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RESEARCH ARTICLE

Innovative Feature Extraction and Machine Learning Joint Approaches for Automated Detection of Focal Cortical Dysplasia Type II

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ABSTRACT Focal cortical dysplasia type II (FCD II) is an epileptogenic lesion often associated with pharmacoresistant epilepsy. Yet, owing to their subtle appearance, identifying these lesions via 3D Magnetic Resonance Image (MRI) remains a complex challenge, rendering them susceptible to evasion by conventional visual analysis. In this study, we consider advancing a novel extraction featuring a volumetric approach dubbed Volumetric Decimal Descriptor Pattern (V-DDP), whereby, data volumetric representations can be effectively captured, providing a comprehensive depiction of the spatial relationships and structural nuances within the dataset. Thus, by applying this unique feature extraction approach, we have been able to decipher more significant information and unlock a relatively rich context, paving the way for a greater recognition scope of such nuanced patterns. This approach has been upheld by three classifiers, namely, the k-nearest neighbors (KNN), the Linear Discriminant Analysis (LDA) and the Support Vector Machine (SVM). Our experimental results demonstrate the significant effectiveness of the proposed approach with the nonlinear SVM classifier. We significantly outperform the state-of-the-art models, especially, in complex volumetric data bound areas.

INDEX TERMS Focal cortical dysplasia, 3D magnetic resonance image, volumetric decimal descriptor pattern.

I. INTRODUCTION

Focal cortical dysplasia type II (FCD II) stands as a significant factor in pharmacoresistant epilepsy, particularly in cases where surgery intervention is imposed [1]. In this respect, magnetic resonance imaging (MRI) findings usually involve cortical thickening, indistinct grey and white matter, increased signal intensity on T2 or FLAIR sequences, and with the persistence of transmantle sign [2], [3]. Despite significant progress in MRI resolution, some FCD type II lesions might be undetected by conventional MRI scans' visual analysis [4], particularly when noninvasive data fail to pinpoint a specific brain region. Hence, retrieving already overlooked lesions holds considerable clinical importance enhancing postoperative seizure outcomes. Indeed, patients with positive MRI findings usually demonstrate somewhat effective postoperative seizure outcomes, compared to those demonstrating negatives MRI results [1].

For individuals with focal FCD lesions, epilepsy relating surgery is a promising treatment option. In this regard, the authors in [5] document that achieving complete removal of FCD lesions and surrounding epileptogenic areas is most often associated with improved prognoses and lower complications. Hence, accurately identifying of the epileptogenic

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lesions' location and scope throughout the pre-surgical assessment stage is crucial. In effect, a thorough determination of such factors is critically essential in surgical decisions, and in formulating the intracranial electroencephalogram (iEEG) implantation strategy, mainly when lesions are discovered to affect the speech or motor skill functional areas [6]. Despite significant progress in neuroimaging and computational methods, identification process of several lesions remains a highly challenging task, with a sensitivity rate of around 70% recorded in FCD affected patients [7], [8]. Such a challenge represents a considerable obstacle, 30% of these patients end up registering MRI results that are visually negative, leading to inherent difficulties in tracking the epileptogenic zone (EZ). Moreover, MRI imaging reevaluation often reveals lesions initially overlooked during primary interpretation. The pre-operative evaluation task is also a time-consuming process, heavily dependent on the interpreters' experiments, which can impede the EZ's accurate localization, thereby, hampering surgical treatment progress.

To address the challenges of FCD radiological assessment, several studies have integrated quantitative computational analyses and machine learning techniques. These approaches consider incorporating a set of feature measures into identification algorithms, in a bid to enhance detection rates (e.g. [9] and [10]).

In [9], an automated classifier was applied using surface-based FCD morphology and intensity features to exploit their covariance. As to the classification procedure, it was performed using Fisher's linear discriminant analysis (LDA). The method's effectiveness was tested on a 19 patients, including 15 with confirmed FCD, who underwent scans at 3.0T. The classifier's performance was cross-validated using a leave-one-out strategy. Specificity was evaluated on twenty-four healthy control cases and eleven disease control cases exhibiting temporal lobe epilepsy. The classifier's performance was also assessed on different datasets including twenty healthy controls and fourteen patients with histologically proven FCD scanned at 1.5T. The reached results appeared to reveal a sensitivity rate of 74% and a specificity rate of 100%. On initially training the classifier on 3.0T data applied to the 1.5T dataset, however, a comparable performance was noticed, demonstrating a sensitivity rate of 71% and a specificity of the rate of 95%.

