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Samah Yahia
National Engineering School of Gabes, Tunisia
Amel Ksibi
College of Computer and Information Sciences
Chahira Mahjoub
National Engineering School of Gabes
Ridha Ejbali
ejbali.ridha@fsg.rnu.tn

National Engineering School of Gabes

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Advanced 3D Methodology for Seizure Identification through Cubic Decimal Descriptor Pattern from MRI

Samah Yahia[1], Amel Ksibi[2], Chahira Mahjoub[3†], Ridha Ejbali[3*†]

[1]Research Laboratory Modeling, Analysis and Control of Systems (MACS), National Engineering School of Gabes, Tunisia, Street Omar Ibn El Khattab, Gabes, Tunisia , Zrig, 6029, Gabes, Tunisia.
[2]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O.Box 84428, 11671, Riyadh, Saudi Arabia.
[3]Research Team on Intelligent Machines, National Engineering School of Gabes, Street Omar Ibn El Khattab, Zrig, 6029, Gabes, Tunisia.

*Corresponding author(s). E-mail(s): ridha_ejbali@ieee.org;
Contributing authors: ysamah4@gmail.com; amelksibi@pnu.edu.sa; chahiramahjoub@gmail.com;
†These authors contributed equally to this work.

Abstract

Background: Volumetric three-dimensional (3D) magnetic resonance imaging (MRI) data are inherently complex, making feature extraction a significant challenge. The large volume of information in 3D MRI requires advanced algorithms to efficiently extract relevant features, which is crucial for identifying abnormal brain activity such as epileptic seizures.

Methods: We propose a novel 3D methodology named the Cubic Decimal Descriptor Pattern (C-DDP) for enhanced feature extraction from 3D MRI data. To evaluate its effectiveness, we conducted experiments using a publicly available 3D MRI dataset comprising 85 individuals with focal cortical dysplasia type II

(FCD II) and 85 healthy controls. Both 3D Fluid Attenuated Inversion Recovery (FLAIR) and T1-weighted isotropic image sequences were processed, and features were analyzed using various machine learning classifiers.
Results: C-DDP consistently demonstrated superior performance in extracting discriminative features across different classifiers. The method improved the detection of FCD II and enabled more accurate identification of epileptogenic lesions compared to conventional feature extraction approaches.
Conclusions: The proposed C-DDP approach represents a notable advancement in 3D MRI feature extraction, offering potential for enhanced diagnostic accuracy in patients with epileptogenic lesions. This methodology may contribute to more effective clinical decision-making and improved patient outcomes.

Keywords: Cubic Decimal Descriptor Pattern, Seizure detection, 3D MRI images

1 Background

The use of three-dimensional (3D) images analysis in disease diagnosis constitutes a significant paradigm shift in medical assessment. It offers a multitude of opportunities to greatly improve the accuracy and depth of diagnosis. A key advantage is the enrichment of 3D imaging with spatial information, providing a more detailed and overall comprehension of the anatomical structures. This is invaluable in identifying subtle abnormalities. This is particularly important in conditions where the spatial distribution of lesions or abnormalities is critical to accurate diagnosis [1–4]. The enhanced visualization provided by 3D imaging enables a more intuitive understanding of disease morphology and extent, helping healthcare professionals to make informed decisions. Furthermore, the quantitative analysis capabilities inherent in 3D imaging allow precise measurements of volumes, distances and shapes, helping to accurately stage disease and assess treatment response. The enhanced diagnostic accuracy offered by 3D analysis minimizes the risk of missed diagnoses, which is critical in conditions where early detection is of paramount importance. 3D imaging also supports personalized treatment planning, optimizing interventions based on specific disease characteristics. Beyond clinical applications, 3D imaging advances research initiatives

and serves as a valuable educational tool, ushering in a new era of nuanced medicine. This paper focuses on the detection of focal cortical dysplasia type II (FCD II), a particularly epileptogenic lesion often associated with pharmacoresistant epilepsy [5, 6]. Despite their clinical relevance, the subtle appearance of FCD II lesions makes their identification by 3D MRI a formidable challenge [2, 3]. The inherent complexity of these lesions, coupled with their subtle manifestations, makes them susceptible to evasion by conventional visual analysis. The detection of their elusive nature requires a more sophisticated approach, especially in the 3D domain of MRI data, where traditional diagnostic methods may be insufficient. The difficulty lies in extracting meaningful features that go beyond the capabilities of conventional visual analysis, requiring innovative methods that can navigate the intricacies of volumetric imaging. Overcoming this challenge is crucial not only for the accurate identification of FCD II, but also to pave the way for more effective treatment strategies for patients struggling with pharmacoresistant epilepsy.

In fact, extracting features from 3D MRIs is challenging because volumetric images are inherently complex and rich. In contrast to their 2D images, 3D MRI images encapsulate a large amount of information, which adds an additional layer of complexity to the extraction of relevant features [1, 2]. The difficulty stems from the need to understand spatial relationships across a number of spatial planes, as the data is distributed over three dimensional planes. Traditional approaches of feature extraction, originally designed for 2D images, may not be sufficient to adequately capture the multifaceted characteristics of the 3D image dataset [3, 4]. In addition, the sheer volume of information stored in each 3D image requires more sophisticated algorithms that are able to navigate through the intricacies to extract the meaningful features. As a result, achieving meaningful feature extraction from 3D MRI images requires dealing with the spatial complexity inherent in voluminous data, and ultimately requires

innovative approaches and advanced computational methods to realize the full diagnostic potential of 3D MRI. In a recent study aiming to improve visual detection, morphometric analysis of T1-weighted images was performed using the Morphometric Analysis Program (v2018; MAP18) [3]. The main focus of the study was on the detection of FCD,a condition that is associated with abnormal development of the cerebral cortex. To do this, this study implemented a feed-forward artificial neural network (ANN). The ANN was trained and cross-validated using data from 113 patients with manually segmented FCDs and 362 healthy controls, acquired from 30 scanners. The ANN algorithm showed impressive specificity and sensitivity rates of 85,4% and 87.4%, respectively, throughout the cross-validation process. These results demonstrated the network's ability to discriminate FCD patients from healthy controls. To further assess its performance, an independent set of 70 healthy controls and 60 FCD patients was used. The ANN presented robust specificity and sensitivity rates of 84.3% and 81.0% respectively.

As regards the study conducted in [2], an experimental voxel-based image post-processing procedure was developed to improve the visibility of blurred grey-white matter transitions in order to refine the identification and presentation of FCD. The technique involves the use of established algorithms within statistical parametric modeling software (SPM99) for the standardization and segmentation of T1-weighted MRI volume data sets. A voxel analysis of grey and white matter is then carried out and compared to a normal database. This comparative analysis serves as the basis for generating of a 3D feature map, highlighting brain regions with blurred grey-white matter transitions. MRI data from 25 epileptic patients with histologically proven FCD were used to evaluate the effectiveness of this approach. The results demonstrated that in 18 of the 25 patients, the newly derived feature maps clearly highlighted dysplastic lesions that were associated with a blurring of the grey-white matter junction. When combined with a previously published voxel-based 3D MRI analysis technique, this

approach was used to identify 21 out of 25 FCD lesions that were associated with either blurring or abnormal extension of the grey matter beyond the typical cortical ribbon. Notably, four cases had lesions either undetected or partially detected by conventional MRI.

