sciendo
ISSN 1335-8871

MEASUREMENT SCIENCE REVIEW

Journal homepage: https://content.sciendo.com

A High-Performance Method Based on Features Fusion of EEG Brain Signal and MRI-Imaging Data for Epilepsy Classification

Fatma Demirezen Yağmur[1*], Ahmet Sertbaş[2]

[1]*IT Department, Bolu Abant-Izzet Baysal University, Gölköy, 14030, Bolu, Turkey,* fatmademirezen@ibu.edu.tr,
[2]*Department of Computer Engineering, Faculty of Engineering, University of Istanbul-Cerrahpasa, Avcılar, 34320, Istanbul, Turkey,* asertbas@iuc.edu.tr

Abstract: A 1-dimensional (1D) and 2-dimensional (2D) biomedical signal analysis based on the Discrete Cosine Transform (DCT) feature extraction method was performed to diagnose epilepsy disorders with high accuracy. For this purpose, Electroencephalogram (EEG) data were used for 1D signal analysis and Magnetic Resonance Imaging (MRI) data were used for 2D signal analysis. The feature vectors were obtained by applying 1D DCT together with statistical methods such as mean, variance, standard deviation, kurtosis, and skewness for EEG data and by applying 2D DCT together with the statistical method of mean for MRI data. The most useful features were selected by applying Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Forward Selection and Backward Selection methods to the obtained feature vectors. Using EEG stand-alone features, MRI stand-alone features and EEG-MRI fused features, the classification of healthy and epileptic subjects was performed in the form of two clusters. The result of epilepsy classification in this work is 96% success of 1D EEG data by using the features selected by the PCA method, 94% success of 2D MRI data using the selected features by applying the Forward Method, 100% classification accuracy of 1D EEG and 2D MRI datasets by LDA method using the obtained fused features . The article shows that the fused features of EEG-MRI can be used very effectively for the diagnosis of epilepsy.

Keywords: Epilepsy, MRI, EEG, discrete cosine transform, medical image analysis, EEG-MRI classification.

1. Introduction

Epilepsy is one of the most common neurological diseases of the brain. Numerous diagnostic tests are used to identify the type of epileptic seizure [1]. These include Electroencephalogram (EEG), Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). From 1982 to the present day, many studies have been carried out to diagnose epilepsy. Anderson and Sijercic trained EEG data with a feed-forward neural network using the Auto-Regressive (AR) model [2]. Kalaycı and Özdamar classified EEG data with Artificial Neural Networks (ANN) using the Wavelet Transform (WT) [3]. Subasi and Gursoy split EEG signals into subbands using the Discrete Wavelet Transform (DWT); they reduced the data size by applying Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA) methods and classified them using Support Vector Machines (SVM) [4].

Ogulata et al. have classified epileptic seizures with Multi-Layer Perceptron (MLP) from EEG signals [5]. Gandhi et al. calculated the energy, entropy, standard deviation, mean, kurtosis, and skewness values of the signal by applying the DWT to the EEG data, created a separation tree and classified epileptic patients using the Probabilistic Neural Networks algorithm [6]. Krishnaveni et al. separated the artifacts contained in the EEG signals using the ICA method and classified them using the Polynomial Neural Network (PNN) and Advanced Propagation Neural Network methods [7]. MRI studies: Loyek et al. developed a model for focal prediction in detecting lesioned tissues and examined MRI data from epilepsy patients using SVM for focal lesion segmentation and tissue-based classification [8]. Clarke et al. proposed a segmentation method using the Fuzzy C-Means algorithm to identify abnormal MRI volumes [9]. Sujitha et al. modeled the prediction of epileptic seizures from MRI using SVM [10]-[12].

The Discrete Cosine Transform (DCT) is a method for converting the frequency of time series into fundamental frequency components [11]. This method is often used for data compression. DCT was previously used by Martius et al. [11] for audio image compression and has by Orłowski [12] for signal filtering. Sharif and Jafari obtained the feature

DOI: 10.2478/msr-2024-0001

**Corresponding author: fatmademirezen@ibu.edu.tr (F. DemirezenYagmur)*

space by Genetic Algorithm (GA) and Shannon Entropy (SE) calculation and then tested the sensitivity with Gaussian RBF-SVM by selecting features with PCA [13].

