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Article

Efficient Epileptic Seizure Detection Method Based on EEG Images: The Reduced Descriptor Patterns

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Abstract: Detecting epileptic seizures through Electroencephalography (EEG) is a crucial but challenging task due to the time-consuming and error-prone nature of visual analysis in long-term EEG recordings. To overcome these limitations, numerous approaches have been proposed. In this work, we present a novel automated approach to seizure detection. Our approach is evaluated using rhythmicity spectrograms extracted from the publicly available CHB-MIT Scalp EEG database. For each channel in this database, both ictal and nonictal segments were converted separately into rhythmic spectrograms by Short-Time Fourier Transform (STFT). Image-based seizure detection is a new technique that utilizes visual representations of EEG data, which can potentially provide complementary interpretations to traditional signal-based analysis. The integration of image-based techniques can improve the accuracy and robustness of seizure detection algorithms, enabling more confident diagnostics and timely treatments for people with epilepsy. This study focuses on a novel seizure detection approach that employs image feature extraction as the main method. By offering this innovative approach, the research aims to improve the effectiveness and credibility of seizure detection Algorithms. The main innovation of this study is the introduction of a novel methodology inspired by the Decimal Descriptor Pattern (DDP) feature extraction technique. DDP involves the representation of images by decimal codes ranging from 0 to 10. The proposed approach, called Reduced Descriptor Pattern (RDP), is characterized by its emphasis on consolidating feature sets to only 5 codes, thus optimizing the process while conserving descriptive integrity. The study compared the Reduced Descriptor (RDP) and the Gray-Level Co-occurrence Matrix (GLCM) methods for feature extraction. A Support Vector Machine (SVM) classifier was utilized to differentiate between seizure and non-seizure EEG 2D images. Our proposed method, when combined with the SVM classifier, achieved excellent results in comparison to the well-known GLCM feature extraction method and DDP. We conducted a comparative study among the RDP, DDP, and GLCM methods. The results demonstrate exceptional accuracy, highlighting the efficacy of our proposed method in seizure detection. Thus, our approach provides a valuable tool for expediting seizure diagnosis and reducing reliance on subjective visual evaluations.

Keywords: seizure; reduced descriptor pattern; decimal descriptor pattern; support vector machine

1. Introduction

Artificial intelligence (AI) systems and machine learning algorithms are playing a critical role in disease detection, and revolutionizing healthcare. By analyzing vast amounts of medical data with unprecedented rapidity Leveraging multiple data sources that include medical images, genetic profiles, patient histories, and clinical records, AI algorithms excel at identifying potentially life-threatening diseases at an early stage, allowing for timely intervention and more personalized treatment plans. In addition, these systems continuously learn and adapt from new data, improving their effectiveness over time. Through their predictive analysis and diagnostic skills, AI and machine learning are making a significant contribution to improving patient outcomes, reducing misdiagnosis rates, and ultimately saving lives in the field of disease detection.

The review of [1] examines the revolutionary impact of advances in machine learning (ML) in the healthcare sector. Highlighting the importance of various datasets, evaluation metrics, and ML techniques, the paper examines their application in three key areas: International Classification of Diseases (ICD) coding, mortality prediction, and disease prediction. With a specific focus on disease prediction, Sharma's review delves into four prominent areas: sclerosis, cardiovascular disease, cancer, and kidney disease, shedding light on the breadth and depth of ML's impact in these critical areas of healthcare.

Numerous studies have concentered their focus on the COVID-19 disease; for instance, we can mention [2] where the authors examine skin cancer, the study of [3] where breast cancer is dressed and researches of [4] that were focused on cancer chemotherapy.

A multitude of studies have concentrated on epilepsy analysis that represents a serious neurological disease affecting around 50 million people worldwide [5], has a profound effect on brain functions and structures. The seizures that characterize the disorder occur as a result of abnormal electrical activities in the central nervous system, and lead to a variety of associated cognitive, emotional and behavioral disorders. In addition, recurrent seizures and the pathology underlying them can cause structural changes in the brain, including changes such as hippocampal sclerosis, malformations of the cortex, and white matter anomalies. An understanding of the multifaceted effects of epilepsy on brain function and structure is critical to optimizing treatment and enhancing the quality of life for individuals with epilepsy.

Seizure detection techniques are a transformational tool that can significantly improve the quality of life for patients with epilepsy. By intervening early, these tools provide a rapid response to seizure events, which minimizes the duration and the severity of seizures and reduces the risk of subsequent injury. This early intervention promotes a feeling of safety and confidence, allowing people with epilepsy to perform daily tasks with greater confidence and self-reliance. In addition, seizure detection data provides valuable insights into seizure patterns and frequency, helping healthcare providers to more effectively tailor treatment plans. This personalized healthcare approach enhances seizure management, improves seizure outcomes and minimizes medication side effects. In addition, the availability of seizure detection systems provides peace of mind to both people with epilepsy and their care providers, alleviating concerns about the unpredictability of seizures and improving overall well-being. In other words, by facilitating timely intervention, promoting personal independence, enabling individualized care and giving peace of mind, seizure sensing technologies profoundly improve the daily quality of life for those suffering from epilepsy.

Epileptic disorders are often monitored with long-term electroencephalographic (EEG) recordings.

Once these records are achieved, they are analyzed by expert neurologists for the purposes of seizure diagnosis. The visual interpretation of long-term EEG signals, however, poses a significant challenge due to its inherently subjective nature, time-consuming requirements, and susceptibility to human error due to fatigue. Therefore, there is an urgent need for automated seizure detectors to reduce the burden on neurologists and speed up the diagnostic process. As a result, a plethora of approaches have been advanced using signal processing on EEG signals, as shown in studies by [6–11].

Recently, several studies have been carried out based on signal-to-image models such as histograms, scalograms, spectrograms, etc., as an alternative to exploiting the EEG signal for feature extraction. In this regard, the CHB-MIT scalp EEG brain activity database was suggested. For all channels in this database, each ictal and nonictal segment was independently converted into a rhythmic spectrogram by Short-Time Fourier Transform (STFT). Image-based seizure detection is a new approach that uses visual displays of EEG data, which may provide supplementary meanings to traditional signal-based analyses. In this study, we considered images generated from signals based on the CHB-MIT scalp EEG database [12].