In [8] the author pointed out that in cases of drug-resistant neocortical focal epilepsy where conventional magnetic resonance imaging fails to reveal abnormalities, approximately one third of candidates for epilepsy surgery face a discouraging prognosis. Forty-six patients were included to assess the efficacy of quantitative MRI measures in this specific patient cohort. The approach involved individualized post-processing of five quantitative measures: cortical thickness, white and grey matter junction signal, relaxation rate, magnetization transfer ratio and mean diffusivity. Scalp video electroencephalography guided the detection of the epileptogenic zone, and a volumetric Fluid Attenuated Inversion Recovery (FLAIR) sequence was used for visual inspection. Thorough follow-up was performed throughout the study. Results showed that within the subgroup classified as having an epileptogenic zone, individualized post-processing detected abnormalities within the region of electro-clinical origin in 9.7% to 31.0% of patients. Notably, abnormalities outside the epileptogenic zone were more common, observed in up to 51.7% of cases. In five patients with initially negative imaging, post-processing led to a new visual MRI inspection, which identified an epileptogenic structural abnormality. In addition, epileptogenic lesions were detected in three patients after visual assessment with a volumetric fluid attenuated sequence guided by video electroencephalography. Although caution is advised due to the apparent low specificity of quantitative MRI findings for the epileptogenic zone, these analyses may reveal hidden structural lesions and prevent visible lesions from being missed, even in referral centers. Furthermore, the positive contribution of the volumetric fluid-attenuated sequence in improving the overall diagnostic approach in patients with drug-resistant neocortical focal epilepsy and negative conventional imaging should be

emphasized.

In [9], the authors proposed a multi-scale 3D Convolutional Neural Network (CNN) using a Deep Neural Network (DNN) model designed to detect non-patient-specific seizures. To start with, the EEG signals get transformed into the Time-frequency domain using the Short Time Fourier Transform (STFT) to extract spectral features. To preserve the spatial information of the electrodes, these spectral features are then mapped onto 2D images. The proposed approach is a fusion of a bidirectional Gated Recurrent Unit (GRU) and a 3D CNN, which allows extracting spatial and temporal features from the 2D mapped images. CHB-MIT and Seoul National University Hospital (SNUH) scalp EEG databases were employed to evaluate this model. Using the CHB-MIT and SNUH databases, the results showed a sensitivity of 89.4% and 97% with false positive rates of 0.5/hour and 0.6/hour, respectively. This represents a promising advance in the automation of seizure detection, offering high sensitivity with a low false positive rate.

In [10], the aim of this study is to establish a broadly applicable method for patient-specific seizure prediction. It is based on the assessment of spatio-temporal correlation in features derived from multi-channel EEG signals. Frequency and time domain features of EEG signals are extracted using spectral band power, statistical moments and Hjorth parameters. These features are fed into a CNN, which is represented as a sequence of multi-color images that are aligned with the channel topology of the EEG. In order to jointly evaluate temporal and spatial correlations in the training data, a novel multi-frame 3D CNN model is proposed. The results demonstrated the effectiveness of the proposed 3D CNN model, which achieved a sensitivity of 85.7%, a false alarm rate of 0.096/h, and a time-in-warning proportion of 10.5% when tested on 16 patients from the CHB-MIT scalp EEG dataset. Significantly, at a 0.05 significance level, the method was statistically superior to a Poisson-based random predictor in

93.7% of patients. The importance of epileptic stage length as a critical factor influencing seizure prediction performance has been highlighted in experiments with different time constraints. The study [11] proposed an innovative CNN designed to accurately predict epileptic seizures, enabling patients to proactively take preventive measures and reduce the risk of potential injury. The model strategically analyses the temporal, frequency and channel information embedded in electroencephalography (EEG) signals. In particular, the proposed CNN uses 3D kernels to facilitate feature extraction across the3D. To enhance the flexibility of the receptive fields, multi-scale dilated convolution is applied to optimize the model's ability to capture critical information. The effectiveness of the proposed CNN model is rigorously evaluated using the CHB-MIT EEG database. The experimental results demonstrate the superior performance of the proposed model compared to the existing state-of-the-art approaches, achieving an accuracy of 80.5%, a sensitivity of 85.8%, and a specificity of 75.1%. These promising results underscore the potential of the CNN model as an advanced tool for accurate seizure prediction. This paves the way for improved patient outcomes and safety.

This study [12] attempted to provide a universally applicable approach to patient-specific seizure prediction by investigating the spatio-temporal correlation within features derived from multi-channel EEG signals. Using spectral band power, statistical moments and Hjorth parameters, the authors [12] combined the features of the EEG signals in the frequency and time domains. These features were then fed into a CNN, which is transformed into a sequence of multi-color images aligned with the EEG channel topology. The proposed multi-frame 3D CNN model, achieved remarkable results, with a sensitivity of 85.7%, a false alarm rate of 0.096/h, and a time-in-warning proportion of 10.5% in tests conducted on 16 patients from the CHB-MIT scalp EEG dataset. Significantly, statistical analysis demonstrates superiority of the method over Poisson random prediction in 93.7% of patients at 0.05 significance level.

It's important to mention that MRI includes several imaging modalities, each intended

to highlight specific tissue characteristics or pathological features within the human body. Two different types of sequence that are widely used in the clinical imaging setting are Fluid Attenuated Inversion Recovery (FLAIR and T1-weighted (T1) sequences [16, 17]. FLAIR sequences are specifically designed to eliminate the signal from the cerebrospinal fluid (CSF), thereby enhancing the visibility of lesions and abnormalities that are located close to spaces filled with CSF. As a result, FLAIR is highly useful in the assessment of conditions such as inflammation, multiple sclerosis and tumors. Conversely, T1-weighted sequences enhance tissue contrast based on inherent relaxation times, providing detailed anatomical information. Often used to visualize normal anatomy, T1 sequences excel at showing structures with high fat density. The choice between FLAIR and T1 depends on the clinical aim, as FLAIR is preferred for detecting pathology, while T1 is useful for visualizing detailed anatomy. Both sequences help to provide a thorough understanding of the underlying tissues and potential abnormalities and play an important role in a complete MRI examination.