Mutlu classified EEG signals with a least-squares support vector machine for epileptic seizure detection based on Hilbert Vibrational Discrimination (HVD) [14]. Kaleem et al. present a novel patient-specific approach for seizure detection using wavelet decomposition of multi-channel EEG data and handcrafted features from the decomposed data [15]. Gupta and Pachori proposed a new method for classification of epileptic seizures based on Weighted Multiscale Renyi Permutation Entropy (WMRPE) and rhythms obtained using the Fourier-Bessel Series Expansion (FBSE) of EEG signals [16]. Serna et al. Taylor-Fourier classified seizures based on EEG-band energy features using classifiers such as K-Nearest Neighbor (KNN) and the Least-Squares Support Vector Machine (LS-SVM) [17].

1-dimensional (1D) and 2-dimensional (2D) biomedical signal analysis based on the DCT feature extraction method was performed to diagnose epilepsy with high-accuracy. For the diagnosis of epilepsy, EEG data were used for 1D signal analysis and MRI data for 2D signal analysis. Subsequently, a new approach based on the fusion of features from EEG-MRI data was proposed as a high-accuracy solution to the problem of epilepsy classification. The 2nd section of the study highlights EEG analysis, the 3rd section highlights MRI analysis and the 4th section highlights the new approach, EEG-MRI Fusion of Features.

2. EEG ANALYSIS

The EEG is a test in which the electrical activity in the brain is measured via electrodes attached to the scalp. The EEG is used to diagnose certain diseases that affect the brain. Epilepsy is the most common one. There are many steps from obtaining the EEG data to classifying it. Classification is about whether the person has epilepsy based on the EEG data.

A. Materials

The Neurofax EEG-1000 was used to record the EEGs of the patients diagnosed with epilepsy in the Neurology Department of Bolu Abant-Izzet Baysal University Hospital in Bolu. In total, the EEG data of 88 epilepsy patients and 40 healthy individuals were recorded. The EEG cap has 16 channels. The recording takes an average of 18 minutes for each patient. The computer system used for the application is an Intel (R) Core (TM) i5-4210U CPU 1.70 GHz, x64 based processor.

B. Method

The EEG data is read out with the Nihon Kohden EEG-1000 fax program, the software of the EEG device. Fig. 1 shows the stages of the EEG from the analysis of the first raw data input to the classification step.

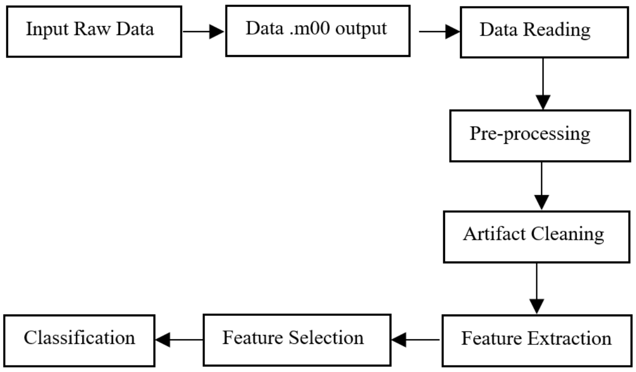

Fig. 1. The flow chart shows steps regarding EEG data analysis from EEG acquisition to data classification.

C. Raw data input and output

The raw data was uploaded to the computer using the EEG reading program Nihon Kohden EEG-1000. Raw data consists of both brain signals and artifacts, such as seizures, contractions, eye movements, swallowing, coughing, and body movements. Fig. 2 shows the transfer of the data to the tool. This tool has been prepared to read data in .m00 format.

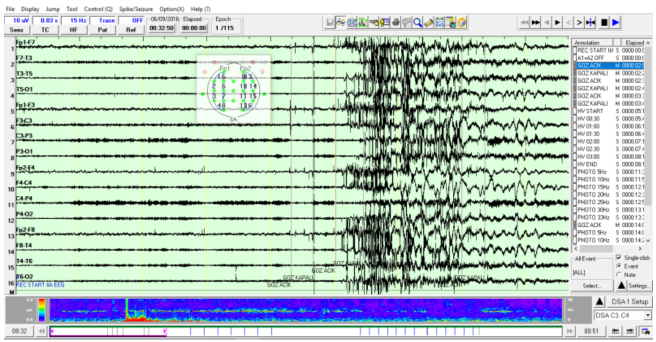

Fig. 2. Nihon Kohden tool.