In [10], an automated detection method was implemented to identify FCD lesions, integrating quantitative multimodal surface-based features and machine learning. The study used neuroimaging data from 74 participants, including 40 cases demonstrating histologically confirmed FCD type II. Accordingly, FCD lesion features were computed on each cortical surface and applied to an ANN. The neural network classifier using multimodal surface-based features demonstrated superior accuracy (70.5%), sensitivity (70.0%), and specificity (69.9%) rates, compared to the unimodal classifier. No significant difference was observed regarding the FCD subtype detection rates (Pearson's chi-square $= 0.001$, $p = 0.970$). As for Cohen's kappa score, indicating the agreement between automated detection results and postoperative resection areas; it recorded a rate of 0.385, which is considered fair.

The study by [11] advances a unique innovative approach to address pediatric epilepsy FCD detection associated challenges. The research involved the implementation of a surface-feature based classifier. Established measures such as cortical thickness, grey-white matter hyperintensity, FLAIR signal intensity, sulcal depth, and curvature were incorporated, alongside a selection of novel features including local cortical deformation and the ''doughnut'' method. The latter is used to help in assessing local variability in cortical morphometry/MRI signal intensity and per-vertex interhemispheric asymmetry. Using a neural network classifier trained on twenty-two focal epilepsy pediatric patients and 28 healthy controls related data, the study indicated that incorporating such novel features in the analyses proved to help significantly in enhancing the FCD identification sensitivity (73%), as compared to the exclusive use of established features (59%). Such findings suggest the possibility of applying such methods for the potential identification of subtle lesions in medication-resistant pediatric epilepsy, as well as for structural analysis of healthy and abnormal cortical development.

The study by [12] aimed to evaluate the diagnostic effectiveness of morphometric analysis compared to the experienced neuroradiologist performing visual analysis, concerning a cohort of ninety-one histologically confirmed FCD II patients. Accordingly, morphometric analysis revealed an increased FCD II a detection rate (82%) compared to visual analysis (65%), while no significant difference was observed in FCD IIb (92% versus 91%). On combining visual and morphometric analyses, the FCD detection rate reached 98%, exhibiting a noticeable increase in diagnostic sensitivity (94% versus 65% for FCD IIa; 99% versus 91% for FCD IIb). The study's results highlight the importance of introducing morphometric MRI analysis to enhance sensitivity in identifying FCD II, thus, maintaining its implementation in patients' diagnoses already classified as MRI-negative by ordinary visual analysis.

In [13], however, the Morphometric Analysis Program (MAP) diagnostic value was assessed concerning focal drug-resistant epilepsy (DRE) with pathologically confirmed focal FCD. The automated MAP analysis program generated z-score maps from T1 images referenced to healthy adult or pediatric controls for each of the 39 FCD pathology confirmed cases. The administered MAP identified abnormal grey matter extension into white matter (MAP-E) and blurred grey-white matter junction (MAP-J) independently of clinical data and other imagery modalities. Regarding sensitivity and specificity, they were computed for MRI, MAP, scalp EEG, PET, and SISCOM about the resection area (RA). In this cohort of 39 histologically confirmed FCD cases, the MAP-J (64% and 96%) and MAP-E (74% and 94%) recorded

sensitivity and specificity rates were higher than those scored via qualitative MRI review, SISCOM, and FDG-PET.

In a more recent study, morphometric analysis of T1-weighted images, applying the Morphometric Analysis Program (v2018; MAP18), was implemented to boost visual detection [14]. In a retrospective investigation, a feed-forward artificial neural network (ANN) was developed to detect focal cortical dysplasia (FCD). The ANN network was trained and cross-validated concerning 113 patients through manually segmented FCDs and 362 healthy controls administered by thirteen scanners. Sensitivity and specificity rates of 87.4% and 85.4% were scored throughout the cross-validation process. Further performance on an independent dataset of sixty FCD patients and seventy healthy controls yielded sensitivity and specificity rates of 81.0% and 84.3%, respectively. Such results highlight well the potential of incorporating morphometric and ANN analyses for FCD detection purposes, owing to the highly promising sensitivity and specificity scores they could record.

