2023 International Seminar on Intelligent Technology and Its Applications (ISITIA) | 979-8-3503-1395-6/23/$31.00 ©2023 IEEE | DOI: 10.1109/ISITIA59021.2023.10221031

Epilepsy Detection using Combination DWT and Convolutional Neural Networks Based on Electroencephalogram

Dwi Sunaryono[1], Joko Siswantoro[2], Riyanarto Sarno[1], Rahardian Indarto Susilo[3], Shoffi Izza Sabilla[4]

[1]*Department of Informatics Engineering, ITS, Surabaya, Indonesia*
[2]*Department of Informatics Engineering, Universitas Surabaya, Surabaya, Indonesia*
[3]*Department of Neurosurgery, Universitas Airlangga, Surabaya, Indonesia*
[4]*Department of Medical Technology, ITS, Surabaya, Indonesia*

***Abstract*—At the present day, smart technology has made life simpler for people in all spheres of life, including medical. It is necessary to have technology that can identify diseases or physical defects in humans since this will influence the course of therapy. One of the cutting-edge technologies used to identify epilepsy is the electroencephalogram (EEG). The signal was obtained by observed brain's electrical activity for a period of time to get these signals. Medical professionals need to be very accurate and confident in their ability to categorize EEG patterns in order to diagnose epilepsy. This study suggested using Zero Crossing Frequency and Mean Crossing Frequency features extracted from transformed singnal using Discrete Wavelet Transform. EEG signals were classified into three categories: ictal, pre-ictal, and normal using Convolutional Neural Network. According to the study's findings, the suggested approach can accurately categorize three categories with a confidence interval (CI) of 0.0013 and an accuracy of 98.09%.**

Keywords— EEG, Discrete Wavelet Transform, Convolutional Neural Network, Epilepsy.

I. INTRODUCTION

Epilepsy is a disease that causes various reactions to the human body. Repeated seizures that occur because electrical impulses in the brain exceed normal limits, until they spread to the surrounding area and cause uncontrolled electrical signals is the characteristic of epilepsy. The severity of seizures in each person with epilepsy is different, can occur briefly or long with involuntary movements involving the whole or part of the body body and occasionally accompanied by a state of unconsciousness. Epilepsy is a prevalent neurological disorder on a global scale, impacting a substantial population of approximately 50 million individuals. About 80% of epilepsy sufferers reside in middle and low income nations, and their risk of dying young is up to three times greater compared to other ages [1][2]. To minimize the risk of premature death, it is necessary to have automatic detection so that patients immediately get the right treatment so that the situation does not worsen [3]. Epilepsy can be confirmed by electroencephalogram (EEG) [4]. An EEG examination is a diagnostic procedure in order to detect and measure the electrical activity occurring within the brain by employing small metallic discs, known as electrodes, which are affixed to the scalp. The procedure puduced an image of basic rhythm waves and epileptiform waves. EEG is a signal acquired by detecting voltage variations in brain neurons over a specific time period to record the spontaneous electrical activity of brain waves [5]. In the medical field, visual analysis of EEG signals is employed to recognize epileptic seizures and normal situations. Because the EEG output provided by EEG monitoring equipment is relatively large and takes a long time, routine visual analysis is not feasible [6]. As a result, automatic detection is required to aid in the study of epilepsy patients.

Detection of EEG signals in epilepsy has been widely developed, in its development every researcher has a research focus. The focus of the researcher can be in the form of improving the method used. Several studies using Machine Learning have been developed to classify EEG signals collected from Children's Hospital in Boston, that called CHB-MIT EEG Scalp dataset [7]. Khaled Abdel-Aziz et al conducted a study of epilepsy classification using the K-class Nearest Neighbor [8]. Duo Chen uses DWT and SVM as a feature extractor and classifier, respectively [9]. In another study conducted by Subasi et al using four classifiers namely ANN, KNN, SVM and random forest to classify 3 classes, namely ictal, pre-ictal, and normal [10]. Siddiqui et al have done a classification by comparing several methods to find out which method has better performance. The author compares SVM, KNN, Decision Tree, and ensemble of trees. and it was found that the results of the ensemble of trees were better than the others [11].