D. Pre-processing

The EEGLab14_1_2b program was used to examine and pre-process the EEG data and remove artifacts. The data then went through many stages such as feature extraction, selection and classification.

1. Data reading

The plugin 1.1.0 from Nihon Kohden is added to EEGLab to solve this problem (due to the unsupported data format). The EEG data (.m00 format) was transferred to the system via the EEGLab installed plugin. The 16-channel EEG signal received in the system was terminated in 1080 seconds with a transfer rate of 200 Hz in a matrix of 16x21600, and the size of the data set was determined to be 15.6 Mb.

2. Filtering

When raw data is read, this data also contains unwanted noise. A high-pass filter with a value between 0.5 – 1 Hz was applied. In the study, the unwanted noise contained the raw data is removed by a high-pass filter when the data is read. The noise is removed from the data using the filter.

3. Channel cleaning

As the filtered data was limited to the frequency values specified for each channel, the sections outside this limitation were cleaned by removing the data.

4. Data cleaning

When raw data is read, there are unwanted artifacts in this data. These artificial effects are the involuntary movements of the person during physical processes such as eye blinking, eye movements, body movements, swallowing, coughing, contractions, seizures. To remove the noise in the channels, you must first calculate the distances. In the EEGLab program, this distance calculation is important for the interval in which the artifact begins and ends. As a result of this calculation, the artifacts caused by movements on the channels were made visible and deleted manually.

5. Determination of channel locations

EEGLab has various channel layouts that differ in the number of channels of the EEG cap, e.g., 19, 25, 33, 47, 81. In EEGLab, the 19-channel layouts that come closest to our data are read into the system. Since the Fz, Cz and Pz channel data in the 19-channel system do not match the channel coordinates, the 16 channels are obtained by subtraction from the standard channel layout.

E. Artifact cleaning

ICA is the most commonly used method for removing artifacts that occur on single channels. The ICA method enables better detection of artifacts in pre-processing. The ICA method is also useful in detecting muscle artifacts in disintegrated components, Delorme et al. [18].

$$X = AS \rightarrow \hat{S} = WX \tag{1}$$

By decoupling this unnecessary information with the ICA method, artificial factors in the data were reduced. *S* in (1) denotes the original statistical source mark; *A* shows the combined matrix of MxM. *W*, calculated by the inverse of the matrix *A*, enables the separation of the signals.

F. Feature extraction

Feature extraction methods are needed to reduce data size.

1. 1D Discrete Cosine Transform (DCT)

The raw data were pre-processed by filtering and channel cleaning, and then the feature was extracted by applying 1D DCT (2) to the 16-channel brain signal. In (2), *u* is the EEG signal value and *N* is the signal length.

$$F(u) = C(u) \sum_{x=0}^{N-1} f(x) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \tag{2}$$

$$Up\ to\ u = 0,1,\ldots,N-1$$

$$u = 0\ when\ C(u) = \sqrt{\frac{1}{N}}$$

$$u \neq 0\ when\ C(u) = \sqrt{\frac{2}{N}}$$

2. Statistical feature extraction

Statistical methods such as mean, variance, standard deviation, skewness and kurtosis were used for feature extraction. Various feature extractions were performed by applying these methods to EEG signals, Chandaka et al. [21].

a. Mean: is the basic statistical quantity and is calculated using the following equation, where i = 1,2,3,... and *D* is the signal.

$$\mu_i = \frac{1}{N} \sum_{j=1}^{N} Dij \tag{3}$$

b. Variance: is obtained by taking the standard deviation squared.

$$\vartheta = \sigma^2 \tag{4}$$

c. Standard deviation: is the mean value of the EEG signal and is calculated using the equation, where *D* is the signal and *N* is the number of samples. μ is the square root of the variance.

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (D_i - \mu)^2} \tag{5}$$

d. Kurtosis: measures the height of the Probability Density Function (PDF) of the time series.

$$k = \frac{E(x-\mu)^4}{\sigma^4} (6)$$

e. Skewness: represents the PDF symmetry of the amplitude of the time series.

$$s = \frac{E(x-\mu)^4}{\sigma^4} \tag{7}$$

The statistical properties of the DCT coefficients were extracted. In the study, the 1x206900 matrix at time *t* is not calculated for the entire signal of a channel, but the time is subsampled by 4. Feature extraction was performed by shifting the 60-second window over the EEG signal in 15-second increments. If the calculations are performed at 4 different time points for each channel, 64 features are extracted for 16 channels. For each statistical feature extraction, 64 features are obtained.

