonic seizure (TCSZ) and myoclonic seizure (MYSZ). Similar to previous state-of-the-art studies, we did not include the MYSZ seizure type in our analysis due to its rarity in the dataset. MYSZ seizure type is only recorded from two patients in the recently released version. In our experimental setup, we specifically considered data from 20 channels (FP1, FP2, F3, F4, C3, C4, P3, P4, F7, F8, T3, T4, T5, T6, O1, O2, A1, A2, FZ, CZ).

B. Feature Extraction and Selection

In our feature extraction process, we integrated multiple features, following a precedent set by previous studies in seizure classification. These works have demonstrated that combining different features results in performance improvements [14], [7]. We derive 55 distinct features, including mean amplitude, power spectral density (PSD), and features from a 7-level discrete wavelet transform (DWT) decomposition for each window segment of EEG data. These features have proven highly effective in capturing essential details within EEG seizure signals. Recent leading studies in multi-type seizure classification often employ extensive feature extraction, such as MP-SeizNet [15], which handles 252 features per signal segment. However, one of the main advantages of utilizing HDC techniques is to eliminate the need for significant data preprocessing and extracting a large number of features. We first filter the EEG signal using a bandpass filter with cutoff frequencies at 0.3 Hz and 45 Hz. Subsequently, we utilize DWT features to decompose the signal and extract permutation entropy, Shannon entropy, Rényi entropy, and Tsallis entropy for detail coefficients at levels 3, 4, 5, 6, and 7. Each of these entropy measures offers unique insights into different aspects of the signal's randomness or complexity. We estimate the band power in the following frequency bands: delta [0.5, 4] Hz, theta [4, 8] Hz, alpha [8, 12] Hz, beta [12, 30] Hz, gamma [30, 45] Hz and also [0, 0.1] Hz, [0.1, 0.5] Hz, [12, 13] Hz. These cutoff frequencies represent a balance between preserving relevant neural information and filtering out unwanted noise, providing

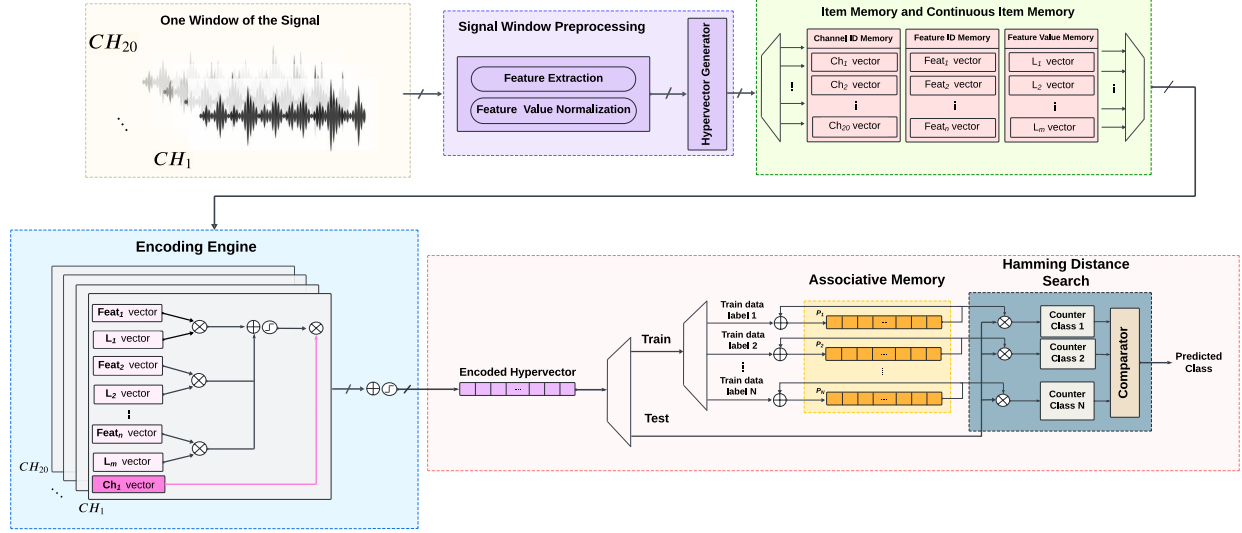


Fig. 2: Overview of the proposed HDC classification algorithm

a common range that has been found effective in EEG signal processing. For each band, we obtain the relative power to the total power. Relative power calculation in each band is important for comparing EEG features across individuals or different recording conditions.