However, an urgent need to develop innovative mechanism simultaneously integrating machine learning and quantitative imaging features for effective identification of potential epileptogenic foci is still perceived. In this respect, it is interesting to draw benefits from various application domains proved methods, as demonstrated by the successful application of biomedical signal classification for epileptic seizure detection [15], [16], [17] and image processing techniques [18], [19], [20] for feature extraction ends on both 2D and 3D images [20]. In [20], a novel feature extraction design has been introduced and effectively applied to 2D images for multiple sclerosis (MS) detection and progression analysis purposes. In this context, and given the absence of a comparable approach in the existing relevant literature, we consider pioneering a new feature extraction architecture, based on the idea developed in [20], which fit for implementation with 3D imagery. Hence, a novel design, useful for applications to detect FCD, based on the newly developed 3D feature extraction approach and integrative machine learning techniques, is put forward within the scope of the present study.

II. METHODS AND MATERIALS

A. DATABASE

For an effective testing of our advanced architecture, we considered applying the Open Presurgery MRI Dataset for Focal Cortical Dysplasia and Control Individuals, a freely available database [21]. The observed dataset, drawn from the Epileptology Department, of the University Hospital of Bonn, Germany (2006-2021), involves individuals with epilepsy associated with focal cortical dysplasia (FCD) and healthy controls. The relevant selections criteria included histologically confirmed FCD type II or radiologically suspected FCD type II regarding participants over eighteen-years old at the time of study conduction or data collection. Demographically, among the eighty-five epilepsy-affected participants, 41.2% were female and 58.8% were male, displaying a first-epileptic-seizure mean age of 10 years, and an MRI-scan mean age of 28.9 years.

The data set includes detailed clinical information regarding FCD classification, site distribution, drug resistance, and surgical outcomes. The imaging data, made available from the Life & Brain Center in Bonn, Germany, through the application of a 3-Tesla MRI scanner, consist of fluid-attenuated inversion recovery (FLAIR) and T1 sequences. The FCD affected individuals underwent high-resolution 3D T1-weighted MRI with varying voxel sizes, while control subjects underwent the same imaging protocol with isotropic T1-weighted and FLAIR sequences.

B. THE DDP APPROACH

In the area of texture analysis, the Decimal Descriptor Pattern (DDP) has emerged as a formidable pattern characterization tool in digital imagery [18], [19], and [20]. DDP rests on encoding the correlation binding a pixel and its neighboring pixels, relying on their respective intensity values. The method aims to depict the texture by creating a feature vector. For an effective feature vector to be achieved, the minimum, maximum, and mean values are computed based on the intricate patterns within the image. At this level, the operator labels every pixel in an image by calculating the mean, maximal, and minimal values drawn from the 3×3 surrounding pixels. The resultant features, drawn from the entirety of the image born patterns, are concatenated into an initial vector, V.

While the highest value reflects the most noticeable characteristics identifying the peaks within patterns, the lowest value depicts the most delicate features or details marking the troughs, i.e., the least prominent aspects. Besides, the average value is a central tendency measure, recognizing the overall concentration distribution. This feature set, drawn from the image's maximum, minimum and mean values, robustly characterizes the various persistent patterns, promoting a thorough understanding that underpins further analysis and interpretation.

Once the feature vector is constructed, the maximum value (max), minimum value (min), and average value (mean) are calculated. Using (max), (min) and (mean), each value in the vector V is assigned a figure within the range of {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. The vector V is then converted into its codes.

Such a process serves to generate decimal patterns, predominantly encapsulating textural information.

C. THE PROPOSED APPROACH: VOLUMETRIC DECIMAL DESCRIPTOR PATTERN (V-DDP)

In a data analysis process of varying nature, a growing need for methods enabling to drawing insights from three-dimensional datasets is usually perceived.

This study is designed to provide a novel volumetric method, called Volumetric Decimal Descriptor Pattern (V_DDP), involving spatial comprehension in 3D datasets. (V_DDP) is enhanced by implementing of an interconnected

voxel grid representing volumetric data, which helps extract features with exceptionally accurate precision. Concerning our volumetric data analysis case, and for spatial accuracy to be highly enhanced, we consider implementing a systematic approach, whereby, 3D images can be subdivided into smaller, more manageable units. The process is initiated by subdividing the 3D space into a grid of window volumes, wherein, each window encloses a particular subset of voxels. The window specified dimensions are set to 3*3*3 voxels (Figure 1).

Suppose, for instance, that a set of Nz (windows) are to be analyzed, with nx pixels in the horizontal direction and ny pixels in the vertical direction, and that each pixel's respective digital value is quantized to ng gray levels.

Let: LX=(lx1,lx2,lx3), LY=(ly1,ly2,ly3) and LZ =lz1,lz2, lz3) be the x, y and Z domains; and let W=[V1(lx1,ly1,lz1), V2(lx1,ly1,lz2), …,V27(lx3,ly3,lz3)] be the a window set englobing 27 voxels V1,V2,…,V27.