G. Feature selection

The DCT coefficients of the EEG data were extracted and t (time) was divided into 4 parts, and the statistical calculations were performed in separate sections. As a result of each statistical calculation, 64 features were extracted. As one feature, a total of 320 features were obtained from a total of 1 sample, including 64 means, 64 variances, 64 standard deviations, 64 skewness values, and 64 kurtosis values. The algorithms PCA, LDA [4], Forward Selection and Backward Selection were implemented. PCA helps to manage high-dimensional data sets by extracting essential information and discarding less relevant features, which simplifies the analysis. PCA performs a linear transformation of the data and searches for directions with maximum variance. The principal components are ranked according to the variance they explain, enabling effective feature selection. LDA is used to find a linear combination of features that characterizes or separates two or more classes of a categorical variable. Forward Selection is an iterative method where we start with having no feature in the model. In each iteration, we add the feature that best improves our model until adding a new variable no longer improves the performance of the model. In backward elimination, we start with all features and at each iteration we remove the least significant feature that improves the model's performance. We repeat this until no more improvement can be observed by removing features.

H. Classification

In Tanagra (data mining tool), classification was performed by using the Tutorial Learning Methods ANN, SVM and KNN. The purpose of classification is whether the EEG signal indicates epilepsy or health. The classification results were compared with the results obtained using each of the feature selection methods. The EEG signal was used as input for classification after undergoing certain pre-processing, feature extraction and selection. The ANN architecture was developed using middleware. The network system consists of an information input (64 features), a hidden layer (number of neurons 20) and an output layer (healthy-epileptic). SVM is a classifier to create hyperplanes that maximize the distance to the nearest training set. The kernel method was set as Radial Based Function (RBF) and our model was created. KNN is a simple model that assigns a feature vector to a class relative to its nearest neighbor. The Euclidean distance measure was used to calculate the distance between the input data point and all training data. 70% of the dataset was used for training, 30% was also used for testing. A 9-layer cross-validation method was applied to the data. In the architecture thus prepared, the data is trained separately according to the data results in different feature selections and the results are shown in Table 1.

Table 1. Different classification algorithms' overall accuracy according to feature selection methods of EEG data.

Method	ANN	SVM	KNN
PCA	95%	81%	81%
LDA	92%	83%	84%
Forward Selection	86%	81%	83%
Backward Selection	91%	81%	82%

Consequently, it was found that selected feature vectors using PCA increased the percentage of accuracy in classification. The high success rate of classification using ANN is shown in Table 1. It is evident form this study that the classifications performed in the literature with ANN have a higher success rate compared to other classification algorithms, Kumar et al. [22].

3. MRI ANALYSIS

MRI is one of the most useful imaging techniques for detecting a symptom that causes epilepsy in the brain.

A. Materials

MRI data were obtained from the Radiology Department of Bolu Abant-Izzet Baysal University Hospital. The MRI images acquired with the 1.5 Siemens Magnetom Symphony scanner included 88 MRIs of epilepsy patients and 40 of healthy individuals. A total of 115 t2_tse_tra_512 MRI slices were used for the epilepsy classification method.

B. Method

The steps of the MRI data from the first reading section to the classification step are shown in Fig. 3.

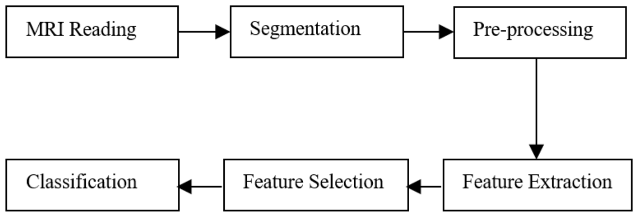

Fig. 3. Flow chart of EEG data.

C. MRI reading

MRI data in Dicom format is read in Matlab. The MRI consists of a 384x306 matrix.