Deep Learning is a machine learning development method using Artificial Neural Networks that imitate the work human brain, Deep Learning is programmed with more complex capabilities to learn, digest, and classify data. Several studies using Deep Learning have been carried out, among others, Catalina Gómez et al conducted research on epilepsy classification using CNN [12]. In research conducted by Rahib Abiyev et al using CNN with 3 double convolutional layers and fully connected layer for in feature extraction and classification, respectively [13]. Another study conducted by Acharya et al. by employing CNN algorithm using 13 deep convolutional layers to classify EEG signals into seizure and normal classes [14]. ZuochenWei et al designed a 12-layer CNN algorithm by combining the Wasserstein Generative Adversarial Nets (WGANs) method as data augmentation to increase sample diversity [15]. Mengni Zhou et al performed a classification of epilepsy using the CNN algorithm to compare binary and ternary epilepsy scenarios [16]. The CNN algorithm used tensor decomposition of the representation the EEG signal as input [17]. The other research employed the Singular Spectrum Analysis (SSA) method, PSD, and CNN for preprocessing, feature extraction, and classifier, resp. to recognize 3 and 5 classes EEG signals [18]. Similar approach was alsoperformed by Yunyuan Gao et al to classify four classes namely, pre-ictal, normal 1, normal 2, and ictal. Hannah Bend et al conducted an experiment to detect EEG signals in Epilepsy using Wavelet Transform, the experiment was applied to one patient and obtained an accuracy of 89.7%. Then the same model applied to other patients resulted in an accuracy of 79.2%. For a multi-patient trial combining data from four patients the accuracy was 83.4% [19].

In this article, we suggest a three-class classification method for EEG signals in epilepsy, with ictal pre-ictal, and normal signals as the classifications. In order to extract features, each class is preprocessed using the DWT. The CNN architecture is used to categorize the feature extraction findings. A review of the classification's specificity, sensitivity, and accuracy is conducted. The structure of the entire document is outlined as follows: In Chapter 2, an account is provided regarding the materials and procedures employed. The findings are deliberated upon in Chapter 3. The conclusion for Chapter 4 is provided.

II. MATERIAL AND METHODS

A. Materials

The system includes the CHB-MIT dataset, software, and hardware. The hardware consists PC with processor Intel (R) Core (TM) i9 3.60GHz, GPU NVIDIA GeForce GTX 1080 Ti, and RAM 32GB. The PC runs Ubuntu Linux 16.04 as its operating system.

B. Methods

1 EEG Signals Dataset

EEG recordings of patiens with untreatable seizures were obtained from CHB-MIT (Children's Hospital Boston - the Massachusetts Institute of Technology). Patients are observed during several days following anticonvulsant discontinuation medication to characterize seizures. Records were categorized into 23 cases, which were collected from 22 individuals. The median time to collect was 36 hours. Occasionally, there are longer than 10-second gaps between recordings, but this is not always the case. In some cases, the digital EEG signal is precisely one hour long; however, there were also cases with two hours and four hours durations. The 256 samples per second and 16-bit resolution were used for sampling all signals.

This EEG recording follows the International 10-20 standard for electrode placement and naming. Most EEG files have 23 recordings of electrodes placed around the patient's head. Each signal data record has a signal at the time of normal or no seizure and a signal at the time of seizure or ictal. In this research, the signal was divided into three classes, ictal, pre-ictal, and normal, which was pre-ictal or the process 5 minutes before the seizure. The division of the 3 classes is illustrated as in Figure 1.

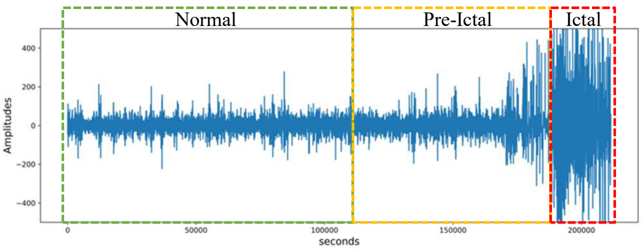

Figure 1. Signal division into three classes

2. Discrete Wavelet Transform

Signal calculation in DWT analysis involves passing the signal through several filters. The signal is filtered low and high-pass filter with an impulse response simultaneously. All frequencies above the cut-off frequency are attenuated or eliminated by a low-pass filter, which passes on the frequency unaltered or with minor modification. whereas the opposite is true for the high-pass filter. It will be possible to derive the output detail and approximation coefficients for the high and low-pass filters, resp.