This investigation focuses on a novel seizure detection approach that adopts image feature extraction as the major technique. By proposing this innovative approach, the research aims to contribute to the effectiveness and credibility of seizure detection algorithms. The primary innovation of this study is to enhance image analysis by the implementation of a novel approach for feature extraction.

Feature extraction is a key step in the classification pipeline, by transforming the raw data into a more concise and informative representation. This is a critical step because it increases the discriminative power of the data, allowing for more accurate and effective classification algorithms. Extracting relevant features from the input data often reduces dimensionality, which not only decreases computational requirements, but also reduces the risk of algorithm overfitting. In addition, feature extraction often helps to reveal the underlying patterns and correlations in the data that may not be visible in raw form. This enables classifiers to reach more robust decisions, which leads to improved performance and better generalization to the unseen data. Overall, the careful selection and extraction of meaningful features is essential for developing meaningful classification models that can accurately discriminate between different classes or categories.

In this paper, a new approach for feature extraction was introduced. It was inspired by the Decimal Descriptor Pattern (DDP) feature extraction method [13]. DDP describes images by decimal codes ranging from 0 to 10. The suggested approach, named Reduced Descriptor Pattern (RDP), is distinguished by its emphasis on reducing feature sets to only 5 codes, thus simplifying the process while preserving descriptive identity.

The study compared the Reduced Descriptor (RDP) and Gray-Level Co-occurrence Matrix (GLCM) methods for feature extraction, using a Support Vector Machine (SVM) classifier to discriminate between seizure and non-seizure 2D EEG images. Our proposed approach, when used in combination with the SVM classifier, achieved excellent results compared to the well-known GLCM feature extraction technique and DDP. We performed a comparative analysis between the RDP, DDP, and GLCM methods. The results show exceptional accuracy, emphasizing the effectiveness of our proposed method in seizure detection. Thus, our approach is a valuable tool for accelerating seizure diagnosis and for reducing the reliance on subjective visual assessment.

Three major contributions have been proposed in this work. First, the implementation of a novel DDP inspired feature extraction approach, RDP. Second, the proposal of an automated diagnosis algorithm for brain level epilepsy, which aims to discriminate between the healthy and the diseased images. Finally, a comparative study is carried out between the new feature extraction approach RDP, DDP and GLCM.

In this study, the research framework is organized into five sections. The first section introduces the context of this research. The second section, "Related Work," reviews existing literature and studies relevant to the research area. This is followed by the Methodology section, which outlines the key components of the research approach. Subsections within this section include a description of the database used, the feature extraction methodology, and the implementation of a Support Vector Machine (SVM) classifier. Furthermore, the proposed approach, which integrates the aforementioned components into a coherent methodology for epileptic seizure detection, is presented. Subsequently, the Results and Discussion section presents the results obtained by applying the proposed methodology, followed by an in-depth discussion of the results and their implications. Finally, the study concludes with a brief summary and reflections on the significance of the research findings in the Conclusion section.

2. Related Work

Intelligent artificial systems are playing a critical role in helping to detect disease. Using advanced algorithmic and machine learning technologies, these systems analyze vast sets of medical data with unprecedented accuracy and speed, aiding in the early diagnosis and treatment of diseases such as cardiovascular cancer. AI systems can identify subtle patterns and indicators that might elude human observation by processing disparate data sources, including those from medical images, genetic profiles, patient histories, and clinical records. This capability can ultimately improve patient outcomes and save lives by enabling healthcare providers to make more informed choices, initiate timely interventions, and personalized treatment plans. In addition, AI-powered disease detection solutions continuously self-learn and adapt based on new data. This enhances their efficacy and keeps them at the forefront of medical advances. The incorporation of intelligent AI systems thus marks a transformational shift in healthcare, providing clinicians with a powerful tool to combat diseases such as heart attack with unprecedented accuracy and effectiveness.

In [1], the authors address the changing impacts of machine learning (ML) advances on healthcare, detailing the integration of ML techniques in this domain. The paper sheds light on the pre-processing and feature extraction tools and methodologies. These are critical components for the effective use of ML in healthcare applications. Through a wide-ranging review, the paper emphasizes on the different data sets, the evaluation metrics and the ML engineering techniques being used by the researchers in three key application areas: International Classification of Diseases (ICD) coding, mortality prediction, and disease prediction. With a specific focus on disease prediction, the review covers four major areas: sclerosis, cardiovascular disease, cancer, and renal disease. The research reinforces a prevailing healthcare industry trend toward the adoption and implementation of deep learning techniques. This trend is consistent with the findings and knowledge provided in this study.

In the study of [3] a computer-aided diagnosis (CAD) system using deep learning approaches is introduced to address breast cancer. The focus is on the accurate classification of histopathological images in breast cancer. The goal is to distinguish between benign and malignant cases. To solve this problem, the authors present a novel mobile net-based classification scheme specifically tailored for breast cancer detection. In order to improve its performance and robustness, the model is rigorously trained using an extended version of the Breakhis dataset. Specifically, comparative analyses show that the proposed model outperforms alternative approaches based on inception and inception-resnet architectures, underscoring the superior performance and potential impact on breast cancer diagnostics.

In [4], the author focuses on cancer chemotherapy. Chemotherapy is a treatment modality that uses drugs that interfere with cell function, resulting in cell destruction. These agents have a narrow therapeutic index. They often cause significant side effects in non-tumor cells. These side effects manifest as a variety of symptoms, including headache, nausea, dyspnea and fatigue. Due to a lack of medical data, healthcare professionals are challenged to accurately assess patient conditions. There is a critical need for effective toxicity prediction and assessment frameworks in order to mitigate chemotherapy-related side effects and aid in clinical decision making. In this study, the researchers propose a prediction methodology to assist physicians in the prediction of patients' toxicity levels after each chemotherapy session. This proactive approach allows early identification of necessary drug adjustments. Thus, further complications can be minimized. The presented model is based on machine learning and on predefined toxicity levels. It uses multi-classification methods trained on real medical data collected from cancer patients undergoing cancer treatment in Tunisia. Through an experimental study, the validity and performance of the learning methods are reviewed, demonstrating the potential of this approach for the improvement of patient care and patient results in cancer chemotherapy.