D. Segmentation

The purpose of image segmentation is to summarize pixels according to image regions, separate surfaces, or objects. The Region-Based segmentation method was used in the study. This method is based on the logic that neighboring pixels are clustered according to common density values. The purpose of this algorithm is to group the regions anatomically and according to their functions, Gumaste and Jadhav [23]. Fig. 4 and Fig. 5 show the original and the segmented MRI.

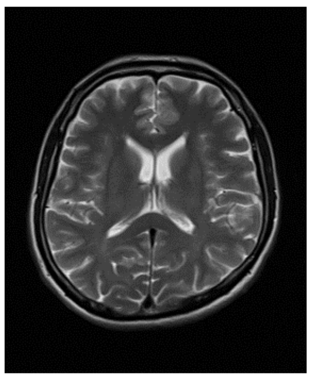

Fig. 4. Original MRI.

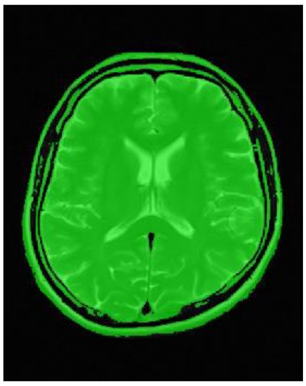

Fig. 5. Segmentation [24].

E. *Pre-processing*

Certain pre-processing was performed on the segmented MRI data. The matrices obtained as a result of the segmentation are transformed to 240x240 and resized. Dimensional MRI matrices are values ranging from 0 to 999, which were then converted to normalized values between 0 and 1.

F. *Feature extraction*

In pattern recognition, feature extraction methods are needed to reduce the size of the pattern. These methods are mathematical functions that perform feature extraction and selection. New features were extracted from MRI images by the hybrid use of DCT and Arithmetic Mean methods, the transformed structural feature extraction methods known in the literature, Meyer-Bäse [25].

1. *2D Discrete Cosine Transform (DCT)*

DCT is particularly useful for easy and fast feature extraction from large data sets. It also plays a vital role in image compression. After pre-processing, segmentation and normalization of the MRI data, the 2D (3) was applied and feature extraction was performed. In (8), *u*, *v* is the value of the MRI matrix and *N*, *M* is the length of the matrix.

$$F(u,v) = C(u)C(v)\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} f(x,y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right]$$

$$Up\ to\ u = 0,1,\ldots N-1\ v = 0,1,\ldots M-1 \tag{8}$$

$$u,v = 0\ when\ C(u),C(v) = \sqrt{\frac{1}{N}}$$

$$u,v \neq 0\ when\ C(u),C(v) = \sqrt{\frac{2}{N}}$$

2. *Arithmetic mean*

The mean is calculated by dividing the sum of all elements in the series by the number of elements in the series. The arithmetic mean is also referred to as the "mean" by Abramowitz and Stegun [26].

3. *2D DCT mean*

This method consists of using the aforementioned two methods as a hybrid. The size of the obtained DCT coefficients is 240x240 pixels. The pixels are divided vertically and horizontally into eight equal, small parts. This results in 64 subsections. The size of each subsection is 30x30 pixels. The arithmetic mean is calculated for each subsection. Thus, the size of the new feature vector is 64 as described by Demirezen-Yagmur and Sertbas [24].

G. *Feature selection*

The feature vector extracted using the DCT_mean method is 64. The PCA, LDA, Forward Selection and Backward Selection algorithms were applied to select the most compelling feature.

H. *Classification*

The classification settings for EEG data also apply to MRI data. The data was trained separately according to the results of the different feature selections and the results are shown in Table 2.

Table 2. Different classification algorithm validation results according to the feature selection methods of the MRI data.

Method	ANN	SVM	KNN
PCA	90%	81%	81%
LDA	81%	81%	82%
Forward Selection	81%	81%	83%
Backward Selection	81%	81%	81%

The success of the feature vectors selected by the PCA method in classification is therefore high. The added metric was needed because other recall and precision metric values were very close to each other. If such metric values are critical, the F_1-score metric result is also examined. The PCA method Backward Selection is shown in Table 5.

4. EEG-MRI FEATURES FUSION APPROACH

A new set of features is created by combining biomedical signals of different sizes. This feature vector consists of a combination of 1D EEG and 2D MRI features of one and the same person.