The study [16] involved 36 patients with a history of partial epilepsy and who underwent brain MRI scans using conventional T1- and T2-weighted pulse sequences, as well as the FLAIR sequence. Abnormalities were found in 20 cases, with a total of 25 lesions or groups of lesions being identified. The FLAIR sequence was shown to be more effective in highlighting 24 of these lesions when compared to the conventional sequences. In eleven cases, lesions that were considered to be etiologically significant were only visible on the FLAIR sequence, and eight of these were solitary lesions. In addition, in three cases, significant lesions were identified using FLAIR alone, and these lesions were located in the hippocampus, the amygdala, the cerebral cortex, or in subcortical and periventricular regions. In sixteen patients (44%), lesions were not detected using any pulse sequence. The localization of the lesions correlated with electroclinical features in the eight cases where FLAIR showed only lesions. Pathological confirmation of imaging abnormalities was obtained in two patients with solitary lesions identified

by FLAIR alone. In one patient with a congenital cavernoma, a contrast-enhanced T1-weighted spin echo sequence was found to be most effective in visualizing the primary lesion. The study concluded that, in this particular group, the FLAIR sequence increased the diagnostic yield of the MRI scan of the brain by 30%. The review conducted in [17] aimed to address the fundamental aspects of MRI that are relevant to healthcare professionals specializing in epilepsy. It included essential information on basic MRI principles, sequences, field strengths and safety measures, with an emphasis on when to perform and repeat an MRI. It also includes subjects such as the epilepsy MRI protocol, basic reader guidelines and common epileptic disease. More specialized topics such as MRI-negative epilepsy, functional MRI and diffusion-weighted imaging are also covered in the review. Although the availability of resources may vary from one center to another, it is hoped that this review serves as a valuable resource and provides general guidance on the routine use of MRI in the care.

To summarize, in the current landscape of diagnosing and treating epilepsy, there is an urgent need to develop an innovative mechanism that utilizes a 3D approach, seamlessly integrating machine learning with quantitative imaging features. This pressing need arises from the understanding that existing methods may not be able to fully capture the spatial intricacies and complexities inherent in the structure and function of the brain, particularly in the context of identifying epileptogenic foci. Using a 3D approach, this innovative mechanism aims to overcome the limitations of conventional 2D analysis and provide a more comprehensive understanding of the spatial dynamics involved in epilepsy. The integration of advanced machine learning algorithms with quantitative 3D imaging features has the potential to revolutionize the accuracy and efficiency of the identification of potential epileptogenic foci. 3D imaging enables a more nuanced analysis of the structural and functional intricacies of the brain. It provides a holistic perspective that is essential for accurate diagnosis and targeted intervention.

The fusion of machine learning and quantitative 3D imaging features is emerging as a promising frontier in epilepsy management as technology continues to advance. This approach will not only improve the sensitivity and specificity of diagnostic methods, but will also allow for a more personalized and tailored treatment strategy. By navigating through the intricate spatial patterns within the volumetric data of the brain, this 3D approach will enable clinicians to quickly and accurately pinpoint the regions that are contributing to epileptic activity. In the current context, we consider the development of a groundbreaking feature extraction architecture. This innovative approach is explicitly tailored for implementation with 3D images, inspired by the concept described in [1]. Therefore, in this study, we propose a novel approach that takes advantage of the recently developed 3D feature extraction approach and integrates advanced machine learning techniques. The current proposal represents a promising avenue for improving the accuracy and efficiency of FCD detection.

2 METHODS AND MATERIALS

2.1 Database

To comprehensively evaluate our advanced strategy, we chose to test its performance on the Open Presurgery MRI Dataset for FCD and Control Individuals [18]. This dataset, strict selection criteria were applied, including individuals over the age of eighteen at the time of study. Demographically, the eighty-five participants with epilepsy were 41.2% female and 58.8% male, with a mean age of 10 years at the onset of the first epileptic seizure and a mean age of 28.9 years at the time of the MRI scan. The dataset provides comprehensive clinical information. This includes FCD classification, site distribution, drug resistance, and surgical outcomes. The imaging data were obtained from the Life and Brain Center in Bonn, Germany. A 3-Tesla MRI scanner was used, with FLAIRand T1 sequences. Individuals with FCD underwent

high-resolution 3D T1-weighted MRI with a range of voxel sizes, while control subjects underwent the same imaging protocol using isotropic T1-weighted and FLAIR sequences. This dataset provides a robust basis for evaluating the performance of our advanced architecture in detecting FCD type II, characterized by its detailed clinical and imaging parameters.

2.2 Decimal Descriptor Pattern (DDP)

In the field of texture analysis, as highlighted in references [1], [4] [7] and [18], the Decimal Descriptor Pattern (DDP) has emerged as a robust tool for characterizing patterns in digital images. The aim of the DDP is to encode the correlation between a pixel and its neighboring pixels on the basis of their respective intensity values. The goal of this method is to represent the texture of an image by constructing a feature vector. In order to obtain an effective feature vector. The DDP systematically labels each pixel in an image by calculating the mean, maximum and the minimum values from the 3x3 surrounding pixels. These computed features, extracted from the entirety of the patterns in the image, are then concatenated into an initial vector Vi.

After the first feature vector Vi is constructed, each value within the vector is transformed using the maximum, minimum, and average values of this vector Vi. This transformation allocates each value in vector Vi to a range 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, resulting in final vector Vf being converted into its corresponding codes. For example, the minimum value of Vi is coded by zero, the maximum and the mean are respectively coded by ten and five. Fig. 1 explains the association of DDP codes.

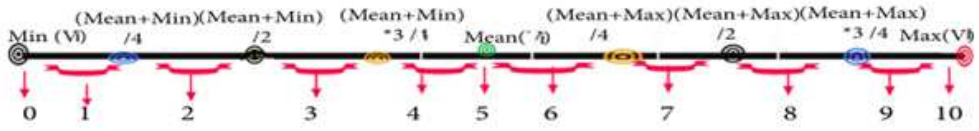


Fig. 1: The DDP codes

This complex process of code generation is used to create decimal patterns that encapsulate and represent the diverse textural information that is embedded in the digital images, demonstrating the effectiveness of DDP in the extraction of meaningful features for further analysis and interpretation.

The significance of the DDP lies in its ability to capture the rich textural information within digital images. Here, the highest value within the constructed feature vector represents the most salient features, effectively identifying peaks within patterns. Conversely, the lowest value indicates the finest features or details, marking troughs and representing the least prominent aspects of texture. In addition, the mean value acts as a measure of central tendency and provides an insight into the overall distribution of the concentration of the intensity values. Together, these features form a robust set that characterizes various persistent patterns present in the image, derived from the image's maximum, minimum and average values.

2.3 The Cubic Decimal Descriptor Pattern (C-DDP)

In the following, we introduce a new approach to 3D image processing and feature extraction called Cubic Decimal Descriptor Pattern (C-DDP). We propose decomposing an image into a set of smaller, uniformly dimensioned cubes, it allows for local analysis of certain regions, while capturing intricate features and patterns within each cube (see Figure 2). A major advantage is the maintenance of spatial relationships, as the connections between neighboring pixels are preserved. This is extremely beneficial in applications such as computer vision, medical imaging and object recognition, where an understanding of the spatial distribution of features is critical. It refines feature extraction by exploring data in detail within each cube, contributing to a richer understanding of the total image. The methodology also reduces the computational complexity by reducing the data into smaller, more easily manageable units, facilitating parallel computing and efficient analysis, particularly in the context of massive datasets.