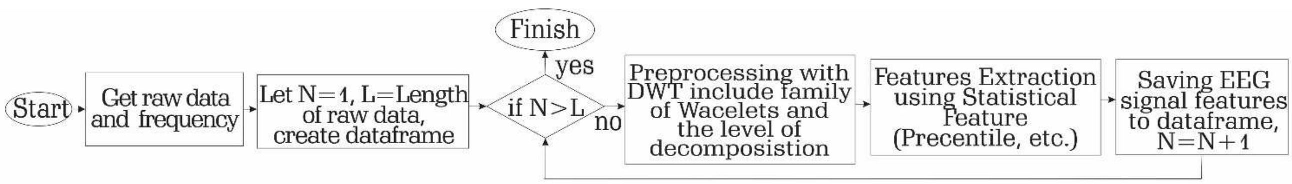

Figure 2. Workflow of processing EEG signal using DWT and Statistical Features

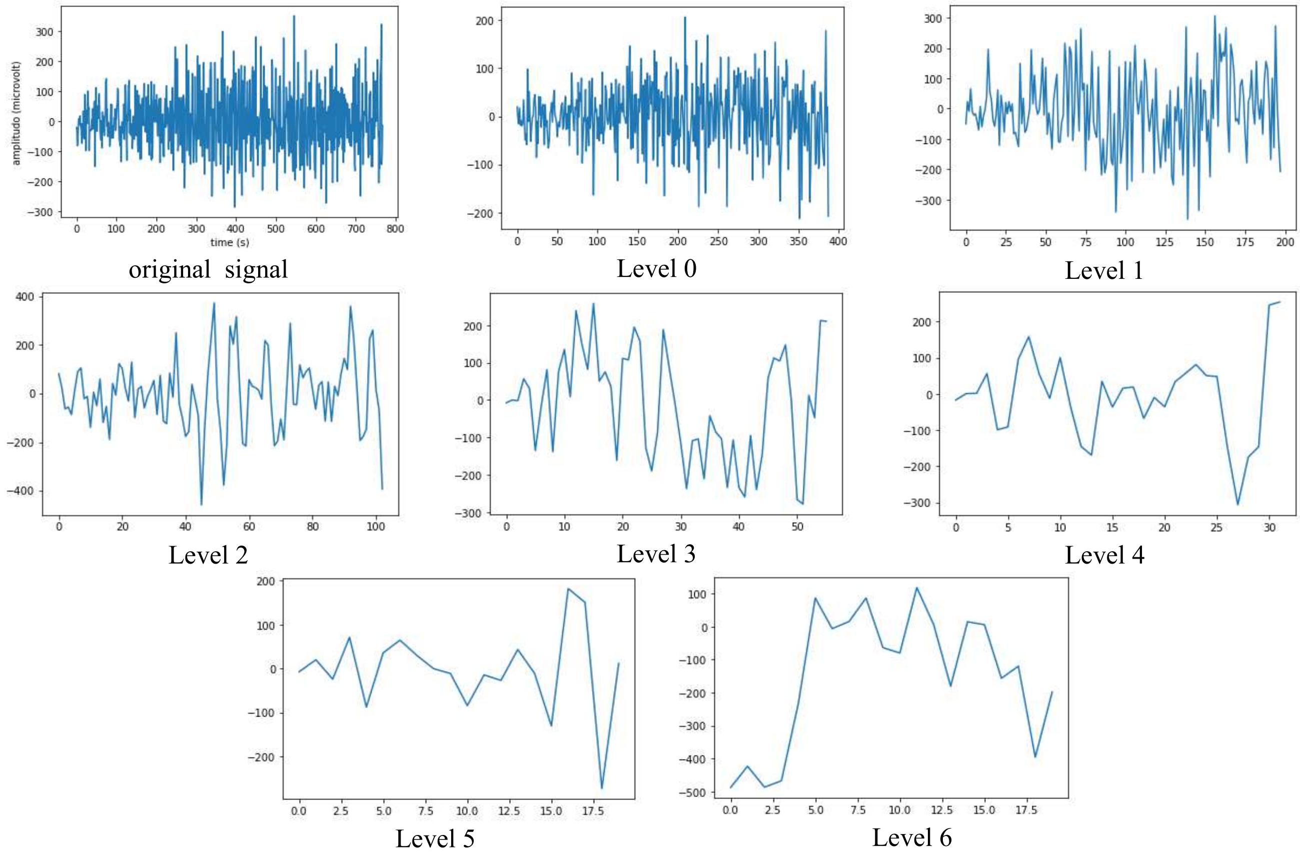

Figure 3. DWT decomposition for EEG Signal using Biorthogonal 2.4

Figure 2 shows that the feature extraction process gets input from preprocessing in the form of data lines and frequencies. Feature extraction will be repeated as much as the length of the data row. The process that must be done is to create a data frame to accommodate the results of feature extraction. The signal is processed by DWT to get a signal that can be a decomposed signal for detecting epilepsy in the feature extraction process,. Figure 4(a) is an example of the original signal before preprocessing. For example, Figure 4(b) of the original signal is processed using a DWT with the Bior2.4. Moreover, signal decomposition is carried out deeper from level 1 to level 6 shows in Figure 4(c) to (h). However, it is not always the deeper the level of the wavelet can produce better results. The approximation coefficient is again filteres using a high and low-pass filters and so on [20]. The equation (1) shows approximation coefficient formula

$$x_o[k] = (x_i * g)[k] = \sum_j x_i[j]\, g[k-j] \qquad (1)$$

In this formula, there is a signal calculation without transformation before it is filtered using a high and low-pass filter. Because the signal using DWT feature extraction must pass through the filter, the results obtained will be more detailed according to the selected level [21].

3. Feature Extraction

3.1 Statistical Features

Feature selection in the EEG classification is used to find the best features in the EEG signal. Each signal will be calculated using five statistical features, which are percentiles5, percentiles25, percentiles50, percentiles75, and percentiles95, and crossing measures. The EEG signal vector is formed by several events that produce the DWT coefficient. There are $n(L+1)$ feature statistics derived from all DWT coefficient vectors with a decomposition level of L. To obtain the percentile p, the members of the coefficient vectors are arranged from least to greatest. The x index of p in the coefficient vector is calculated using equation (2).

$$x = \frac{p}{100}(S+1) \qquad (2)$$