In [2], the authors examine skin cancer, a disease that results from the abnormal development of skin cells, and emphasize the critical importance of early detection to protect human health. In particular, malignant melanoma stands out as a particularly dangerous form of skin cancer. Accurate and automatic detection of melanoma is paramount for effective diagnosis. To address this need, the proposed model integrates Histogram Equalization (HE) and Adaptive Gamma Correction with Weighting Distribution (AGCWD) techniques to enhance texture regions and improve segmentation results. In addition, the model focuses on automatic skin lesion detection by combining DeepLabV3+ with various base networks such as ResNet 18, ResNet 50, and MobileNetV2. Extensive testing on various image datasets from ISIC 2016, ISIC 2017, and ISIC 2018 validates the effectiveness and robustness of the proposed approach.

Machine vision, which includes both qualitative and quantitative aspects in its analysis, serves as a common analytical technique used to identify blood cells. Qualitative aspects involve distinguishing between red and white blood cells, while quantitative aspects involve counting cells within specific images. However, a common problem is overlap, which is particularly pronounced in images of red blood cells and often leads to errors in the accuracy of image processing.

In this research study [14], the authors assess the image segmentation process for red blood cells using convolutional neural network algorithms with the goal of predicting single and overlapping classification groups among red blood cells. Probability tests and ANOVA were used to determine the optimal preprocessing strategy for each classification parameter. These parameters include precision, recall, F1-score, and accuracy.

For the diagnosis of blood disorders, distinguishing between normal white blood cells and leukemic cells is crucial. Various automated methods such as YOLO, SVM, CNN, and Faster CNN have been applied to improve the efficiency, timing, and accuracy of this process. In [15], the authors proposed the use of YOLOv8 for the detection, classification, and counting of both normal white blood cells and leukemia cells. To provide insights into the effectiveness of our approach, authors also conduct a comparative analysis of the accuracy of their method with studies using different versions of YOLO.

In this context, Electroencephalography (EEG) which is the cornerstone of detecting epileptic seizures has been studied based on ML techniques. Manual analysis of long-term EEG recordings is prone to subjectivity, time constraints, and potential inaccuracies. A variety of epileptic seizure detection techniques have been developed to overcome these challenges. In particular, rather than relying solely on EEG signals, recent work has moved toward the use of signal-to-image models such as histograms, scalograms, and spectrograms for feature retrieval. For instance, in [16], the Short-Time Fourier Transform (STFT) was used to extract spectrogram images from EEG signals collected at the University of Bonn, Germany, and used in conjunction with a convolutional neural network (CNN) to classify seizures. In a similar manner,[17] used the Continuous Wavelet Transform to transform EEG signals into wavelet spectrograms and then proposed a semi-diluted convolutional network to predict seizures. Their methodology was rigorously evaluated using three publicly available large-scale EEG/iEEG datasets. In addition, Ref. [18] performed a large-scale classification of seizure types into eight classes using spectrogram representatives of 19-channel EEG time series from the Temple University Hospital EEG corpus. They used CNNs and transfer learning algorithms and achieved robust classifications.

A comprehensive examination of epileptic seizure detection using machine learning classifiers was presented in [19]. This review aimed to provide a comprehensive overview of the diverse techniques employed in recent years, categorized by the taxonomy of statistical features and machine learning classifiers - distinguishing between "black-box" and "non-black-box" approaches. By presenting state-of-the-art methods and findings, this review has attempted to facilitate a deeper understanding of seizure detection and classification, thereby illuminating future research directions.

In the study of [20], a machine learning methodology aimed to construct personalized classifiers for the early detection of epileptic seizures by analyzing scalp EEG signals, a non-invasive measure of electrical brain activity. This task is particularly challenging due to the complex and overlapping nature of different classes of brain activity. Key steps in developing a highly effective algorithm included framing the problem within an appropriate machine learning framework and identifying critical features for distinguishing seizure activity from other brain patterns. After training on at least two seizures per patient and testing on a 916-hour continuous EEG dataset from 24 patients, our algorithm successfully detected 96% of 173 test seizures with a median delay of 3 seconds and a median false alarm rate of 2 per 24-hour period.

The work of [21] provided an overview of various seizure detection and prediction algorithms and offers a comparative analysis between them. Several conclusions can be drawn from this review. First, the majority of these methods rely on time- or wavelet-domain features for their analysis. In particular, the adoption of a five-level decomposition in wavelet domain methods was widespread for robust feature extraction. In addition, hybrid approaches incorporating both time and wavelet domain features tend to outperform methods using features from a single domain. The emerging trend of Empirical Mode Decomposition (EMD) showed promise for seizure detection and prediction, but required further investigation. Furthermore, methods that used classifiers showed superior performance compared to those that do not implement classifiers. In addition, techniques using multi-channel data outperformed those using single-channel data, indicating the importance of using multiple channels for improved performance.

In [22] a real-time automatic epileptic seizure onset detection approach was introduced, tailored to the individual patient and using both scalp and intracranial electroencephalogram (EEG) data. The developed technique extracted robust seizure onset features from EEG signals by integrating harmonic multiresolution and self-similarity-based fractal features. To attain higher frequency resolutions without recursive computations, a fast wavelet transforms decomposition method called Harmonic Wavelet Packet Transform (HWPT) based on Fourier transform was employed. Fractal dimension (FD) estimates were also computed to identify self-similar repetitive patterns within the EEG signal. These features, along with HWPT energy features, were sorted across EEG channels for each epoch while preserving spatial information based on electrode placement on the skull. The temporal information of the EEG was collected by combining the feature orientations of each epoch within a specified moving time window into a final feature vector. The relevant vector machines were then used for classification due to their efficiency in handling sparse but high-dimensional datasets. The proposed method was evaluated on two public databases: one containing long-term scalp EEG data (Dataset A) and the other containing short-term intracranial and scalp EEG data (Dataset B). The results indicated the effectiveness of the proposal for seizure onset detection, with a sensitivity of 96%, a median false alarm rate of 0.1 per hour, and a mean detection latency of 1.89 seconds. When analyzing short-term data, the classification accuracy was 99.8%. These results underlined the effectiveness of the proposed method for both short-term and long-term EEG signal analysis, recorded in either scalp or intracranial modes. In addition, the use of less computationally intensive feature extraction techniques allows for faster seizure onset detection compared to similar methodologies in the existing literature, thus suggesting its potential utility in real-time applications.