C. Proposed HDC Multi-type Seizure Classifier

In the proposed implementation, we initially discretize the signal into non-overlapping windows, each with a duration of 2 seconds. As illustrated in Figure 2, during the signal window preprocessing, features are extracted and quantized to 20 levels for each channel of the signal window. These normalized features are then mapped into HD space. In the Hypervector Generator block, a random hypervector is generated for each channel, ensuring that these hypervectors are orthogonal. The hypervectors representing channels and features are stored in item memory (IM). Each feature has a discrete quantized value regulated to 20 levels, resulting in the generation of 20 random feature value hypervectors that are not orthogonal. The reason for this non-orthogonality is that these hypervectors correspond to a range of discrete feature values; hence, starting from the hypervector for the smallest value, subsequent levels are generated to be increasingly further apart. These feature value hypervectors are stored in the continuous item memory (CIM). In the Encoding Engine, for each channel, the feature hypervectors and their corresponding feature level values are selected and bound together using bitwise XOR. All bound vectors are then bundled by bitwise summing them. The result is normalized to a binary representation and then bound with the channel vector representing the current channel. The final result for each channel is summed together and rounded to a binary representation. The obtained hypervector demonstrates the spatial information between the channels for the given signal window. Temporal correlation is captured as this process is repeated for each 2-second window of the signal.

In the last stage, the Associative Memory (AM) holds prototype hypervectors for each data class. In the training phase, it performs bundling on the hypervectors obtained from the encoding block to represent the classes. To classify, the incoming hypervector is compared with each stored prototype

using Hamming distance. The predicted class is the one with the smallest distance. The Hamming distance assesses the dissimilarities between two hypervectors by counting differing positions. It binds the query hypervector with each prototype hypervector for the respective classes. Subsequently, it selects the class label based on the minimum population count among the bound hypervectors.

IV. RESULTS AND ANALYSES

In this section, we present the outcomes of our experiment on multi-type seizure classification employing hyperdimensional computing. Due to the class imbalance issue present in the TUSZ dataset, the accuracy metric alone is not a reliable measure of performance. Therefore, to ensure the robustness of our results, we employ the weighted F1-score as an evaluation metric for our proposed approach. Weighted F1-score combines the F1-scores of individual classes by weighting them according to the relative frequency or sample count of each class. The F1-score for each class is computed as the harmonic mean of the True Positive Rate (TPR) and the Positive Predictive Value (PPV). The weighted F1-score formula is as follows:

$$\text{Weighted F1-score} = \frac{\sum_{i=1}^N w_i \cdot \text{F1}_i}{\sum_{i=1}^N w_i} \quad (2)$$

$$\text{F1}_i = 2 \cdot \frac{\text{TPR}_i \cdot \text{PPV}_i}{\text{TPR}_i + \text{PPV}_i} \quad (3)$$

$$w_i = \frac{\text{Number of samples in class } i}{\text{Total number of samples}} \quad (4)$$

In this evaluation, we assess the model using 5-fold cross-validation. The TUSZ dataset shows a significant disparity in signal duration among seizure types, with FNSZ, GNSZ, and CPSZ signals notably longer than others. The dataset's imbalance poses a challenge to achieving reliable accuracy results in predictive modeling. In our evaluation, We only utilized a subset of the total duration of FNSZ, GNSZ, and CPSZ signals, ensuring a balanced representation of patients. However, for the remaining classes, we employed the entire duration of the signal provided in the main dataset. This approach enabled us to maximize the utility of available

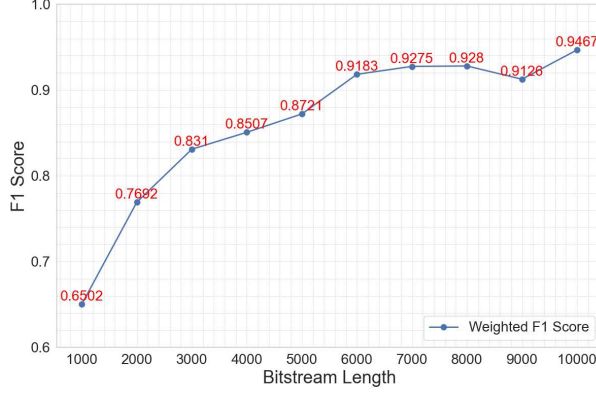


Fig. 3: Performance of single-shot HDC trained with different lengths of bitstream for seven classes of seizures