where S is the coefficient vector's length. The p-th percentile is the x-th member of the sorted coefficient vector if n is an integer. Linear interpolation using the fractional part of the elements is used if x is not an integer. x, x and x+1 is used to get the p-th percentile. The numpy package is used in this study's percentile implementation to extract this features.

3.2 Cross-Frequency Features

Feature extraction from each DWT vector coefficient has 2 cross-frequency features, namely Zero Cross-Frequency (ZCF) and the Mean Cross-Frequency (MCF). Zero cross-frequency (ZCF) is a representation of the complexity or randomness in the signal. The definition of Zero cross-frequency or single vector is the number of sign transitions (sgn) of the n sample plus the sign of the

$(n+1)$ sample devided by two times the number of samples, where the sign of the n sample will be one of the samples is positive, or vice versa [22]. Therefore the cross-frequency features (ZCF) can be calculated using the equation (3)

$$ZCF = \frac{\sum_{k=1}^{N-1} |\text{sgn}\,(x(k+1)) - \text{sgn}\,(x(k))|}{2N} \quad (3)$$

where $x(k)$ is the coefficient vector element, N is the coefficient vector's length, and sgn(x). Moreover, MCF is a measurement that reflects how many times the sign of two consecutive elements of the m cross vector. Formula for mean cross-frequency is as in equation (4)

$$MCF = \frac{\sum_{k=1}^{N=-1} |\text{sgn}\,(x(k+1)-a)) - \text{sgn}\,(x(n-a))|}{2N} \quad (4)$$

where a is coefficient vector mean.

4 Convolutional Neural Network (CNN)

CNN is an algorithm based on a neural network that works into two main parts, namely Convolution and Neural Network. Convolution aims as a feature extraction and has several parameters that are determined depending on the needs. The number of convolutions will have an impact on the accuracy value due to the extracted detail. however, the greater the number of feature extractions the impact on the duration of the computation time. Feature extraction results are sorted on one line so that they can be processed using the Neural netwrok approach [23]–[25]. The convolution operation $s(t)$ can be shown in the following equation (5)

$$s(t) = \sum_a I(a).K(t-a) \quad (5)$$

where $I(a)$ is the input and $K(a)$ is the kernel. The length value of the convolution process output data needs to be reduced by the pooling method. Parameters of the number of nerves can be determined as needed or commonly referred to as Hidden Layer and Neurons. Each value will be compared using the weight and bias values until it approaches the smallest error value.