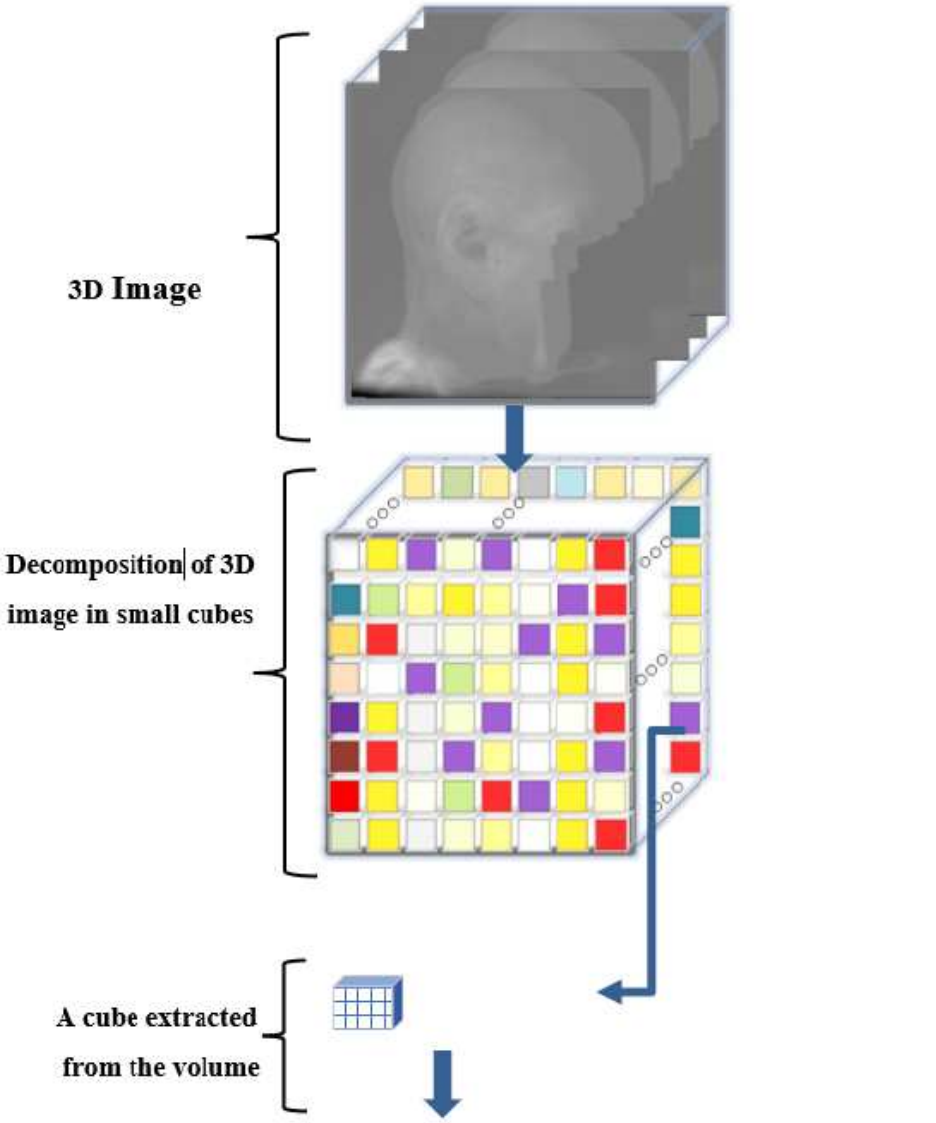


Fig. 2: The Cubic Decimal Descriptor Pattern approach

In a precise analysis scenario, let's examine in detail a set of Nz cubes, each one defined by nx horizontal pixels and ny vertical pixels. Within this analytical framework, we refer to the x, y and z dimensions as LX, LY and LZ respectively, reflecting the spatial domains of the dataset analyzed.

The focus of the analysis is the region of interest, denoted W, which consists of 27 complexly arranged voxels (V1 to V27), each positioned within the x, y, and z dimensions represented by Lx, Ly, and Lz. It is crucial to note that the basic DDP definition initially identified three pixels (maximum, minimum, and mean) within each 3x3 pixel neighborhood. Evolving to our C-DDP construct, the analytical scope expands significantly.

Within each 3x3x3 voxel neighborhood, three pixels (max-c, min-c and mean-c values) are extracted, resulting in a total of 27 voxels. The max-c, min-c and mean-c values are meticulously computed as the maximum, minimum and average of the respective voxel values within neighborhood. These computed voxel values are combined to form a comprehensive feature vector, named F-c, which encapsulates all the features extracted from the cube. This feature vector serves as a rich representation of the intricate patterns within the analyzed data and in the final stage of this analytical process, the associated maximum, minimum and mean values (maximF-c, minimF-c and meanF-c) with the feature vector F-c are rigorously computed. This calculation follows the established protocol of the 2D-DDP approach, where a decimal code is systematically assigned to the resulting feature vector RF, as documented in references [1, 4] and illustrated in Fig 1. This method ensures that the inherent complexity of the multidimensional dataset is effectively captured, paving the way for robust and detailed analysis in image processing and feature extraction.

The above steps are summarized in Algorithm 1.

ALGORITHM 1. The Cubic DDP approach

begin

```
Input: a 3D image
Output: Features vector
// Features extraction
for i:=1 to size (image) do
    Extract a cube C (3*3*3 neighborhood points);
    //From each cube calculate the three features:
    Feature1=Maximum of (C);
    Feature2= Minimum of (C);
    Feature3= mean of (C);
    Insert Feature1, Feature2 and Feature3 in a vector F–c;
// Calculate the maximum, the minimum and the mean of F–c
for i:=1 to size of (F–c) do
    Calculate max = maximum (F–c);
    min = minimum (F–c) ;
    mean = mean (F–c);
 //Assign to each value of the vector F–c a code
for j:=1 to size of F–c do
    if j = min(F–c ) then
    code = 0
    if j in ]minimF–c  (meanF–c+minimF–c)/4 ] then
    code = 1 ;
    ....
    if j = max(F–c) then
    code = 10
    Insert the code in the features vector RF
```

2.4 The Cubic DDP parameters

When adopting the Decimal Descriptor Pattern (DDP) approach, the flexibility of neighbourhood sizes allows a dynamic dimension to analysis. This approach facilitates

the use of neighbourhoods of varying dimensions, as distinguished from a rigid structure where neighborhoods of fixed size are prescribed. By varying the distance and size parameters, the size of the feature vector and the resulting classification scores can be modified. A larger distance parameter can result in the consideration of spatially dispersed patterns, capturing a broader contextual understanding of the data. Conversely, a smaller distance parameter may focus on more closely spaced patterns, highlighting local subtleties.

Similarly, adjusting the Size parameter influences the level of granularity analyzed. A larger size parameter encompasses a broader spatial range within each pattern, potentially capturing more comprehensive information within each neighborhood. Conversely, a smaller size parameter limits the focus to finer details within the patterns and refines the analysis to more local features.

We propose varying the distance D-c between cubes as it is illustrated in Fig. 3. This ability to adjust the distance in the three axis underlines the versatility of the C-DDP approach.