Worth recalling, at this level, is that in the original definition of DDP, as figuring in [1], three pixels (maximum, minimum and mean values) were identified in each neighborhood of 3*3 pixels.

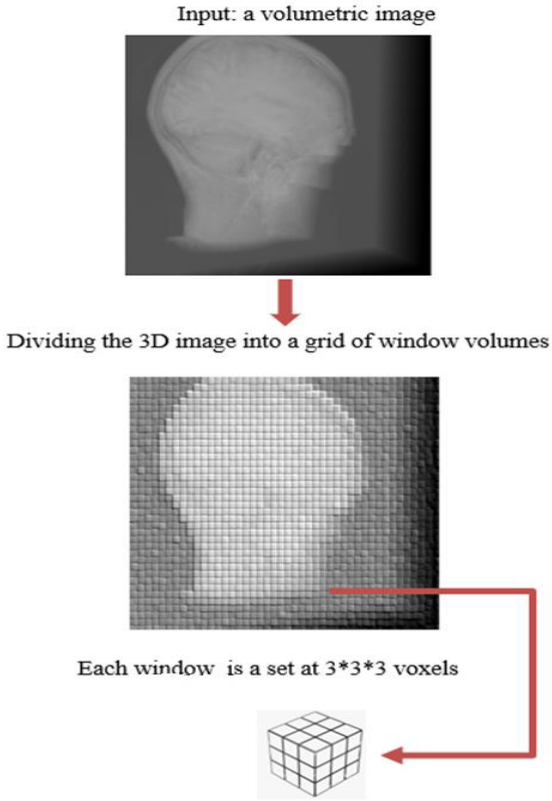

FIGURE 1. V_DDP approach.

With respect to our set V-DDP construct, however, three pixels (maxv, minv and meanv values) have been identified for each neighborhood of 3*3*3 voxels, so that a total of 27 voxels are considered, wherein:

$$\text{maxv} = \text{Maximum}(V1, V22 \ldots, V27) \quad (1)$$

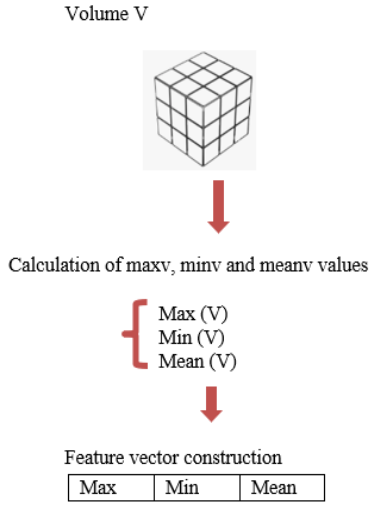

FIGURE 2. Feature extraction from 3*3*3 pixels.

$$\text{minv} = \text{Minimal}(V1, V22 \ldots, V27) \quad (2)$$

$$\text{meanv} = \text{mean}(V1, V22 \ldots, V27) = (V1, V22, V27)/27 \quad (3)$$

The entirety of the image windows drawn features are then jointly concatenated into a single feature vector (fV).

In a last stage, the feature vector (fV) associated maximum, minimum and mean values (maxim-fv, minim-fv and mean-fv) are computed. As it is the case with the 2D- DDP [18], [19], [20], a decimal code is assigned to the established feature vector (fV). For example, the minimal value is coded by 0 and values that are in this interval]minim-fv (mean-fv+minim-fv)/4] are coded by 1.

TABLE 1. The V-DDP relevant codes.

Values	V-DDP codes
Minfv	0
]minim-fv (mean-fv+minim-fv)/4]	1
] (mean-fv+minim-fv)/4 (mean-fv+minim-fv)/2]	2
] (mean-fv+minim-fv)/2 (mean-fv +minim-fv)*(3/4)]	3
] (mean-fv +minim-fv)(3/4) mean-fv [	4
Mean-fv	5
] mean-fv (mean-fv +maxim-fv)/4 [	6
] (mean-fv +maxim-fv)/4 (mean-fv +maxim-fv)/2]	7
](mean-fv +maxim-fv)/2 (mean-fv +maxim-fv)*3/4]	8
](mean-fv +maxim-fv)*3/4 maxim-fv [	9
Maxim-fv	10

D. CONSIDERED CLASSIFIERS

1) SUPPORT VECTOR MACHINES (SVM)

Initially introduced in [22], the SVM classifier belongs to the kernel-based family of classifiers, and is designed to construct a hyperplane that separates two classes of data, while

maximizing the distance span separating them. It provides enough flexibility to handle both linear and nonlinear classifications, depending on the applied kernel type. For cases wherein relevant data is linearly separable, a linear kernel is used to map the data space into the feature space.