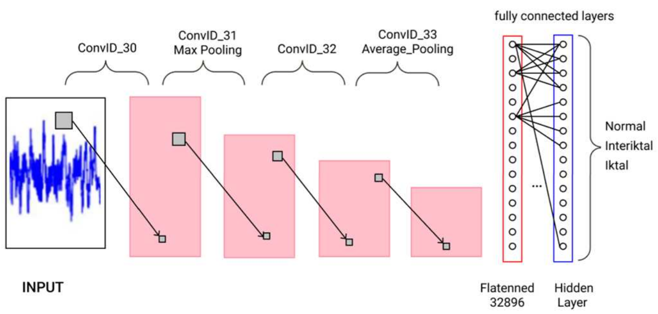

Figure 4. CNN Architecture Proposed

III. Result and Discussion

To determine the performance of proposes method, some experiment were carried out in a predetermined test environment. Each research subject's data was devided into three classes based on the time of the seizure or ictal, namely normal, pre-ictal, and ictal. This research balanced the data using the Synthetic Minority Oversampling Technique (SMOTE) method, because there is a variation in the amount of data after trimming.

1. First Scenario

The first scenario is validating the signal processing method that has been proposed in this study, where the success rate is measured by observing the accuracy value. Several combinations of wavelet families and decomposition levels have been constructed, then tested in this first scenario. Table 1 shows the top ten rankings of the wavelet family that produce the highest accuracy. Eighteen channels were used in the EEG during this research. (Num Scalp Selected (N)), and Feature Extracted (FE) are seven FE, namely, percentile5, percentile25, percentile50, percentile75, percentile95, ZCF, and MCF. The features used in the first scenario can be calculated by $N \times FE(L+1)$, where L is level of decomposition wavelets. The results of the first scenario, the combination of wavelets and the composition level which has the highest accuracy of 98.09%, is bior2.4 and level 6. The accuracy was generated determined by using the features are 882.

Table 1. Comparison of results from the first scenario

Wavelets	**Level of Decomposition (*L*)**	**Features $N \times FE(L+1)$**	**Accuracy (Acc)**
Bior2.4	6	882	98.09%
Db6	6	882	98.03%
Db12	5	756	98.02%
Db14	4	630	98.00%
Sym8	5	756	97.97%
Coif3	5	756	97.96%
Bior3.1	6	882	97.94%
Bior2.2	6	882	97.90%
Sym4	5	756	97.83%
Bior3.9	4	630	97.81%

Table 2. Some examples of parameter of CNN that produce the best accuracy

Optimizer	**Acc (%)**	**Sensitivity (%)**			**Specificity (%)**		
		1	**2**	**3**	**1**	**2**	**3**
Adam	98.09	98.33	98.87	99.93	97.63	96.85	99.78
RMSprop	92.57	92.29	96.80	99.76	93.24	84.98	99.49
SGD	86.33	84.00	96.53	98.95	93.94	70.32	94.73
Adagrad	73.92	81.00	89.56	90.32	77.50	58.97	85.28
Adadelta	66.44	82.05	73.89	93.73	62.75	70.79	65.79

2. Second Scenario

In the second scenario, the classification method was tested, especially the parameters of the proposed classification method, namely CNN. The parameter is the optimizer of CNN. Given several types of optimizers, each optimizer will be calculated the average of specificity sensitivity, and accuracy for each class. Number 1 indicates class 1, which is normal, number 2 indicates class 2, which is pre-ictal, and number 3 indicates class 3, which is ictal. The optimizer parameter trial on the CNN architecture is used to find out which optimizer produces the best performance from the signal classification model using CNN. The optimizers that will be tested are Adam, SGD, and Adagrad. The experiment was carried out with 0.0001 as learning rate. The train results with several optimizers are obtained. Table 2 shows, Adam has a much better classification result compared to Adagrad and SGD with an accuracy of 98.09%. In addition to accuracy, in terms of computational time, Adam has the best computation time, which takes 1 hour 55 minutes for the training process.