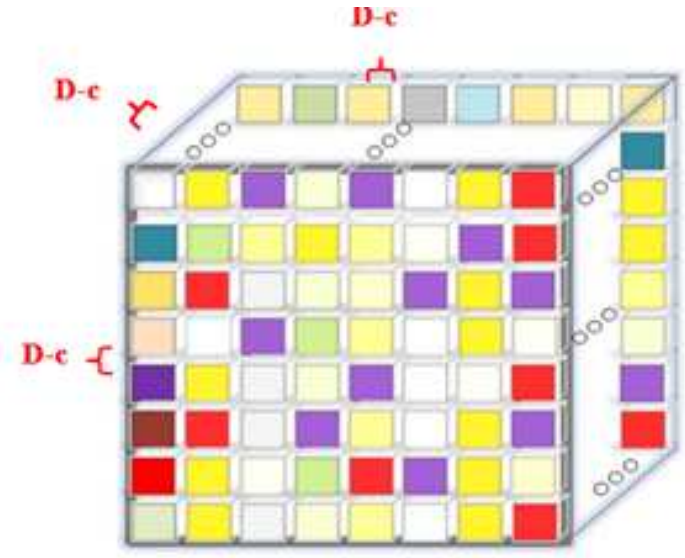


Fig. 3: Distance (D-c) between cubes in C-DDP approach.

2.5 Considered classifiers

2.5.1 Support Vector Machines (SVM)

The Support Vector Machine (SVM) classifier, originally introduced in [13], is a prominent member of the kernel-based family of classifiers, well known for its ability to construct a hyperplane that optimally separates two classes of data while maximizing the distance between them. This hyperplane serves as the decision boundary, effectively discriminating between different classes within the dataset.

The versatility of the SVM is underlined by its ability to perform both linear and nonlinear classifications, depending on the choice of kernel type [1, 4, 6]. In cases where the data in consideration is separable in a linear fashion, a linear kernel is used. This kernel models the data space into a feature space and simplifies the classification task through the definition of a linear decision boundary. This allows for effective linear separation in the resulting transformed space, and the radial basis function (RBF) kernel transforms the data space into a high-dimensional feature space.

This process underscores SVMs' effectiveness in handling sophisticated and nonlinear data relationships. In particular, an RBF kernel allows SVMs to excel at tasks where the underlying patterns may not be linearly separable in the original space. The ability of SVMs to adapt to different types of data, and their ability to accommodate different kernel functions, has contributed to their widespread popularity as a versatile machine learning architecture. This versatility positions SVMs as a cornerstone in the field of machine learning and pattern recognition, making them valuable tools applicable to a wide range of fields and applications.

2.5.2 k-Nearest Neighbors (kNN)

The k-Nearest Neighbours (KNN) algorithm stands out as a powerful and flexible non-parametric method that is suitable for both classification and regression tasks.

Its predictive power lies in its ability to exploit k-nearest neighbor information in feature space, either by determining the majority class in classification or by averaging in regression tasks. The algorithm operates on the basic principle of finding the k-nearest neighbors of a given data point in the feature space and making predictions based on the majority class among these neighbors. During the learning phase, the algorithm memorizes the complete training data set, and when confronted with new data, it dynamically estimates the proximity using a specified distance metric. The choice of the number of neighbors (k) and the distance metric are critical parameters that influence the performance of the model. This flexibility makes KNN a valuable tool in diverse applications, where its adaptability contributes to its wide application. A noteworthy feature of KNN is its support for multiple distance measures, allowing researchers to adjust the algorithm to specific data conditions. This adaptability is useful when dealing with data sets with non-linear relationships. KNN can effectively capture and model these complex patterns. Although simple and interpretable, it requires attention to computational efficiency, especially when handling large datasets. KNN emerges as a robust and broadly applicable machine learning tool, offering solutions for a wide range of applications. The ability to handle both classification and regression tasks, adapt to different distance metrics, and capture nonlinear relationships make it a valuable asset in the machine learning toolbox.

2.5.3 Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) is a prominent classification and dimensionality reduction technique [14]. It is widely used in machine learning and statistics. As a supervised learning algorithm, LDA requires labeled training data in order to perform prediction tasks and dimensionality reduction effectively. Essentially, LDA aims to derive a linear combination of features that effectively characterizes or separates two or more classes. The basic assumption that guides LDA is that the features follow a normal distribution and that the classes have identical covariance matrices.

The methodology involves transforming the original features into a new set, called discriminant functions. This transformation is achieved by linear combination of the original features so as to maximize the separation between class means and minimize the spread within each class.

The key steps in LDA include the calculation of the relevant eigenvalues and eigenvectors, which are based on the covariance matrix associated with the data. The eigenvectors highlight the directions of maximum variance and thus represent the discriminative power of the features, while the eigenvalues indicate the magnitude of this variance. LDA is a useful tool for classification purposes beyond its use in linear transformations and dimensionality reduction. By making use of the resulting discriminant functions, LDA can be used to efficiently classify new samples into pre-defined classes. In addition, by decreasing the number of features while retaining the most discriminating information available in the data, LDA offers an alternative use as a dimension reduction technique.

2.5.4 The MultiLayer Perceptron (MLP)

A Multilayer Perceptron (MLP) is a distinctive form of artificial neural network characterized by its multi-layer architecture, which contains multiple layers of nodes, or artificial neurons [15]. As a feed-forward neural network, MLP information travels unidirectionally. It flows from the input layer, through the intermediate hidden layers, and finally to the output layer. This unidirectional flow of information is a fundamental feature of feed-forward networks.

At its core, an MLP has three essential layers: the input layer, the hidden layer (which can vary in number), and the output layer. Nodes in each layer are intricately connected to nodes in subsequent layers, creating a complex network of interconnected neurons. The links between nodes, often called weights, are significant because they represent the strength of the links between neurons. The input layer allows data to

enter the network, with each node relating to a specific feature of the input data. Information is then propagated. The activation function introduces non-linearity, which enables the network to capture complex patterns and relations within the data. These weighted sums and activations are iteratively updated through the hidden layers to reach the final layer. The output layer provides the definitive result or prediction of the network.

The power of an MLP lies in its ability to recognize intricate patterns and images from complex data sets through a process known as training. During training, the network adjusts its weights based on the error, or difference, between its predictions and actual results. This repetitive adjustment, made easier by algorithms such as backpropagation, fine-tunes the network and enhances its ability to make accurate predictions on previously unseen data.

2.5.5 Convolutional Neural Network (CNN)

CNNs are sophisticated artificial neural architectures carefully designed for the complex task of processing visual information, such as images and video [7, 9–12]. In essence, the CNN is an orderly sequence of convolutional layers, pooling layers, activation functions, fully connected layers, and additional elements to facilitate effective feature extraction and hierarchical representation learning. Convolution, equipped with filters or cores, selectively scans the input data to extract local patterns such as edges and textures. Following pooling layers help to downsample and discard redundant details, effectively capturing the most salient features. The activation functions, notably Rectified Linear Units (ReLU), introduce non-linearity, enabling the network to model complex relationships. The fully connected layers integrate these learned features to generate final predictions. Including flattening, dropout, batch normalization and other elements improves the network's efficiency and ability to generalize.