The purpose of [23] was to automatically detect epileptic seizures, which had the potential to improve patients' quality of life. However, in this work, the author demonstrated that current Electroencephalogram (EEG)-based seizure detection systems encounter several challenges in real-world situations, besides, EEG signals were inherently non-stationary, and seizure patterns varied significantly across patients and recording sessions. EEG data could be affected by different types of noise, which can significantly affect the accuracy of seizure detection. To address these challenges, the authors proposed a deep learning-based approach that automatically learns distinctive EEG features related to epileptic seizures. The time-series EEG data was segmented into non-overlapping epochs to reveal the correlation between successive data samples. A Long Short-Term Memory (LSTM) network is used to obtain high-level representations of normal and seizure EEG patterns. These representations are then input into a

Softmax function for training and classification. The proposed approach outperforms existing state-of-the-art methods, as demonstrated by evaluation on a well-known clinical dataset. Additionally, the approach was robust in noisy and real-world conditions.

The primary objective of [24] was to advocate for the implementation of seizure detection systems with the overall goal of improving patient outcomes by facilitating personalized treatment strategies. In addition, such systems holded promise for reducing accidents and cases of Sudden Unexpected Death in Epilepsy (SUDEP). Through a wide-reaching review, the paper provided insight into multiple seizure detection and prognostic methods and explored their potential applications within closed-loop warning models for the epilepsy management.

A review in [25] was conducted of the combined use of multiple modalities in the non-electroencephalography (EEG)-based detection of motor seizures in children and adults. A search of the literature was performed for articles on multimodal seizure detection, extracting data on the type of modalities, study design and algorithms used, as well as sensitivity, false alarm rate and seizure types. The search aimed to find evidence of the superiority of the use of multiple modalities over single modalities. Seven articles were identified from 2010 to 2017, primarily using contact sensors such as accelerometers (n = 5), electromyography (n = 2), heart rate (n = 2), electrodermal activity (n = 1), and oximetry (n = 1). Remote sensors included video, radar, motion, and sound. All but one study were conducted in the hospital, with video-EEG as the gold standard. Protocols were based on physiologic and supervised machine learning, although not all of the studies had a separate test dataset. Sensitivity varied from 4% to 100%, and the false alarm rate ranged from 0.25 to 20 per 8 hours. Tonic-clonic seizure detection performed best, with false detections usually affecting a minority (16–30%) of patients. The use of different sensors improved sensitivity, and while false detections decreased in one study, they increased in another.

The objective of the multi-institutional proposed in [26], prospective clinical cohort study was to evaluate the potential of automated seizure monitoring and alerting as a means to improve the quality of life of people with severe epilepsy, with the potential additional goal of preventing sudden, unexpected death. Given the current concentration of available systems on tonic-clonic seizures, the goal was to broaden the focus to detect a wider range of seizure types, including tonic, hypermotor, and cluster seizures. Non-electroencephalographic (non-EEG) signals, such as heart rate and accelerometry, were measured during the night in patients undergoing diagnostic video-EEG studies at multiple centers. Seizures were classified based on clinical video-EEG data and categorized as clinically urgent or not. The classification study included features reflecting physiological variations in cardiac rate and movement, and algorithm development was based on stepwise conditions during the increase of these parameters. While a training set allowed for algorithm development, an independent validation set was used to measure performance. Findings from the 95-patient study showed that although acceptable sensitivities were achieved, particularly for clinically relevant seizures (sensitivity = 71–87%), there were high false alarm rates (2.3–5.7 per night, positive predictive value = 25–43%). Furthermore, there was considerable variability in the number of false alarms per patient.

While the development of a detector with high sensitivity appears feasible, the current false alarm rates are considered too high for clinical use. To overcome this limitation, further optimization, possibly including personalization of the algorithms, may be required.

The goal of this study published in [27] was to identify an optimized approach that is capable of learning features from multi-channel time series EEG data to facilitate the automatic detection of seizures. Typically, due to intra- and inter-patient variability, learning robust features from EEG signals is challenging. However, unlike conventional EEG analysis techniques that ignore spatial aspects, the authors employed an algorithm designed to capture spectral, temporal, and spatial information to achieve effective generalization. In the first stage of this algorithm, the EEG signals were transformed into a sequence of topology-preserving multi-spectral and temporal images. These images were then used as input to a convolutional neural network. Our convolutional neural network successfully acquired a general spatially invariant representation of a seizure in a reasonable time frame by addressing the lack of data, especially positive samples, and implementing a method to handle unbalanced data sets while optimizing the complexity of the network. This led to improved sensitivity, specificity, and accuracy, yielding results comparable to those obtained using state-of-the-art methods.

In a recent study [28], an automatic seizure detection method has been introduced. The feature extraction process uses the Decimal Descriptor Pattern (DDP) approach, which is applied to 2D images for the first time. Subsequently, a Support Vector Machine classifier discriminates between seizure and non-seizure EEG 2D images. The performance of the proposed method has been evaluated using rhythmicity spectrograms (2D images) obtained from a publicly available EEG database (CHB-MIT Scalp EEG database). The results obtained show a high accuracy performance.

3. Methodology

3.1. Database

To test the proposed classification task, we considered images generated from signals based on the CHB-MIT scalp EEG database [12]. This is a collection of EEG recordings from young patients with uncontrollable seizures. It contains 844 hours of multichannel scalp EEG. A recording frequency of 256 Hz was used to identify 198 seizures. Each patient has a dedicated folder containing a summary and 1-4 hours of EEG data in EDF format. The folders also provide details on the start and end times of seizures in different EDF files. In [12], 15 EEG channels were selected for further analysis, including F7-T7, T7-P7, P7-O1, F3-C3, C3-P3, and P3-O2. To produce a balanced and constant dataset, he transformed channel-wise ictal and random non-seizure segments into rhythmic spectrograms using the STFT method. Figure 1 shows an example of rhythmicity-based spectrograms from 1D seizure and non-seizure EEG signals. Two files (A) and (B) were presented, containing a seizure and non-seizure segment, respectively. The EEG signal was calculated across specific channels, such as F7-T7 and F4-C4, and converted them into spectrograms. The image size obtained was 360*360. The used data set contains 105 frames from chb01, 30 frames from chb02, 90 frames from chb05 and 75 frames from chb05 separately from ictal and nonictal files. The study has a total of 600 frames and 25 minutes of ictal time.