A. *Material*

After applying the 1D DCT with Mean method to EEG data, 64 features were obtained. Similarly, 64 features were obtained after applying the Mean method with 2D DCT on MRI data. In the application, 1D and 2D biomedical signals of different sizes are fused, and a total of 128 feature data are obtained. A vector of 128 data features contains both EEG and MRI features. In our study, a 128-feature data set was obtained form 128 samples.

B. *Method*

The combination of EEG and MRI data, the feature selection and the classification flowchart are shown in Fig. 6.

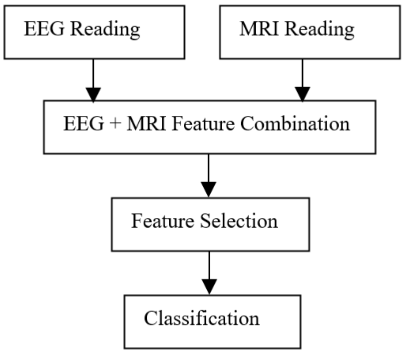

Fig. 6. EEG-MRI combination flow.

C. Feature selection

The feature vector formed using the combination of EEG and MRI is 128. The PCA, LDA, Forward Selection and Backward Selection algorithms are used to increase the accuracy of these feature vectors.

D. Classification

The classification settings for EEG and MRI also apply to the EEG-MRI combination. The data was trained separately according to the results of the different feature selections and the results are shown in Table 3.

Table 3. Different classification algorithm validation results according to feature selection methods of EEG-MRI feature fusion.

Method	ANN	SVM	KNN
PCA	96%	87%	84%
LDA	100%	81%	84%
Forward Selection	99%	83%	85%
Backward Selection	97%	90%	83%

5. CONCLUSION AND DISCUSSION

In this article, high-precision diagnosis of epilepsy is realized by 1D and 2D biomedical signal analysis based on the DCT feature extraction method.

In the study, artificial factors were removed by performing certain pre-processing on the EEG data obtained from Bolu Abant-Izzet Baysal University Faculty of Medicine Department of Neurology, and the data was classified using various algorithms. The 1D EEG data were selected using various feature selection methods. Among the methods listed in Table 4, the most successful classification accuracy of 95% was obtained by ANN using the features selected by PCA. In the results of the F_1-score metric (Table 5), the other analysis of classification estimation, the success of the ANN and the KNN method was higher.

Table 4. Accuracy results.

Method	ANN	SVM	KNN
EEG	95%	83%	84%
MRI	90%	81%	83%
EEG-MRI	100%	90%	85%

The second important factor in the diagnosis of epilepsy is the 2D MRI data of the patients. This data is used to find conditions that cause epilepsy in the brain. In our study, the MRI data was segmented, certain pre-processing was performed and classified as Epileptic/Healthy. The 2D MRI data was selected using different feature selection methods shown in Table 4. Among these methods, the most successful classification accuracy of 90% was achieved by using the features selected by the PCA method. The F_1-score metric (Table 5), the other analysis of classification estimation, was more successful with ANN.

Table 5. F_1-score results.

Method	ANN	SVM	KNN
EEG	96%	90%	96%
MRI	96%	89%	90%
EEG-MRI	100%	94%	90%

In our study, it was claimed that the combination of EEG and MRI features is more effective in the diagnosis of epilepsy. As can be seen from the results of our application, 100% accuracy (Table 4) and F_1-score (Table 5) were obtained by applying LDA to the data set obtained from the EEG-MRI feature fusions. As shown in the results of our application, by applying LDA (to the data set obtained from the EEG-MRI feature fusions), 100% validation of the selected features (Table 4) and F_1-score (Table 5) were obtained. Many studies have been carried out in the literature on the use of EEG data in the diagnosis of epilepsy. The most recent studies are summarized and compared in Table 6.

Table 6. Classification comparison of data in recent years.

Researcher	Feature Extraction	Classifier	Result
Sharif and Jafari [13]	GA-SE	RBF-SVM	91.8%
Mutlu [14]	HVD*	LS-SVM	97.6%
Kaleem et al. [15]	DWT	SVM, KNN	99.6%
Gupta et al. [27]	DCT	SVM	97.7%
Gupta and Pachori [16]	WMRP*	LS-SVM, RF*	97.3%
Serna et al. [17]	TF*	LS-SVM	96.7%
Deivasigamani [28]	CWT*	ANFIS*	96.7%
Current study	DCT	ANN, SVM, KNN	100%

Note: * RF: Random Forest, TF: Taylor Fourier, CWT: Continuous Wavelet Transform, ANFIS: Adaptive Neuro Fuzzy Inference System.