This sophisticated architecture, inspired by visual processing in the human brain,

makes CNNs ideal for Computer Vision tasks such as image classification, object detection and segmentation, showcasing their ability to automate the task of extracting powerful features from complicated visual data.

3 RESULTS AND DISCUSSION

We conducted several experiments using two types of IRM: FLAIR and T1-weighted sequences (examples are illustrated in Fig 4, 5 and 6). As previously mentioned, FLAIR sequences are specifically designed to suppress the signal from the cerebrospinal fluid (CSF), thereby improving the visualization of lesions and irregularities that are located in close proximity to spaces filled with CSF. T1-weighted sequences, on the other hand, enhance tissue contrast by exploiting inherent relaxation times, thus revealing subtle anatomical details.

The database contains imaging data from 85 individuals with FCD and 85 healthy controls. The individuals with epilepsy underwent high-resolution 3D T1-weighted MRI. The isotropic T1 sequences had varied voxel sizes. Specifically, 43 individuals with FCD (50.6%) had voxel sizes of 1 mm $\times$ 1 mm $\times$ 1 mm, while 42 individuals (49.4%) had voxel sizes of 0.8 mm $\times$ 0.8 mm $\times$ 0.8 mm. Of the individuals with FCD, 91.8% (78) received an isotropic FLAIR sequence, while 8.2% (7) received a 2D FLAIR sequence (flair-2D). The control group consisted of 85 individuals who received high-resolution isotropic T1-weighted and isotropic FLAIR sequences, as well as the same isotropic FLAIR sequence. T1-weighted isotropic images were acquired for both individuals with FCD and controls. The voxel size was 0.8 mm $\times$ 0.8 mm $\times$ 0.8 mm for 78 controls (91.8%) and 1 mm $\times$ 1 mm $\times$ 1 mm for seven control individuals (8.2%). Table 1 provides an overview of the MRI sequences performed in patients with epilepsy and healthy controls. Examples of images associated with both FCD and healthy individuals, along with their T1 and FLAIR images, are shown in Fig 4 and 5.

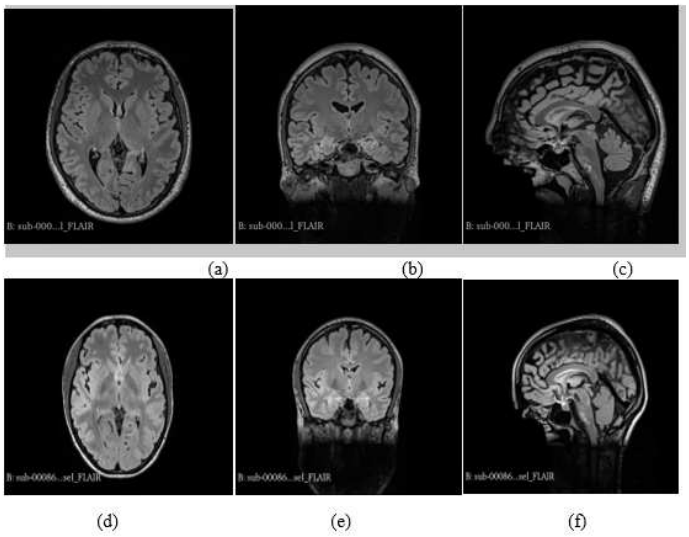


Fig. 4: Examples of flairs sequences presented in coronal, axial and sagittal planes: (a, b, c) a diseased brain, (d, e, f) a healthy brain presented in three orthogonal planes.

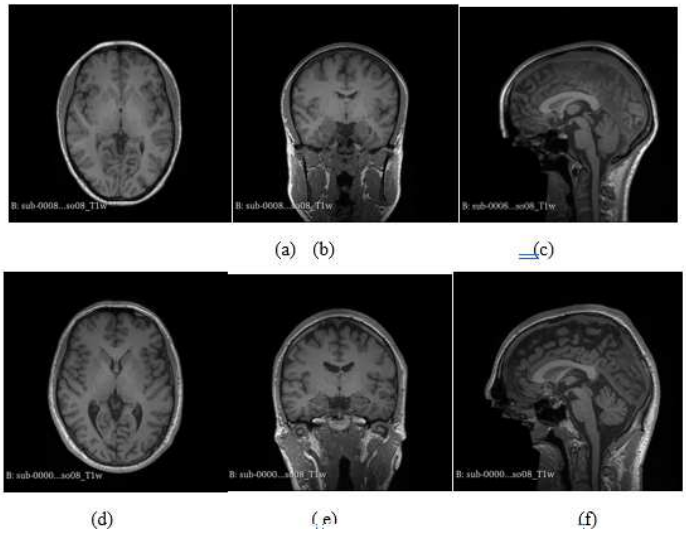


Fig. 5: Examples of T1 presented in coronal, axial and sagittal planes: (a, b, c) a diseased brain presented in three orthogonal planes, (d, e, f) a healthy brain presented in three orthogonal planes.

Table 1: Overview of MRI sequences in patients with epilepsy and in healthy control subjects

	Images					
	T1		FLAIR			
	isotropic T1 sequences	isotropic FLAIR sequences	2D FLAIR			
	t1-iso0.0	t1-iso1	flair-tr5	flair-tr7	flair-tr6	flair-2D
FCD patients	42 (49.4%)	43 (50.6%)	41 (48.2%)	36 (42.4%)	1 (1.2%)	7 (8.2%)
Healthy control	78 (91.8%)	7 (8.2%)	85 (100%)	0 (0%)	0 (0%)	0 (0%)

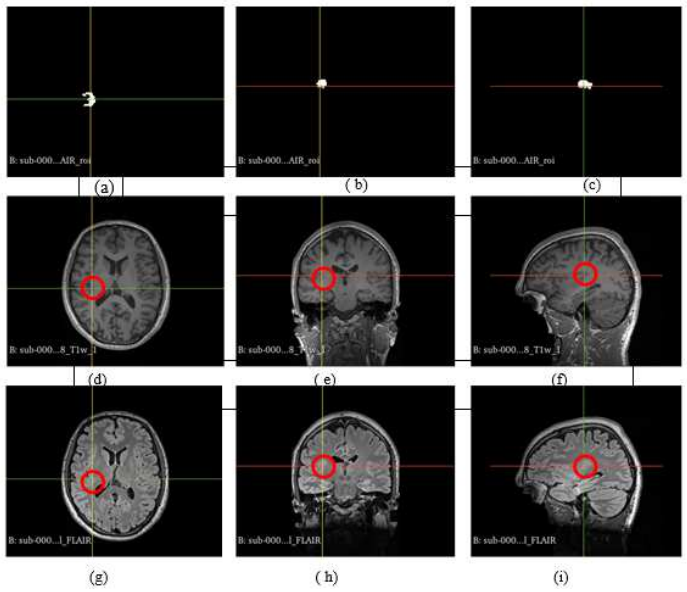


Fig. 6: Example of a lesion identification in coronal, axial and sagittal planes: (a, b, c) Lesion extraction, (d, e, f) Lesion identification in T1 sequences and (d,e f) Lesion identification in flair sequences.