For nonlinear classification tasks, such as seizure detection [16], and automatic sleep stage classification [23], however, a nonlinear kernel, such as the Gaussian-type Radial Basis Function (RBF) kernel, is applied. This procedure serves to transform the data space into a high-dimensional feature space, liable to effective linear separation. It is actually this process that has rendered the SVM gain popularity as a versatile machine learning architecture, useful for implementation in a wide range of application fields.

2) K-NEAREST NEIGHBORS (KNN)

The k-Nearest Neighbors (KNN) algorithm is a nonparametric method simultaneously useful for implementation with classification as well as regression tasks. It helps in making predictions by considering the majority class or the average of the k-nearest neighbors in the feature space. Known for its versatility, KNN supports different distance metrics and is adept at handling data persistent non-linear relationships. Despite its simplicity and interpretability, users should be mindful of computational efficiency, particularly regarding large dataset involving scenarios. In sum, the KNN stands out as a valuable and broadly applicable machine-learning tool, capable of providing robust solutions within a wide range of applications.

3) LINEAR DISCRIMINANT ANALYSIS (LDA)

The Linear Discriminant Analysis (LDA) is a classification and dimensionality reducing technique widely used in areas of machine learning and statistics.

As a supervised learning algorithm, it entails labelled training data to execute prediction making and perform dimensionality reduction tasks. In what follows, is a brief overview of the Linear Discriminant Analysis.

The LDA's primary goal consists in retrieving a linear combination of features, characterizing or separating two or more classes. The idea of LDA lies in the assumption that features are normally distributed, and that classes have identical covariance matrices. It also involves transforming the original features into a newer set of features, dubbed discriminant functions, by linearly combining the original features. This transformation process is designed to maximize the class means separating span, while minimizing spread within each class.

Based on the data associated covariance matrix, the LDA undertakes to compute the relevant eigenvalues and eigenvectors, wherein, the eigenvectors mark the maximum variance trend directions (the discriminative power), and the eigenvalues display the variance magnitude.

Further to the linear transformation process, the LDA is also applicable for classification maintaining purposes. Alternatively, it can also be used as a dimensionality reducing technique, enabling to reduce the number of features while retaining the most discriminative data.

III. RESULTS AND DISCUSSION

The experiment has been performed in two phases; a training phase followed by testing one. During the training phase, the proposed model is exposed to a labeled dataset, enabling it to learn its underlying patterns and relationships. This process is essential for constructing a sturdy and flexible model capable of effectively predicting outcomes for the new data sets.

In the testing phase, the trained model's performance is assessed on a distinct and previously unnoticed or overlooked dataset, thus, providing a crucial evaluative process of the model's accuracy level in making predictions on novel instances, while testing its overall capacity. In effect, the thoroughly detailed separation of the training and testing procedures should ensure that our model does not merely commit the training data into memory but detects and highlights any crucial aspects likely to be implemented in novel and undiscovered cases, acknowledging the practical circumstances targeted by our approach.

In this study, we harnessed the power of 161 T1 and 163 Flair sequences obtained by 3D MRI. Given their ability to capture detailed structural information within the imaged subject, the choice to use T1 and Flair sequences in our experiments was deliberate. This information is invaluable for various medical applications, including but not limited to disease diagnosis and treatment planning [19], [20].

The data set was split into two subsets: a training set comprising 80% of the data and a test set comprising 20%. This division was crucial to assess the generalization ability of our model. The 80-20 split was chosen based on established best practices in machine learning. It strikes a balance between providing the model with sufficient data to learn and reserving an independent set for rigorous evaluation. This methodology increases the likelihood that the model will perform well on unseen data, thereby increasing the reliability and applicability of the model in real-world scenarios.

The classification aims to identify the provided image's attachment category and nature (Figure 3). Therefore, extracting a series of features from the image is necessary to draw a relevant thorough description. The image classification process is executed fusion the features' descriptor, wherein, the texture classification procedure depends on comparing two feature vectors.

The analysis technique involves selecting representative samples and marking different categories, before executing the analysis process. The extracted features are then used to define a vector of parameters regarding each image. The test feature vectors are computed for every sample following the same approach as illustrated in Figure 4.