6. FINAL RESULT

Various feature extraction methods and classifiers were used in the studies. This resulted in high performance. In the study with DCT, the highest success rate so far was 97.7%; however, in our study on EEG_MRI fusion, a higher success rate of 100% was achieved. We plan to continue our work by expanding the data set and applying deep learning methods. We therefore believe that our study with the combination method can greatly contribute to the diagnosis of epilepsy.

ACKNOWLEDGMENT

All procedures performed in studies with human participants comply with the ethical standards of the institutional and/or national research board (Bolu Abant-Izzet Baysal University Ethics Committee Ethics Approval Certificate dated 25/05/2017 and numbered 2017/45). We thank the Neurology and Radiology Department for their support in data collection.

REFERENCES

[1] World Health Organization. (2005). *Atlas: Epilepsy Care in the World*. ISBN 92-4-156303-6.

[2] Anderson, C. W., Sijercic, Z. (1996). Classification of EEG signals from four subjects during five mental tasks. In *Proceedings International Conference on Engineering Applications of Neural Networks (EANN'96)*. Systems Engineering Association, 407-414.

[3] Kalaycı, T., Özdamar, O. (1995). Wavelet preprocessing for automated neural network detection of EEG spikes. *IEEE Engineering in Medicine and Biology Magazine*, 14 (2), 160-166. https://doi.org/10.1109/51.376754

[4] Subasi A., Ismail Gursoy, M. (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Systems with Applications*, 37 (12), 8659-8666. https://doi.org/10.1016/j.eswa.2010.06.065

[5] Oğulata, S. N., Şahin, C., Erol, R. (2009). Neural network-based computer-aided diagnosis in classification of primary generalized epilepsy by EEG signals. *Journal of Medical Systems*, 33 (2), 107-112. https://doi.org/10.1007/s10916-008-9170-8

[6] Gandhi, T. K., Chakraborty, P., Roy, G. G., Panigrahi, B. K. (2012). Discrete harmony search based expert model for epileptic seizure detection in electroencephalography. *Expert Systems with Applications*, 39 (4), 4055-4062. https://doi.org/10.1016/j.eswa.2011.09.093

[7] Krishnaveni, V, Jayaraman, S., Gunasekaran, A., Ramadoss, K. (2008). Automatic removal of ocular artifacts using JADE algorithm and neural network. *International Journal of Information, Control and Computer Sciences*, 1.0 (4). https://doi.org/10.5281/zenodo.1333386

[8] Loyek, C., Woermann, F. G., Nattkemper, T. W. (2008). Detection of focal cortical dysplasia lesions in MRI using textural features. In *Bildverarbeitung für die Medizin 2008*. Springer, 432-436. https://doi.org/10.1007/978-3-540-78640-5_87

[9] Clark, M. C., Hall, L. O., Goldgof, D. B., Clarke, L.P., Velthuizen, R. P., Silbiger, M. S. (1994). MRI segmentation using fuzzy clustering techniques. *IEEE Engineering in Medicine and Biology Magazine*, 13 (5), 730-742. https://doi.org/10.1109/51.334636

[10] Sujitha, V., Sivagami, P., Vijaya, M. S. (2011). Predicting epileptic seizure from MRI using fast single shot proximal support vector machine. In *ICWET '11: Proceedings of the International Conference & Workshop on Emerging Trends in Technology*. ACM, 525-529. https://doi.org/10.1145/1980022.1980135

[11] Martisius, I., Birvinskas, D., Jusas, V., Tamosevicius, Z. (2011). A 2-D DCT hardware codec based on Loeffler algorithm. *Electronics and Electrical Engineering*, 113 (7), 47-50. http://dx.doi.org/10.5755/j01.eee.113.7.611

[12] Orlowski, P. (2010). Simplified design of low-pass linear parameter-varying, finite impulse response filters. *Information Technology and Control*, 39 (2), 130-137. https://itc.ktu.lt/index.php/ITC/article/view/12301