3. *Third Scenario*

In the last scenario, the optimal amalgamation of DWT, statistical features, and CNN optimizer in relation to prior research.. Five recent studies from 2017 to 2022 use the same dataset and advanced classification methods that successfully detect three classes of epilepsy. Table 3 shows, the proposed combination of this study was able to give very satisfactory results compared to the four existing studies for both detecting two-class (normal, ictal) and three-class (normal, pre-ictal, ictal) epilepsy.

The method with the highest accuracy results are displayed in the form of a confusion matrix to show the percentage of correct or incorrect data. Figure 5 shows that the pre-ictal class has the most incorrect data, which is 1.05%.

Confident Interval (CI) is another parameter that can be used to measure how accurately sample mean represents population mean. CI produces a range between two values where the value of a Sample Mean is exactly in the middle in the equation (6)

$$CI = \bar{x} \pm z\frac{s}{\sqrt{n}} \quad (6)$$

where $\bar{x}$ is the SampleMean or the average of the accuracy generated using DWT and CNN against the Population Mean and n is sample size. Confident level value (z) is the comparison between the difference in the value of x which will determine for the probability of occurrence and the Mean with its standard deviation (S) with the equation (7)

$$z = \frac{(X - sampleMean)}{S}. \quad (7)$$

$$constanta \times \left(\frac{\sqrt{(error \times (1-error))}}{n}\right) \quad (8)$$

If the constanta of 90% is 1.64. Then, calculate using equation (8) become, 98.09% ±0.0011. If the constanta of 95% is 1.96, then the result of CI is 98.09% ±0.0013, and if the constanta of 98% is 2.33, the result is 98.09% ±0.0016.

Table 3. The comparison of the proposed method with certain current methods

Authors	Year	Features	Classifier	Accuracy (%)	Sensitivity (%)
Khan et al [26]	2017	Continuous wavelet transform	CNN	-	87.80
Truong et al [27]	2018	Short-time Fourier transform	CNN	-	81.20
Ozcan et al [28]	2019	Hjorth parameters	3DCNN	-	85.71
Ryu and Joe [29]	2021	DWT	DenseNet -LSTM	93.28	92.92
Dwi et al [30]	2022	DWT	1DCNN	89.04	-
Dwi et al [31]	2023	DWT	1DCNN - WOA	91.84	-
Proposed Method*	2023	DWT and Statistical features	1DCNN	96.85	97.40
Proposed Method **	2023	DWT and Statistical features	1DCNN	98.09	99.04

Note: *2 Classes (pre-ictal and normal) with bior1.1 level 4; **3 Classes (pre-ictal, normal, and ictal) with bior2.4 level 6.

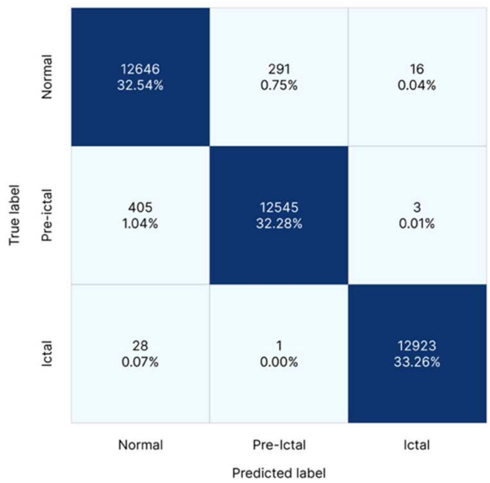

Figure 5. Confusion Matrix of the proposed method

IV. CONCLUSION

Three scenarios for detecting epilepsy using EEG signals and the proposed method have been successfully carried out in this study. Several conclusions can be drawn:

1. DWT for feature extraction EEG Epilepsy signal was managed to produce a better signal to be served as a feature using combination of Bior2.4, and the level of decomposition is 6. Furthermore, statistical features and crossing frequency features, which are percentile5, percentile25, percentile50, percentile75, percentile95, ZCF, and MCF, could improve the results.
2. Classification using CNN with the best parameters and hyperparameters can classify three classes (ictal, pre-ictal, and normal) with a satisfactory result of 98.09%. The best parameter used is Adam for the optimizer and the best hyperparameters are ReLu for convolutions and Softmax for the output layer in Neural Network.