The system is comprised of two principal phases: feature extraction and classification. The initial phase entails the application of the V_DDP feature extraction method to the three-dimensional (3D) images. The extraction result will be

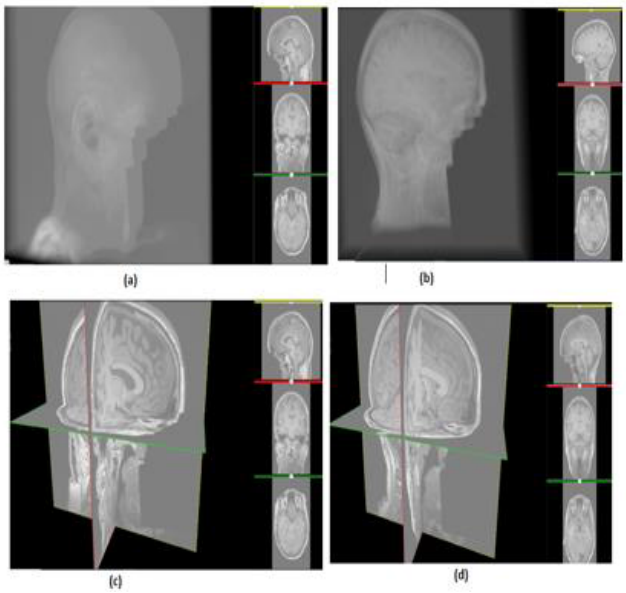

FIGURE 3. Examples of 3D images from the Open Presurgery MRI Dataset for Focal Cortical Dysplasia and Control Individuals: (a) a volumetric diseased brain, (b) a volumetric healthy brain, (c) a diseased brain presented in three orthogonal planes, (d) a healthy brain presented in three orthogonal planes.

represented by a vector comprising features that describe the entire image. The feature vector will then be utilized by the classification algorithms, which will employ the extracted features from the V_DDP method. Consequently, the learning and classification processes will be based on the extracted features.

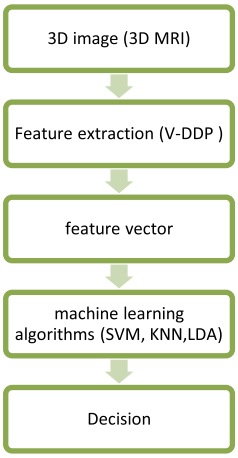

FIGURE 4. FCD II detection overview.

For a thorough evaluation of our advanced V-DDP design's versatility and generalizability, we have considered introducing a range of classifiers as part of our experimental procedure. In this respect, several classifiers, specifically, the K-Nearts Neighbor Nearest (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM) classifiers have also been observed, to help in the effective assessment of our approach associated performance across the entirety of learning paradigms.

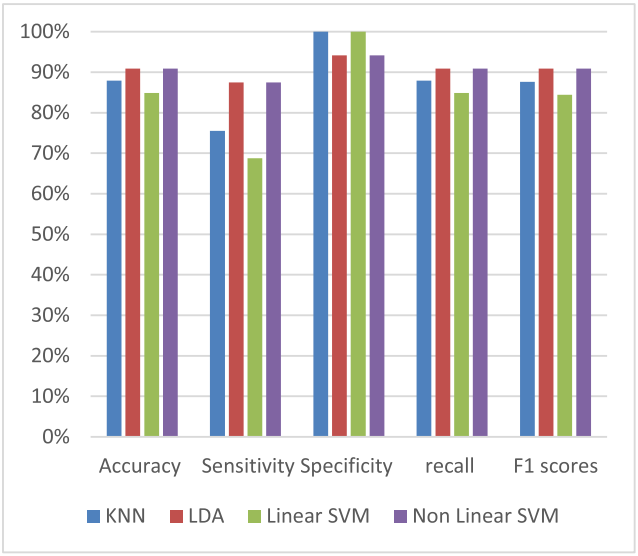

FIGURE 5. Comparison of performance metrics between the used classifiers using 3D MRI Flair sequences.