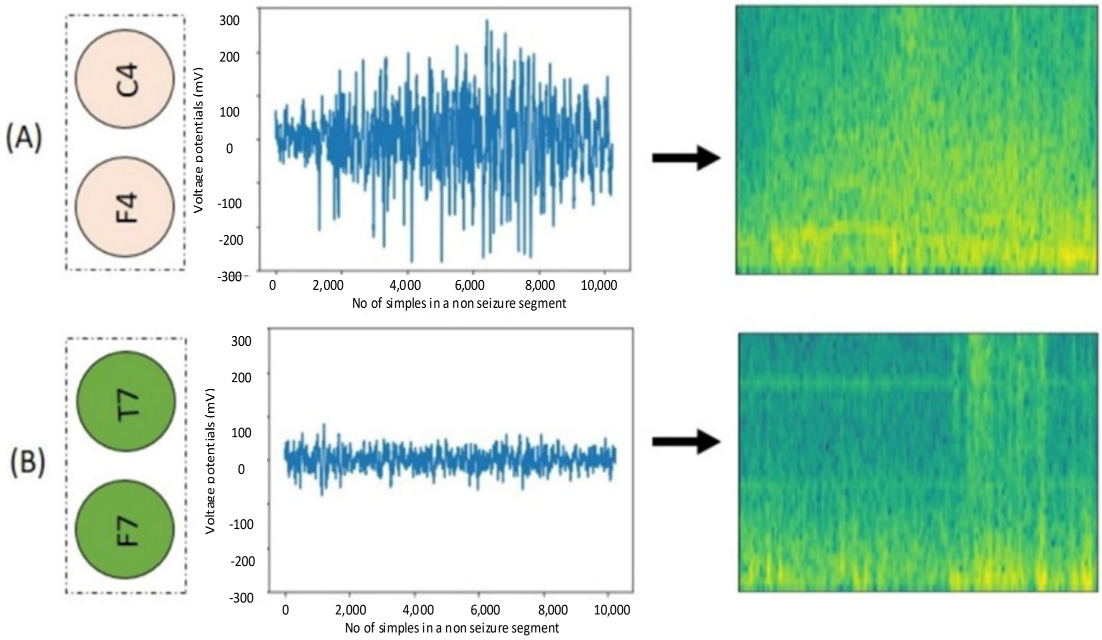

Figure 1. Spectrogram conversion from a 1D EEG data that includes (A) a seizure segment and (B) a non-seizure segment

The Table 1 provides details about seizure events, including their respective numbers, locations within the record folders, and durations measured in seconds. Notably, the total cumulative seizure time across all recorded segments is approximately 25.33 minutes.

Table 1. Details about seizure events.

Seizure ID	Folder Location	Duration (Seconds)
1	chb01 03	40
2	chb01 04	27
3	chb01 15	40
4	chb01 16	51
5	chb01 18	90
6	chb01 21	93
7	chb01 26	101
8	chb02 16	82
9	chb02 16+	81
10	chb03 01	52
11	chb03 02	65
12	chb03 03	69
13	chb03 04	52
14	chb03 35	66
15	chb03 36	53
16	chb05 06	115
17	chb05 13	110
18	chb05 16	96
19	chb05 17	120
20	chb05 22	117

3.2. Feature Extraction

3.2.1. The Decimal Descriptor Pattern (DDP)

The Decimal Descriptor Pattern (DDP) was introduced by [13]. It stands out as a promising approach for feature extraction in diverse applications. Based on the idea of describing images using decimal codes ranging from 0 to 10, the DDP provides a concise and yet informative view of image features. By summarizing complex image features into a sequence of decimal codes, the DDP approach can greatly simplify the feature space while maintaining essential information, enabling it to be applied to tasks such as image classification, object recognition, and pattern analysis. In addition, the inherent extensibility and efficiency of the DDP makes it particularly attractive for large datasets and real-time applications. Overall, the Decimal Descriptor Pattern represents a strong feature extraction approach with the potential to improve the efficiency and effectiveness of various image enhancement and analysis tasks.

While the DDP strategy has been mainly used in the analysis of 3D images, the study aims to investigate its effectiveness in the analysis of 2D images. First, the image is decomposed into a series of local patterns, each consisting of 9 pixels that are arranged in a 3 × 3 grid. Next, the maximum, minimum, and average pixel values within each pattern is computed, which results in a set of three characteristics for each pattern element (Figure 2). These features are then combined to generate a vector V representative of the features obtained from the image patterns. Finally, the minimum, average, and maximum scores of V are computed, and each score is matched with a respective code that encapsulates the essential features of the image patterns (Figure 3).

This codes a numeric value within the set C = {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10}, indicating a range of possible scores. The descriptive vector that results include a set of ten metrics derived from the maximum (max), minimum (min), and average (mean) values resulting from this vector (see Table 2). To illustrate, the code 10 is associated with the maximum value of the V vector.

It is interesting to note that different neighbor sizes can be used in this process. As shown in the work of [13], the DDP approach introduces two different parameters: the distance between patterns (D) and the size of each pattern (S), as illustrated in Figure 4. Therefore, changes in the size of the feature vector and the classifier results can occur based on these two parameters.

Table 2. DDP codes.

Values		**DDP Code**
Min		0
]min	(mean+min)/4]	1
] (mean+min)/4	(mean+min)/2]	2
] (mean+min)/2	(mean+min)*(3/4)]	3
] (mean+min)(3/4)	mea n[	4
Mean		5
] mean	(mean+max)/4 [	6
] (mean+max)/4	(mean+max)/2]	7
](mean+mx)/2	(mean+max)*3/4]	8
](mean+max)*3/4	max[	9
max		10

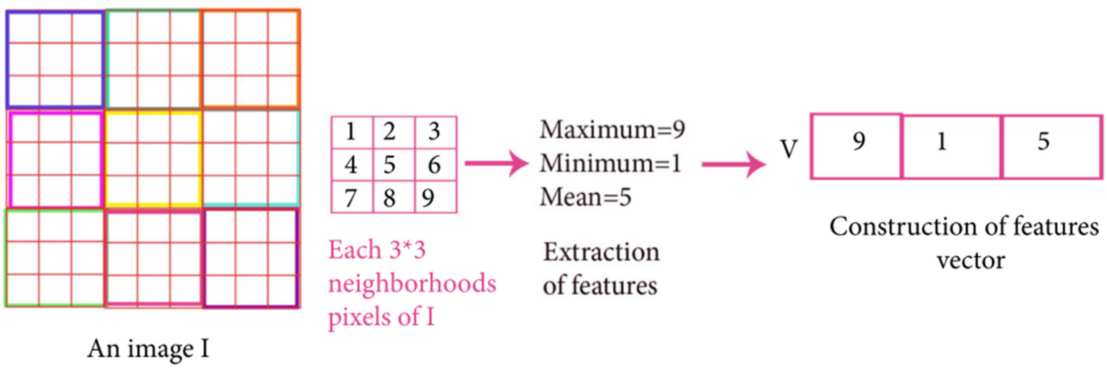

Figure 2. Example of Extracting Features from a 3*3 Pattern Using the DDP Approach.