3. The accuracy from this study has a CI of 98.09%±0.0013 if the constant used is 95%.

ACKNOWLEDGE

The funding for this research was provided by the Ministry of Research, Technology, and Higher Education of the Republic of Indonesia as part of the Doctoral Dissertation Research program (PDD) No. 009/E5/PG02.00.PL/2023 and 1235/PKS/ITS/2023, the scholarship program No. T/929/IT2/HK.00.01/2021, and the project plan of the Publication Incentive Program and Intellectual Property Rights (PPHKI), supervised by the Institute of Technology Sepuluh Nopember.

REFERENCES

[1] "Epilepsy." https://www.who.int/news-room/fact-sheets/detail/epilepsy (accessed Feb. 09, 2022).

[2] S. Coelli, E. Maggioni, A. Rubino, C. Campana, L. Nobili, and A. M. Bianchi, "Multiscale Functional Clustering Reveals Frequency Dependent Brain Organization in Type II Focal Cortical Dysplasia with Sleep Hypermotor Epilepsy," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 10, pp. 2831–2839, 2019, doi: 10.1109/TBME.2019.2896893.

[3] "EEG tests and epilepsy," *epilepsy.org.uk*. .

[4] Z. Chen, G. Lu, Z. Xie, and W. Shang, "A unified framework and method for EEG-Based early epileptic seizure detection and epilepsy diagnosis," *IEEE Access*, vol. 8, pp. 20080–20092, 2020, doi: 10.1109/ACCESS.2020.2969055.

[5] "Electroencephalogram (EEG)," *hopkinsmedicine*. .

[6] S. N. A. Hasanah, "Ekstraksi Ciri Sinyal Eeg Untuk Gangguan Penyakit Epilepsi Menggunakan Teknik Sampling," *J. Inform. Polinema*, vol. 5, no. 1, p. 1, 2018, doi: 10.33795/jip.v5i1.127.

[7] A. H. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," Harvard University, 2009.

[8] M. S. Kirschbaum, "Needs of parents of critically ill children," *Dimens. Crit. Care Nurs.*, vol. 9, no. 6, pp. 344–353, 1990, doi: 10.1097/00003465-199011000-00009.

[9] T. Wu *et al.*, "Automatic Lateralization of Temporal Lobe Epilepsy Based on MEG Network Features Using Support Vector Machines," *Complexity*, vol. 2018, 2018, doi: 10.1155/2018/4325096.

[10] Y. Wang, Z. Li, L. Feng, C. Zheng, and W. Zhang, "Automatic Detection of Epilepsy and Seizure Using Multiclass Sparse Extreme Learning Machine Classification," *Comput. Math. Methods Med.*, vol. 2017, 2017, doi: 10.1155/2017/6849360.

[11] M. K. Siddiqui, M. Islam, and A. Kabir, "Analyzing Performance of Classification Techniques in Detecting Epileptic Seizure," 2017, doi: 10.1007/978-3-319-69179-4_27.

[12] C. Gómez, P. Arbeláez, M. Navarrete, C. Alvarado-Rojas, M. Le Van Quyen, and M. Valderrama, "Automatic seizure detection based on imaged-EEG signals through fully convolutional networks," *Sci. Rep.*, vol. 10, no. 1, pp. 1–13, 2020, doi: 10.1038/s41598-020-78784-3.

[13] R. Abiyev, M. Arslan, J. B. Idoko, B. Sekeroglu, and A. Ilhan, "Identification of epileptic eeg signals using convolutional neural networks," *Appl. Sci.*, vol. 10, no. 12, 2020, doi: 10.3390/APP10124089.

[14] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," *Comput. Biol. Med.*, vol. 100, pp. 270–278, Sep. 2018, doi: 10.1016/J.COMPBIOMED.2017.09.017.

[15] Z. Wei, J. Zou, J. Zhang, and J. Xu, "Automatic epileptic EEG detection using convolutional neural network with improvements in time-domain," *Biomed. Signal Process. Control*, vol. 53, p. 101551, 2019, doi: https://doi.org/10.1016/j.bspc.2019.04.028.

[16] M. Zhou *et al.*, "Epileptic seizure detection based on EEG signals and CNN," *Front. Neuroinform.*, vol. 12, no. December, pp. 1–14, 2018, doi: 10.3389/fninf.2018.00095.