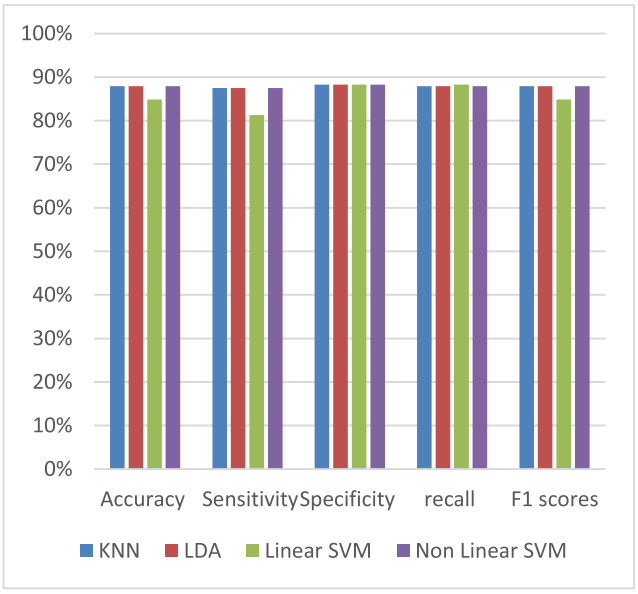

FIGURE 6. Comparison of performance metrics between the used classifiers using 3D MRI T1 sequences.

An extensive performance evaluative procedure has been undertaken to determine the suggested V-DDP architecture's effectiveness extent, along with establishing an evaluative comparison with the most leading studies' provided solutions in the field. In effect, our approach displayed exceptional results across several metrics, particularly, regarding the accuracy, sensitivity, specificity, precision, recall and F1 score aspects.

The best results were obtained with the following parameters for T1 and FLAIR sequences. For LDA, the number of components was set to 64. The Linear SVM used a parameter of $C = 1$. For the Non-Linear SVM, the parameters were $C = 10$, kernel = rbf, degree = 3, and gamma = scale. Lastly, the KNN method was configured with the number of classes set to 2.

TABLE 2. Performance evaluation: confusion matrix for different classifiers using 3D T1 MRI sequences.

KNN			**LDA**		
True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
Seizure	15	2	Seizure	15	2
Normal	2	14	Normal	2	14
Linear SVM			**Nonlinear SVM**		
True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
Seizure	15	2	Seizure	15	2
Normal	3	13	Normal	2	14

TABLE 3. Performance evaluation: confusion matrix for different classifiers using 3D flair MRI sequences.

KNN			**LDA**		
True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
Seizure	17	0	Seizure	16	1
Normal	4	12	Normal	2	14
Linear SVM			**Nonlinear SVM**		
True/Predict	Normal	Seizure	True/Predict	Normal	Seizure
Seizure	17	0	Seizure	16	1
Normal	5	11	Normal	2	14

TABLE 4. Comparison of the proposed approach with state-of-the-art methods.

Ref and years	Datasets/ studied cases details	Classifiers	Accuracy	Sensitivity	Specificity
Ref 24, 2024	Private dataset (the Second Affiliated Hospital of Zhejiang University School of Medicine) composed by 82 patients	3D CNN	90.3%	85%	
Ref 14 , 2021	Private dataset (Swiss Epilepsy Clinic Zurich, Switzerland) A cross-validated dataset composed by 113 patients with manually segmented FCDs and 362 healthy controls	3D-ANN		81%	84,3%
Ref 14 , 2021	Private dataset (Swiss Epilepsy Clinic Zurich, Switzerland) An independent validation data set composed by 60 FCD patients and 70 healthy controls	3D-ANN		87,4%	85,4%
Ref 25, 2021	CHB-MIT EEG database (time, frequency, and channelinformation of electroencephalography signals analysis)	3D-CNN	80,5%	85,8%	75,1%
Ref 26, 2024	Private dataset (the Hamburg Epilepsy Center, Germany) A dataset of 300 MRIs from daily clinical practice. The dataset included 30 FCD cases and a control group of 150 normal cases along with 120 non-FCD pathological cases	3D-CNN	72.0%	90.0%	70.0%
Our contribution Feature extraction using V-DDP	The Open Presurgery MRI Dataset for Focal Cortical Dysplasia and Control Individuals T1 MRI 78 patients and 83 healthy controls	Linear SVM	84,85%	81,25%	88,24%
		Non Linear SVM	87,88%	87,5%	88,24%
		KNN	87,88%	87,5%	88,24%
		LDA	87,88%	87,5%	88,24%
	The Open Presurgery MRI Dataset for Focal Cortical Dysplasia and Control Individuals flair MRI 78 patients and 85 healthy controls	Linear SVM	84,85%	68,75%	100%
		Non Linear SVM	90,91%	87,5%	94,12%
		KNN	87,88%	75%	100%
		LDA	90,91%	87,5%	94,12%

Figure 5 and 6 show the performance metrics of three classifiers:

The results obtained with FLAIR sequences for various classifiers demonstrate consistent and high performance

across several evaluation metrics. The Linear SVM achieved an accuracy of 84.85%, a sensitivity of 81.25%, a specificity of 88.24%, a recall of 84.85%, and an F1 score that reflects these balanced metrics. The Non-Linear SVM exhibited an accuracy of 87.88%, a sensitivity of 87.5%, a specificity of 88.24%, a recall of 87.88%, and an F1 score of 87.88%. The KNN classifier showed similar performance with an accuracy of 87.88%, a sensitivity of 87.5%, a specificity of 88.24%, a recall of 87.88%, and an F1 score of 87.88%. The LDA classifier matched these results, also achieving an accuracy of 87.88%, a sensitivity of 87.5%, a specificity of 88.24%, a recall of 87.88%, and an F1 score of 87.88%. These results indicate that the Non-Linear SVM, KNN, and LDA classifiers perform equally well, with high accuracy and balanced sensitivity, specificity, recall, and F1 scores, making them effective for analyzing FLAIR sequences in this context.

The results obtained with T1 sequences for various classifiers exhibit notable performance metrics across multiple evaluation criteria. The Linear SVM achieved an accuracy of 84.85%, a sensitivity of 68.75%, a specificity of 100%, a recall of 84.85%, and an F1 score of 84.42%. The Non-Linear SVM demonstrated enhanced performance with an accuracy of 90.91%, a sensitivity of 87.5%, a specificity of 94.12%, a recall of 90.91%, and an F1 score of 90.89%. The KNN classifier showed an accuracy of 87.88%, a sensitivity of 75%, a specificity of 100%, a recall of 87.88%, and an F1 score of 87.65%. Lastly, the LDA classifier also exhibited strong performance, with an accuracy of 90.91%, a sensitivity of 87.5%, a specificity of 94.12%, a recall of 90.91%, and an F1 score of 90.89%. These results indicate that both the Non-Linear SVM and LDA classifiers provide high accuracy and well-balanced sensitivity, specificity, recall, and F1 scores, making them particularly effective for analyzing FLAIR sequences.

This analysis underscores the critical role of selecting the appropriate kernel to achieve optimal classifier performance. It also emphasizes the need for careful consideration of multiple metrics, including accuracy, sensitivity, specificity, precision, recall, and F1 score, to make informed decisions in classifier selection, recognizing the inherent trade-offs among these performance indicators.

To further illustrate the effectiveness of our proposed approach and the SVM RBF classifier, Table 2 and 3 present the confusion matrix for the tested classifiers.

In conclusion, based on the comparative analysis, the RBF SVM and LDA are designated as the optimal choices for seizure detection in 3D IRM images, aligning seamlessly with our proposed feature extraction approach.

The results of numerous experiments conducted to validate the V_DDP approach have demonstrated that it is significant but a resource-intensive approach, requiring a significant amount of time and computational power, especially for large datasets.

In addition, the volumetric nature of 3D data introduces a multitudinous array of intricate patterns and variations that are often subtle and elusive, necessitating a considerable investment of time and computational resources.

The proposed approach can be applied in various fields that utilize 3D images. For instance, in facial recognition, it can enhance the accuracy and reliability of identifying individuals. In medical diagnostics, it can be used to detect diseases such as cancer, multiple sclerosis, and COVID-19 by analyzing 3D medical imaging data, potentially improving early detection and treatment outcomes.

Table 4 present a comparison study of the proposed approach with some state-of the art methods.

IV. CONCLUSION

The proposed feature extraction approach V-DDP for automated detection of focal cortical dysplasia (FCD) shows promising results in improving the accuracy and efficiency of FCD detection from 3D MRI data. In addition, implementing of machine learning algorithms, such as KNN, LDA and SVM, has proven effective in learning complex patterns from the extracted features, further improving the accuracy of FCD detection. The accuracy, sensitivity and specificity achieved in the experimental results suggest that the proposed approach holds promise for assisting clinicians in the early and accurate diagnosis of FCD.

Exploration of more advanced deep learning architectures, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), may further improve the model's ability to capture hierarchical and spatial dependencies in the image data.

DATA AVAILABILITY

The data used to support the findings of this study are restricted by the Open Presurgery MRI Dataset for Focal Cortical Dysplasia and Control Individuals. The observed dataset, drawn from the Epileptology Department, University Hospital of Bonn, Germany (2006–2021)

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

SUPPLEMENTARY MATERIAL

No Supplementary Material.

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