As shown in Fig. 4 and 5, it is not possible to simply separate the two classes (healthy and seizure) through a visual comparison between the T1 and FLAIR varieties. The need for an objective classification tool to differentiate between the two classes prompted the search.

The proposed classification method was evaluated on two distinct scenarios involving

datasets of T1 and FLAIR images, as detailed in Table 1. The binary classification aimed to distinguish between healthy and seizure classes. Various classifiers, encompassing both machine and deep learning approaches, were employed to assess different cases, allowing for a comprehensive evaluation of the approach.

The method starts by applying our proposed feature extraction step. For each classification case, follow these steps:

• First, apply the feature extraction approach to the 3D image datasets (T1 and FLAIR).

• Then, divide the data into a training set and a testing set. The training data should make up 90% of the available data.

• Subsequently, train the classifier using the computed features and the training data. For the nonlinear SVM, we tested different combinations of its parameters.

• Finally, we applied the trained classifier to the test data using the computed features.

The table 2 presents a comparative analysis of six classifiers — KNN, LDA, SVM (with Linear and RBF kernels), MLP, and CNN — applied to T1 and FLAIR brain MRI sequences. Their performance is assessed using three key metrics: Accuracy (ACC), Sensitivity (SEN), and Specificity (SPE), with the goal of evaluating each model's ability to distinguish between normal and abnormal brain tissues. On the T1 modality, LDA achieves the highest accuracy (90.91%) but suffers from extremely low sensitivity (8.5%), indicating a poor ability to detect true positives. CNN attains perfect specificity (100%), meaning it avoids false positives, but its low sensitivity (68.75%) compromises its overall reliability. In contrast, SVM with RBF kernel and KNN offer balanced and robust results across all metrics, suggesting greater consistency and diagnostic value. MLP performs reasonably but falls short of SVM RBF and KNN in both sensitivity and specificity. For the FLAIR modality, SVM (RBF) again stands out, delivering the highest accuracy (90.91%), strong sensitivity (87.5%), and excellent specificity (94.12%), which indicates strong generalization and diagnostic reliability.

KNN and LDA also achieve perfect specificity (100%), but their sensitivity (75% and 62.5%, respectively) suggests a tendency to miss actual positive cases. CNN maintains its perfect specificity (100%) but has the lowest sensitivity (56.25%), reinforcing its overly cautious approach. MLP performs the weakest, with the lowest accuracy (79.7%) and specificity (70.58%). When comparing across modalities, SVM (RBF) emerges as the best overall performer, especially in the FLAIR sequence, thanks to its optimal trade-off between sensitivity and specificity. KNN remains a consistent and balanced alternative, particularly in the FLAIR modality. However, LDA's performance is undermined by its extremely poor sensitivity in T1. CNN, despite its flawless specificity, underperforms in sensitivity, which is critical in medical imaging, where missing true cases can have serious consequences. MLP consistently lags across all metrics, suggesting limited effectiveness without further optimization. In conclusion, SVM with RBF kernel is the most effective classifier overall, CNN is the most conservative (risk-averse to false positives), and KNN provides a solid balance between detection and precision. This study underscores the necessity of evaluating both sensitivity and specificity—beyond mere accuracy—when selecting classifiers for sensitive applications like medical diagnostics.

The performance evaluation in Table 3 compares six classifiers for seizure detection using T1 and FLAIR MRI sequences with a distance parameter set to one. Results reveal a significant improvement in performance when using FLAIR images across most classifiers. For the T1 modality, all classifiers generally show limited effectiveness, with KNN performing particularly poorly in sensitivity (18.75%) despite high specificity (94.12%), indicating it detects very few seizure cases but avoids false positives. LDA also struggles in T1, with the lowest accuracy (45.45%) and modest sensitivity (31.25%). In contrast, SVM (linear and RBF), MLP, and CNN all show identical or close accuracy (66.67%) but vary in sensitivity and specificity, with CNN achieving the best sensitivity (68.75%) in T1. In the FLAIR modality, performance markedly

improves: CNN achieves the highest accuracy (87.87%) and perfect specificity (100%) alongside strong sensitivity (75%), making it the most reliable classifier in this setting. MLP follows closely with high accuracy (84.84%) and also perfect specificity, though slightly lower sensitivity (68.75%). SVM (both kernels) and LDA show solid and balanced performance in FLAIR, with equal accuracy (78.79%) and matching sensitivity (75%) and specificity (82.35%). Overall, FLAIR images significantly enhance seizure detection performance, and CNN emerges as the most effective classifier, while KNN and LDA perform the weakest on T1, highlighting the critical impact of both imaging modality and model choice.

Table 4 evaluates the performance of various classifiers for seizure detection using T1 and FLAIR MRI sequences, with the distance parameter set to two, and it reveals several notable trends. For the T1 modality, overall performance remains modest across classifiers, with KNN showing the lowest sensitivity (6.25%) despite perfect specificity (100%), indicating it correctly identifies non-seizure cases but fails almost entirely to detect seizures. LDA performs the worst in T1, with the lowest accuracy (33.33%) and specificity (23.53%), despite a slightly better sensitivity (43.75%). SVM (both linear and RBF) and MLP offer moderate and balanced results in T1, while CNN leads in sensitivity (68.75%) but suffers from lower specificity (52.94%). The FLAIR modality once again significantly boosts performance across all classifiers. CNN achieves the highest overall accuracy (84.84%) and perfect specificity (100%), along with high sensitivity (86.7%), confirming its strong generalization capability. MLP also performs well on FLAIR with high sensitivity (91.66%) and good specificity (81.43%), yielding an accuracy of 81.81%. SVM (RBF) and LDA also benefit from FLAIR, each reaching an accuracy of 81.82% and strong specificity (94.12%). Comparatively, FLAIR outperforms T1 for all classifiers, and CNN remains the top performer, particularly due to its ability to maintain high sensitivity and perfect specificity. These results underscore the importance of both imaging modality and distance parameter tuning, with FLAIR

combined with a distance of two proving most effective for reliable seizure detection. Across all three tables, a clear pattern emerges highlighting the superior performance of the FLAIR MRI modality over T1 in seizure detection tasks, regardless of the classifier or distance parameter used. Table 2 (distance= 0) shows that classifiers like SVM (RBF) and KNN offer balanced and strong performance, while CNN consistently achieves perfect specificity but often at the cost of lower sensitivity. Table 3 (distance = 1) and Table 4 (distance = 2) further confirm that FLAIR sequences significantly enhance classification accuracy, sensitivity, and specificity compared to T1. As the distance parameter increases from 1 to 2, most classifiers — particularly CNN, MLP, and SVM (RBF) — demonstrate improved results in FLAIR, indicating that a larger neighborhood size may help capture more discriminative features for seizure detection. Notably, CNN consistently emerges as the top-performing classifier on FLAIR, offering high or perfect specificity along with strong sensitivity, especially when the distance parameter is set to two. Conversely, KNN and LDA tend to underperform on T1 and show highly imbalanced sensitivity-specificity trade-offs. Overall, the findings suggest that the combination of CNN, FLAIR imaging, and a distance parameter of two provides the most effective setup for accurate and reliable seizure detection.