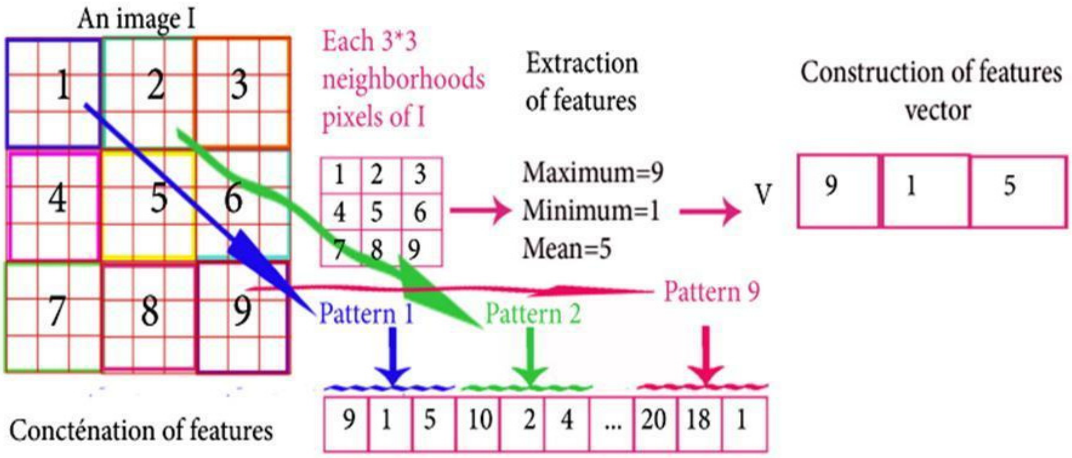

***Figure* 3**. Example of using the DDP approach to extract features from an image.

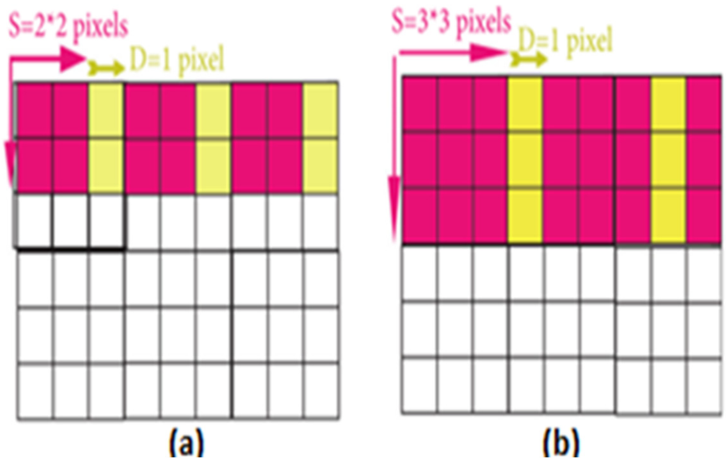

Figure 4. Examples of $DDP_{(S, D)}$: (**a**) $DDP_{(2,1)}$, (**b**) $DDP_{(3,1)}$.

3.2.2. The Reduced Descriptor Pattern (RDP)

In certain applications, reducing the number of features extracted from images can lead to improved classification results. This phenomenon is due to the concept of feature selection, where not all features contribute equally to the classification task. By reducing the number of features, the classifier can focus on the most relevant information, potentially increasing its discriminative power. Furthermore, a reduced feature set can reduce the risk of overfitting, where the classifier learns to memorize noise in the data instead of generalizing patterns. In addition, reducing the dimensionality of the feature space can speed up the training process and reduce computational cost, making the classification model more efficient. Overall, judicious selection and reduction of the number of features extracted from images can optimize the performance of classification algorithms in various applications.

When using the Reduced Descriptor Pattern (RDP) approach, the same phases are typically applied as in the DDP method. However, the final step in the RDP approach involves pattern code reduction. This reduction process involves condensing the extracted features into a more compact representation while preserving their discriminative information. Overall, this final step in the DDP approach plays a critical role in optimizing the efficiency and effectiveness of the classification process.

The proposed approach RDP is characterized by its emphasis on consolidating feature sets to only 5 codes (Table 3). The first stage consists of the extraction of patterns from the image to find the features that distinguish each pattern, which results in the generation of the initial feature vector. Then, in the second stage, the maximum, minimum and average values from this initial feature vector are calculated. Finally, in the ultimate step, the final feature vector is created by assigning an RDP code to each of the values within the feature vector.

Table 3. RDP codes.

Values	DDP Code
Min	1
]Min Mean [	2
Mean	3
]Mean Max[	4
Max	5

3.2.3. The Grey Level Co-Occurrence Matrix (GLCM)

Haralick introduced the Grey Level Co-occurrence Matrix (GLCM) in 1973 [29,30], establishing it as one of the most prominent methods for texture analysis. It is a feature extraction approach used in image and object analysis. It quantitatively measures the spatial relationships between pairs of pixels in an image by determining how frequent different pixel combinations of grey levels occur at certain pixel spacings and orientations (Figure 5).

In essence, GLCM offers a statistical characterization of the texture or patterns of an image by measuring the frequency of pixel pairs with specific gray levels and corresponding spatial relations. This matrix can be used to obtain various statistics, such as contrast, correlation, energy, and homogeneity, which can then be used as features for later analysis tasks, such as segmentation or classification. GLCM based feature extraction is of particular interest in applications where texture data is critical, such as in medical imaging, distributed sensing, and material description.

The core concept involves quantifying texture features through the creation of a Co-occurrence Matrix [29,30]. This matrix, depicted as a square array, records the frequencies of pixel pairs appearing at specified directions and distances. Co-occurrence matrix can be defined by the following equation:

CD,i,j=y=1yz=1z{1 if fy,z=i and fy+dy,z+dz=j 0 otherwise (1)

where D is a particular distance between two pixels of image.