[17] M. Taherisadr, M. Joneidi, and N. Rahnavard, "EEG Signal Dimensionality Reduction and Classification using Tensor Decomposition and Deep Convolutional Neural Networks," no. August, 2019.

[18] N. Bayu and H. Tjandrasa, "Klasifikasi Eeg Epilepsi Menggunakan Singular Spectrum Analysis , Power Spectral Density Dan Convolution Neural Network," pp. 185–194.

[19] Y. S. and S. T. Hannah Bend, Sathish Kumar, "Detecting epileptic seizures from EEG signals," *Github*, 2016. .

[20] D. M. Ballesteros, A. E. Gaona, and L. F. Pedraza, "Discrete Wavelet Transform in Compression and Filtering of Biomedical Signals," no. June, 2015, doi: 10.5772/19529.

[21] R. V. Yuliantari, R. Hidayat, and O. Wahyunggoro, "Ekstraksi Ciri Dan Pengenalan Tutur Vokal Bahasa Indonesia Menggunakan Metode Discrete Wavelet Transform (Dwt) Dan Dynamic Time Warping (Dtw) Secara Realtime," *Proc. Natl. Semin. Sci. Technol. 7th Fac. Eng. Wahid Hasyim Univ. Semarang*, pp. 173–178, 2016.

[22] M. Mulimani and S. G. Koolagudi, "Segmentation and characterization of acoustic event spectrograms using singular value decomposition," *Expert Syst. Appl.*, vol. 120, pp. 413–425, 2019, doi: https://doi.org/10.1016/j.eswa.2018.12.004.

[23] D. Sunaryono, C. Z. Mukhlishah, S. Rochimah, and I. A. Sabilla, "Information Systems Of School Financial Management With Digital Signature Recognition Using MobileNet Algorithm," in *2021 IEEE International Conference on Health, Instrumentation Measurement, and Natural Sciences (InHeNce)*, Jul. 2021, pp. 1–6, doi: 10.1109/InHeNce52833.2021.9537258.

[24] D. Sunaryono *et al.*, "Enhanced Gradient Boosting Machines Fusion based on the Pattern of Majority Voting for Automatic Epilepsy Detection," *IJACSA) Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 7, p. 2022, Accessed: Oct. 19, 2022. [Online]. Available: www.ijacsa.thesai.org.

[25] D. Sunaryono, R. Sarno, and J. Siswantoro, "Gradient boosting machines fusion for automatic epilepsy detection from EEG signals based on wavelet features," *J. King Saud Univ. - Comput. Inf. Sci.*, Dec. 2021, doi: 10.1016/J.JKSUCI.2021.11.015.

[26] H. Khan, L. Marcuse, M. Fields, K. Swann, and B. Yener, "Focal onset seizure prediction using convolutional networks," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 9, pp. 2109–2118, 2018, doi: 10.1109/TBME.2017.2785401.

[27] N. D. Truong *et al.*, "Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram," *Neural Networks*, vol. 105, pp. 104–111, 2018, doi: 10.1016/j.neunet.2018.04.018.

[28] A. R. Ozcan and S. Erturk, "Seizure Prediction in Scalp EEG Using 3D Convolutional Neural Networks with an Image-Based Approach," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 11, pp. 2284–2293, 2019, doi: 10.1109/TNSRE.2019.2943707.

[29] S. Ryu and I. Joe, "A hybrid densenet-LSTM model for epileptic seizure prediction," *Appl. Sci.*, vol. 11, no. 16, 2021, doi: 10.3390/app11167661.

[30] D. Sunaryono *et al.*, "Enhanced Salp Swarm Algorithm Based On Convolutional Neural Network Optimization For Automatic Epilepsy Detection," *J. Theor. Appl. Inf. Technol.*, vol. 15, p. 19, 2022, Accessed: Oct. 19, 2022. [Online]. Available: www.jatit.org.

[31] D. Sunaryono *et al.*, "Optimized One-Dimension Convolutional Neural Network for Seizure Classification from EEG Signal based on Whale Optimization Algorithm" *International Journal of Intelligent Engineering and Systems*, Vol.16, No.3, 2023 DOI: 10.22266/ijies2023.0630.25