The comparison between deep learning and traditional machine learning algorithms across Tables 2, 3, and 4 highlights the superior performance of deep learning models, particularly CNN and MLP, in seizure detection tasks. Deep learning consistently outperforms classical methods, especially when applied to FLAIR MRI sequences. CNN emerges as the most effective classifier, achieving the highest accuracy, sensitivity, and perfect specificity, particularly when the distance parameter is set to two. MLP also shows strong results, notably higher sensitivity than most machine learning models, which is critical in medical diagnosis. In contrast, traditional machine learning algorithms like KNN and LDA often suffer from poor sensitivity, especially on T1 images, despite occasionally reaching perfect specificity. SVM (especially with the RBF

kernel) is the most competitive among machine learning methods, offering balanced performance across both modalities. However, its sensitivity remains generally lower than that of CNN and MLP. Overall, deep learning algorithms demonstrate greater robustness, better generalization, and a superior ability to capture complex patterns in medical imaging, making them the preferred choice for reliable and accurate seizure detection.

Table 2: Performance evaluation of the proposed approach in terms of accuracy (ACC), sensitivity (SEN) and specificity (SPE) of different classifiers for seizure detection using T1 and FLAIR image sequences and distance parameter of zero value.

	Cases					
Classifiers	T1			FLAIR		
	Performance measure (%)			Performance measure (%)		
	ACC	SEN	SPE	ACC	SEN	SPE
KNN	87.88	87.5	88.24	87.88	75	100
LDA	90.91	87.5	94.12	81.82	62.5	100
linear SVM	84.85	81.25	88.24	84.85	68.75	100
RBF SVM	87.88	87.5	88.24	90.91	87.5	94.12
MLP	87.88	78.79	78.93	79.7	68.75	70.58
CNN	84.85	68.75	100	78.79	56.25	100

Table 3: Performance evaluation of the proposed approach in terms of accuracy (ACC), sensitivity (SEN) and specificity (SPE) of different classifiers for seizure detection using T1 and FLAIR image sequences and distance parameter of one value.

Cases						
Classifiers		T1		FLAIR		
	Performance measure (%)			Performance measure (%)		
	ACC	SEN	SPE	ACC	SEN	SPE
KNN	57.58	18.75	94.12	63.64	25	100
LDA	45.45	31.25	58.82	78.79	75	82.35
linear SVM	66.67	62.5	70.59	78.79	75	82.35
RBF SVM	66.67	68.75	64.71	78.79	75	82.35
MLP	66.67	56.25	76.47	84.84	68.75	100
CNN	66.67	68.75	64.75	87.87	75	100

Table 4: Performance evaluation of the proposed approach in terms of accuracy (ACC), sensitivity (SEN) and specificity (SPE) of different classifiers for seizure detection using T1 and FLAIR image sequences and distance parameter equal to two.

Cases						
Classifiers		T1		FLAIR		
	Performance measure (%)			Performance measure (%)		
	ACC	SEN	SPE	ACC	SEN	SPE
KNN	54.55	56.25	100	63.64	25	100
LDA	33.33	43.75	23.53	81.82	68.75	94.12
linear SVM	57.58	56.25	58.82	78.79	68.75	88.24
RBF SVM	63.64	43.75	76.47	81.82	68.75	94.12
MLP	60.61	43.75	76.47	81.81	91.66	81.43
CNN	60.61	68.75	52.94	84.84	86.7	100

Table 5: Performance Evaluation: Confusion Matrix for Different Classifiers using the retained cubic parameters

			Cases			
Classifiers		T1		FLAIR		
	Performance measure (%)			Performance measure (%)		
	ACC	SEN	SPE	ACC	SEN	SPE
KNN	True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
	Normal	8	2	Normal	17	0
	Seizure	2	14	Seizure	4	12
LDA	True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
	Normal	16	2	Normal	17	0
	Seizure	1	14	Seizure	6	10
linear SVM	True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
	Normal	15	2	Normal	17	0
	Seizure	3	13	Seizure	5	11
RBF SVM	True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
	Normal	15	2	Normal	16	1
	Seizure	2	14	Seizure	2	14
MLP	True/Predict	Normal Seizure		True/Predict	Normal	Seizure
	Normal	13	4	Normal	12	5
	Seizure	3	13	Seizure	5	11
CNN	True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
	Normal	17	0	Normal	17	0
	Seizure	5	11	Seizure	7	9

These results, in Table 5, underline the effectiveness of the classifiers. In particular, they highlight the differences in the performance of different sequences and algorithms.

4 CONCLUSION

This paper introduces a feature extraction approach: the Cubic Decimal Descriptor Pattern (C-DDP). It emerges as a promising advancement in the field of automated FCD Type II detection from 3D MRI data, demonstrating notable improvements in both accuracy and efficiency. The C-DDP approach is based on decomposing the image into a set of small cubes. It captures complex features and patterns within each cube, while allowing local analysis of specific regions. The methodology effectively extracts discriminative features that lead to more accurate FCD identification. In addition, a successful strategy for understanding the complex patterns inherent in the extracted features is the integration of machine learning algorithms, including traditional classifiers such as KNN, LDA and SVM and deep learning ones such as CNN and MLP. Experimental results highlight the effectiveness of the proposed approach, with metrics such as accuracy, sensitivity and specificity showing promise. These positive results suggest that the Cubic DDP based approach has the potential to be a valuable tool to clinicians, allowing for the early and accurate diagnosis of FCD, a condition often associated with epilepsy.

Designed primarily for use in medical imaging and neurology, the adaptability of the method allows it to be extensively tested in a variety of medical contexts involving different data sets, patient profiles and imaging protocols. Its potential impact extends to epileptology and neurosurgery, where accurate FCD detection can significantly improve pre-surgical planning and help advance precision medicine for epilepsy patients. Beyond healthcare, the method's feature extraction and machine learning components have broader applications in pattern recognition and image analysis. Testing the effectiveness of the method in biomedical research will further broaden its

usefulness and help researchers to understand neurological diseases. Interdisciplinary cooperation, including computer science and imaging, will facilitate cross-disciplinary testing and ensure robust evaluation from multiple viewpoints.

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Abbreviations

Not applicable.

Ethics approval and consent to participate

Not applicable.

Consent for publication

No, all of the material is owned by the authors and/or no permissions are required.

Availability of data and materials

The dataset used in this study is publicly available at : https://openneuro.org/datasets/ds004199/versions/1.0.6.

Competing Interests

The authors declare that they have no competing interests as defined by BMC, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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Authors' contributions

All authors contributed equally to the conception, design, writing, and revision of this manuscript. All authors read and approved the final version of the paper.

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