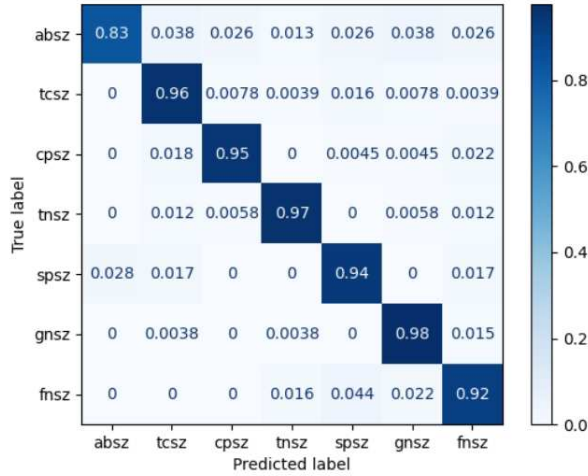


Fig. 4: Confusion matrix of single-shot HDC trained with 10000 lengths of bitstream for seven classes of seizures

data while optimizing computational resources. The data is divided into 5 folds ensuring each fold contains a proportional distribution of all classes. The model undergoes training using 4 folds while reserving the remaining fold for evaluation. This iterative process continues until each fold has been utilized as the test data. In the end, the average weighted F1 score is computed across the 5 folds to provide an overall evaluation metric for the model's performance. Figure 3 shows the F1 score obtained by a single-pass training using different lengths of bitstream. Increasing the dimension of the high-dimensional (HD) space from 1000 to 10000 enhances the model's performance by 29%. We achieve a weighted f1 score equal to 94.67% when the length of the hypervectors is 10000 bitstream. In typical machine learning approaches, reducing the size of the training dataset often leads to lower classification performance. However, our results demonstrate that the evaluated F1 score of the proposed model, trained on a subset of the dataset, is both acceptable and comparable to state-of-the-art machine learning research, which trained models using the entire dataset. The result of the confusion matrix of 7-class classification is shown in Figure 4. According to the confusion matrix, the true positive

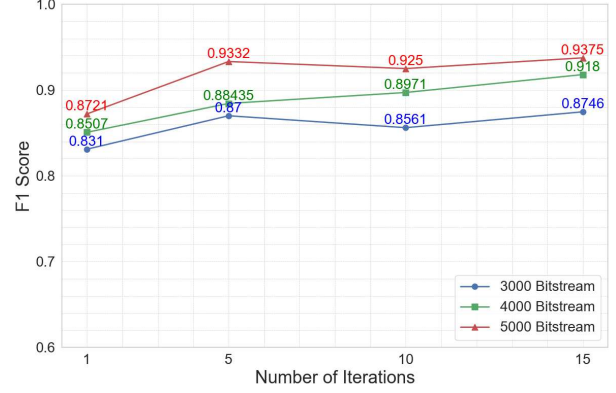


Fig. 5: Performance of the proposed classifier, retrained with different numbers of epochs

(TP) values for the seizure types ABSZ, TCSZ, CPSZ, TNSZ, SPSZ, GNSZ, and FNSZ respectively reach 0.83, 0.96, 0.95, 0.97, 0.94, 0.98 and 0.92. The F1 score for the absence seizure type (ABSZ) is relatively lower compared to other seizure types. This discrepancy is primarily due to the significantly shorter duration of absence seizures in the dataset compared to other seizure types.

Figure 5 illustrates the impact of retraining iterations on the performance of the model trained with shorter bitstream lengths. One of the key advantages of the proposed HDC classifier is its ability to achieve high performance with a single-shot training process. However, to further reduce computational complexity, latency, and power consumption during inference, the model can be retrained using shorter bitstreams. As shown in Figure 5, retraining the model with 5000-bit streams for 5, 10, and 15 iterations enhances performance by 6%. Additionally, for a 4000-bit stream length, the F1 score improves from 85% to 91% after 15 iterations. These findings are particularly valuable for the development of real-time wearable seizure classification devices, which often face hardware resource constraints.

V. CONCLUSION

In this study, we successfully applied Hyperdimensional Computing (HDC) for multi-class classification of epileptic seizures, demonstrating its effectiveness in distinguishing seven different types of seizure. Our evaluation, conducted using a balanced subset of the TUHZ dataset and a 5-fold cross-validation technique, highlights the robustness and reliability of our model. By addressing the class imbalance issue inherent in the dataset, we ensured a fair and comprehensive assessment of the model's performance. Employing HDC for seizure-type classification leads to more efficient hardware implementation for wearable devices compared to state-of-the-art machine-learning approaches. This efficiency is due to the simplicity of the computations involved and the reduced memory requirements, making HDC a promising solution for developing advanced, real-time seizure detection systems in wearable healthcare technology.

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