In the computation of grey-level co-occurrence matrix (GLCM) features, four different directions for the position angle θ are commonly used: horizontal, vertical, diagonal, and anti-diagonal. These directions correspond to different orientations in the image grid and capture different spatial relationships between pairs of pixels. The horizontal direction refers to pairs of pixels arranged side by side in a row, while the vertical direction captures pairs of pixels stacked on top of each other in a column. Diagonal pairs involve pixels that are diagonal to each other, forming either a positive or negative slope, depending on the direction. Finally, anti-diagonal pairs are diagonally positioned pairs with an opposite slope to the diagonal pairs. By considering these four directions, the GLCM can comprehensively characterize the spatial dependencies and patterns present in the image, enabling the extraction of texture features that capture various aspects of image structure and organization (Figure 6). The offset parameter described in this set: (0 d, -d d,-d 0, -d–d).

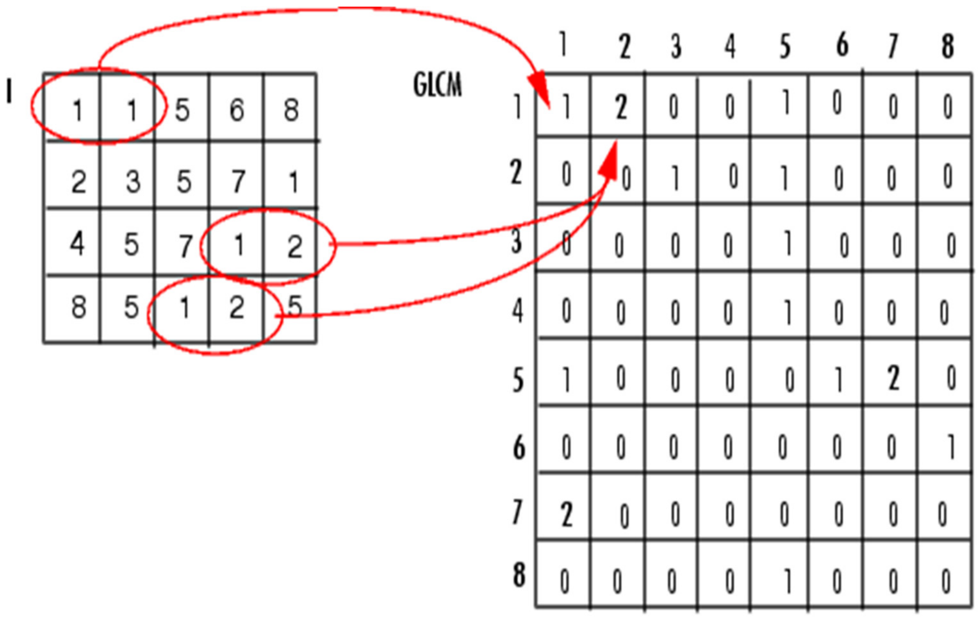

Figure 5. Example of an image and the GLCM associated with it.

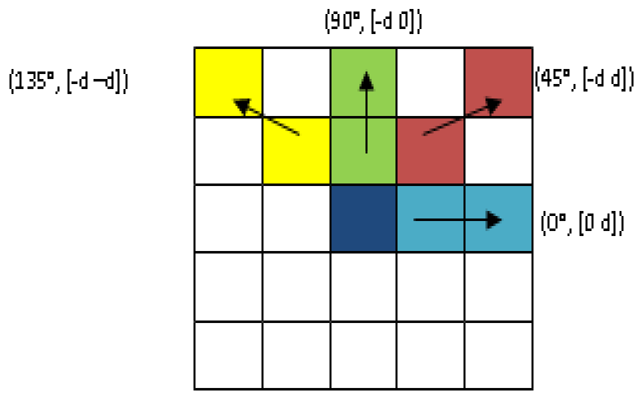

Figure 6. The GLCM Approach Offset Parameters.

Haralick's features include various statistical measures computed from the co-occurrence matrix that provide insight into different aspects of texture characteristics. These features include contrast measures that quantify local variations in pixel intensities, such as contrast, dissimilarity, and homogeneity.

In addition, Haralick's features include measures of spatial order, such as entropy and energy, which describe the randomness or uniformity of pixel arrangements in the image. Other features, such as correlation and angular second moment, capture the degree of linear dependence and uniformity of pixel intensity distributions, respectively. Taken together, Haralick's features provide a comprehensive set of descriptors that enable the characterization and analysis of texture patterns within images, facilitating various applications ranging from medical imaging to remote sensing and beyond.

Specifically, contrast, energy, homogeneity and the correlation are the most used features for texture description (Table 4).

Table 4. The most popular Haralick's features.

Texture Features	Formula
Energy	$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} C_{ij}^2$

Correlation	$COR = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(1-\mu_i)(1-\mu_j)}{\sigma_i \sigma_j} C_{ij}$
	i=i=0N-1iC(i);
	j=j=0N-1jC(j)
	i=i=0N-1(i-i)2C(i);
	j=i=0N-1(j-j)2C(j);

Contrast	$CON = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2 .Cij$
Homogeneity	$ENT = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{C_{ij}}{1+\lvert i-j \rvert}$

3.3 Support Vector Machine (SVM) Classifier

SVM, first introduced in (Cortes, 1995). The SVM attempts to maximize the distance between data categories by finding a hyperplane that separates them. Depending on the type of its kernel, it has the property of carrying out both linear and nonlinear classifications. If the data is linear separable, the data is mapped into the feature space using a linear kernel. In the case of a non-linear classification issue, a non-linear kernel is used to map the data space into a large-dimensional feature space in which linear separation can be performed.

In this context, the SVM has proven to be a popular machine learning architecture which is useful for the development of [31].

3.4. Proposed Approach

In this study, we explore a novel method for classifying EEG images. The classification process is divided into two primary phases: the training phase and the testing phase, as shown in Figure 7. First, a feature extraction step using the RDP and the GLCM approaches are employed. In this process, distinctive features are extracted from the EEG images to create feature vectors that provide a detailed representation of each image. When applying the GLCM approach, four measures are calculated: contrast, energy, homogeneity and the correlation.