[13] Sharif, B., Jafari, A. H. (2017). Prediction of epileptic seizures from EEG using analysis of ictal rules on Poincaré plane. *Computer Methods and Programs in Biomedicine*, 145, 11-22. https://doi.org/10.1016/j.cmpb.2017.04.001

[14] Mutlu, A. Y. (2018). Detection of epileptic dysfunctions in EEG signals using Hilbert vibration decomposition. *Biomedical Signal Processing and Control*, 40, 33-40. https://doi.org/10.1016/j.bspc.2017.08.023

[15] Kaleem, M., Guergachi, A., Krishnan, S. (2018). Patient-specific seizure detection in long-term EEG using wavelet decomposition. *Biomedical Signal Processing and Control*, 46, 157-165. https://doi.org/10.1016/j.bspc.2018.07.006

[16] Gupta, V., Pachori, R. B. (2019). Epileptic seizure identification using entropy of FBSE based EEG rhythms. *Biomedical Signal Processing and Control*, 53, 101569. https://doi.org/10.1016/j.bspc.2019.101569

[17] de la O Serna, J. A., Paternina, M. R. A., Zamora-Méndez, A., Tripathy, R. K., Pachori, R. B. (2020). EEG-rrhythm specific Taylor–Fourier filter bank implemented with O-splines for the detection of epilepsy using EEG signals. *IEEE Sensors Journal*, 20 (12), 6542-6551. https://doi.org/10.1109/JSEN.2020.2976519

[18] Delorme, A., Sejnowski, T., Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *Neuroimage*, 34 (4), 1443-1449. https://doi.org/10.1016/j.neuroimage.2006.11.004

[19] Krishnaveni, V., Jayaraman, S., Manoj Kumar, P. M., Shivakumar, K., Ramadoss, K. (2005). Comparison of independent component analysis algorithms for removal of ocular artifacts from electroencephalogram. *Measurement Science Review*, 5 (2), 67-78. https://www.measurement.sk/2005/S2/krishnaveni.pdf

[20] Demirezen Yağmur, F., Sertbaş, A. (2020). Automatic diagnosis of epilepsy from EEG signals using Discrete Cosine Transform. In *2020 28th Signal Processing and Communications Applications Conference (SIU)*. IEEE. https://doi.org/10.1109/SIU49456.2020.9302300

[21] Chandaka, S., Chatterjee, A., Munshi, S. (2009). Cross-correlation aided support vector machine classifier for classification of EEG signals. *Expert Systems with Applications*, 36 (2), 1329-1336. https://doi.org/10.1016/j.eswa.2007.11.017

[22] Kumar, Y., Dewal, M. L., Anand, R. S. (2014). Epileptic seizures detection in EEG using DWT-based ApEn and artificial neural network. *Signal, Image and Video Processing*, 8 (7), 1323-1334. https://doi.org/10.1007/s11760-012-0362-9

[23] Gumaste, P. P., Jadhav, D. V. (2015). Image segmentation techniques for brain MRI images: A survey. *International Journal of Modern Trends in Engineering and Research (IJMTER)*, 2 (7).

[24] Demirezen Yağmur, F., Sertbaş, A. (2018). Diagnosis of epilepsy in brain MR images using DCT-means. In *2018 26th Signal Processing and Communications Applications Conference (SIU)*. IEEE, 2439-2443. https://doi.org/10.1109/SIU.2018.8404758

[25] Meyer-Bäse, A. (2004). *Pattern Recognition in Medical Imaging.* Academic Press, 22-35. https://doi.org/10.1016/B978-0-12-493290-6.X5000-7

[26] Abramowitz, M., Stegun, I. A. (1972). Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables; 9th printing. Dover Publications, ISBN 0-486-61272-4.

[27] Gupta, A., Singh, P., Karlekar, M. (2018). A novel signal modeling approach for classification of seizure and seizure-free EEG signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26 (5), 925-935. https://doi.org/10.1109/TNSRE.2018.2818123

[28] Deivasigamani, S., Senthilpari, C., Yong, W. H. (2021). Machine learning method based detection and diagnosis for epilepsy in EEG signal. *Journal of Ambient Intelligence and Humanized Computing*, 12, 4215-4221. https://doi.org/10.1007/s12652-020-01816-3

Received May 10, 2023
Accepted January 09, 2024