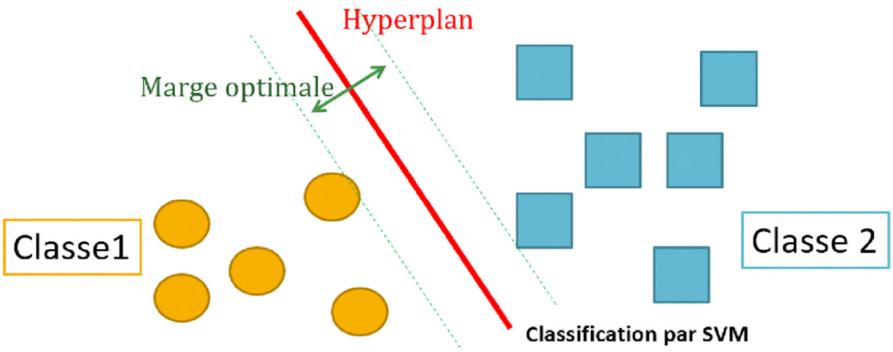

Figure 7. The SVM classifier.

The classification step is then performed using the SVM classifier. Before the classifier can effectively categorize the images in the test phase, it undergoes a training phase to learn the distinguishing features of each class. This training phase is crucial for the classifier to develop an understanding of the unique characteristics associated with different classes, thus facilitating accurate classification. The entire process, including feature extraction and classification, is illustrated in Figure 8, which provides a visual representation of the methodology used in this study.

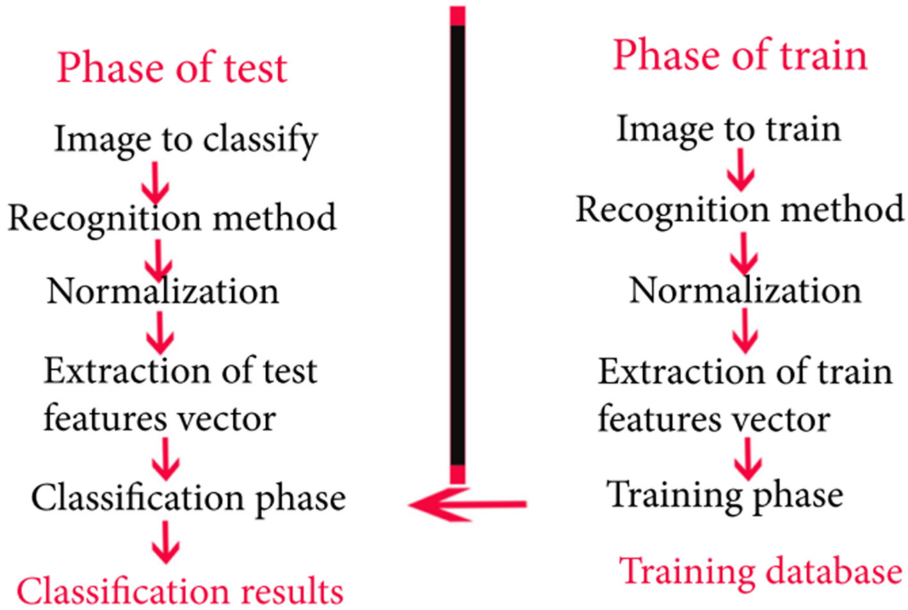

***Figure* 8.** Seizure detection overview.

4. Results and Discussion

The obtained results from our research are promising and indicative of the effectiveness of the proposed methodologie. Specifically, employing the DDP approach with SVM yielded an accuracy of 96.67%, as reported by [23]. However, our contribution in this study lies in introducing a new approach, the RDP method, combined with SVM, which resulted in achieving a remarkable accuracy of 100%. This significant improvement highlights the efficacy of the RDP approach in accurately detecting epileptic seizures from EEG data. Moreover, when compared with the GLCM method combined with SVM, which yielded an accuracy of 86%, our approach outperforms existing techniques, underscoring its superiority in seizure detection accuracy. This surpasses the performance reported by Zhang in [10], who achieved an accuracy of 85.7% using a Multiframe 3D CNN. Additionally, our approach outperforms Handa et al.'s STFT CNN method from 2021, which yielded an accuracy of 61%.

Moreover, our methodology compares favourably with Shankar et al.'s RP CNN approach in 2021, which achieved an accuracy of 93% [32]. These results highlight the effectiveness and superiority of our proposed RDP method combined with SVM in epileptic seizure detection, demonstrating its potential to significantly advance the field and improve patient care (Table 5).

These findings underscore the potential of our proposed methodology to significantly enhance the accuracy and reliability of epileptic seizure detection systems, ultimately contributing to improved patient care and management.

Table 5. Comparison of the results of the proposed approach with the state-of-the-art approaches performed on the CHB-MIT database.

Ref and Years	Features/Methods	Classifiers	Accuracy
Zhang ,2019 [10]	Multiframe 3D	CNN	85.7
Handa, 2021 [8]	STFT	CNN	61
Shankar, 2021 [32]	RP	CNN	93
Yahia, 2023 [23]	DDP	SVM	**96.67**
Our contribution	RDP	SVM	**100**
	GLCM	SVM	**86**

5. Conclusions

This study presents a new automatic seizure detection approach. Rhythmicity spectrograms derived from the publicly available CHB-MIT Scalp EEG Database are used to evaluate our method. This study presents two key contributions to the field of seizure detection. Firstly, our proposed approach, termed the Reduced Descriptor Pattern (RDP), streamlines the feature extraction process by condensing feature sets into a succinct 5-code representation. This consolidation optimizes the process while maintaining descriptive integrity, enhancing the efficiency and effectiveness of seizure detection algorithms. Secondly, the study conducts a comprehensive comparison between the RDP and the Gray-Level Co-occurrence Matrix (GLCM) feature extraction methods. Leveraging a Support Vector Machine (SVM) classifier to differentiate between seizure and non-seizure 2D EEG images, our method, in conjunction with the SVM classifier, outperforms DDP and GLCM feature extraction methods. These findings underscore the superiority of our proposed approach and its potential to significantly advance the field of seizure detection. Thus, our approach provides a valuable tool to streamline the diagnosis of epileptic seizures and to reduce the dependence on subjective visual assessments. In future work, we intend to evaluate the efficiency of our proposal by applying other classifiers such as k-NNs, Artificial Neural Networks, CNN, Autoencoders, etc.

Author Contributions

S.Y. and C.M. developed the initial idea, performed the validation experiments and wrote the first draft. R.E. and M.N.A. supervised the study. All authors collaborated on the methodology and reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

Data Availability Statement

We used images generated from signals based on the CHB-MIT scalp EEG database.

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