International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

Epilepsy Identification using Hybrid CoPrO-DCNN Classifier

Ganesh Basawaraj Birajadar[1], Dr. Altaf Osman Mulani[2], Dr.Osamah Ibrahim Khalaf[3], Prof. Dr. Sameer Algburi[4], Dr.Pravin G. Gawande[5] and Dr.Kishor Kinage

[1,2]Electronics & Telecommunication, SKN Sinhgad College of Engineering, Pandharpur, Maharashtra, India
[3]Department of Solar, Al-Nahrain Research Center for Renewable Energy, Al-Nahrain University, Jadriya, Baghdad, Iraq
[4]Al-Kitab University, College of Engineering Techniques, Kirkuk, Iraq
[5]Electronics & Telecommunication, Vishwakarma Institute of Information Technology, Pune, India
[6]Electronics & Telecommunication, Pimpri Chinchwad College of Engineering, Pune, India

E-mail address: ganesh.birajadar@sknscoe.ac.in, altaaf.mulani@sknscoe.ac.in, usama81818@nahrainuniv.edu.iq, sameer.algburi@uoalkitab.edu.iq, pravin.gawande@viit.ac.in and kskinage@gmail.com

Received ## Mon. 20##, Revised ## Mon. 20##, Accepted ## Mon. 20##, Published ## Mon. 20##

Abstract: Electroencephalogram (EEG) is progressively developing as a remarkable structure of neuron action. It comprises of massive information that is used for identifying abnormality and dealing with intellectual disorders and irregularities. Present paper shows study related to EEGs of abnormal subjects and those are analyzed with respect to normal subject. Numerous topographies like Mean, Entropy, Wavelet bands are evaluated and compared. Building upon the adaptive hunting strategies observed in coyotes, this hybrid computational model is fused with deep learning architectures to enhance diagnostic accuracy. The methodology involves the creation of a unique computational algorithm inspired by coyote hunting behaviors, integrated with deep neural networks. This hybrid model is applied to analyze EEG data for brain disorder detection, leveraging both the biological-inspired algorithm and the data-driven capabilities of deep learning. Regarding the results, the proposed scheme exhibits promising diagnostic accuracy, achieving an accuracy rate of 98.65% for training (True Positive - TP) and 98.82% utilizing k-fold validation. These preliminary results demonstrate the potential effectiveness of the hybrid approach in accurately detecting brain disorders from EEG signals. However, it's important to note that these results are indicative of the initial success and represent a part of the comprehensive evaluation conducted in this study.

Keywords: Epilepsy, classifier, Electroencephalogram, wavelet, deep learning

1. INTRODUCTION

"Epilepsy, a neurological disorder characterized by recurrent seizures, poses a significant public health challenge globally. According to the World Health Organization (WHO), it is estimated that up to 65 million people in India are affected by epilepsy, making it a devastating reality for individuals, families, and the entire society (WHO). This statistic highlights the profound societal impact and underscores the urgent need for accurate diagnostic methods and effective interventions in managing this condition."

Electroencephalogram (EEG) shows graph of electrical activities of brain recorded from scalp. [2] It can be done either invasive or non-invasive. Most probably used method is non-invasive where electrodes are placed on scalp using 10-20 electrode system. These recordings resemble the actual working of brain.

Epilepsy can cause changes in behavior, movement or alertness. It may last a few seconds or a few minutes. The exact cause of epilepsy is often unknown but risk factors include head injuries, stroke, brain tumors and genetic factors. Treatment for epilepsy is often with medication but more severe cases may require surgery or dietary therapy. Epilepsy is also known as a seizure disorder, since that is characterized by having recurrent seizures. These seizures vary from insignificant to significant and can manifest differently in each individual. Treatment for epilepsy usually involves medication but, in some cases, may also include surgery or diet therapy.

So, in case of any abnormalities or unwanted functions in brain, abnormal EEGs are recorded. Any such abnormal functions of brain can be identified by analyzing normal and abnormal EEGs. [5] The database used consists of brain seizure EEGs as well as normal EEGs. Numerous geographies are extracted. These features are further diversified using simple classification methods.

With proper diagnosis, treatment and management, it can be made possible for people with epilepsy to lead full and independent lives. [1]

E-mail:author's email

2. LITERATURE SURVEY

Several studies have explored diverse methodologies for epilepsy identification, ranging from traditional signal processing techniques to advanced machine learning approaches. Traditional methods often rely on feature extraction and manual analysis of electroencephalogram (EEG) signals, which can be labor-intensive and subjective. With the rise of machine learning, automated approaches have gained prominence.

Traditional methods for epilepsy identification often involve visual inspection by trained neurologists. While effective, this approach is subjective, time-consuming, and may lack consistency. The need for automated and objective methods has led to a surge in research exploring various computational techniques.

Dinghan Hu et al. [4] explores opportunity of combining traditional hand-crafted features with DL designs to identify epilepsy states from EEG recordings. The paper proposes a multi-model fusion framework that exploits the characteristics of both methods and their complementarities. The outcomes presented that fusion model outperforms its constituent components for all datasets. Compared to presentation of individual models, the fusion framework improved the Fscores on average from 0.81 to 0.94, from 0.82 to 0.95 and from 0.79 to 0.91 in CHB-MIT, Freiburg and Puhua datasets respectively. Therefore, the paper demonstrated that fusing multiple deep learning models and hand-crafted features, as well as learning the complementarity between them, can significantly improve the capacity of EEG for epileptic state classification.

This paper by Furui et al. proposes utilizing a multivariate scale mixture model for detecting non-Gaussianity in Epileptic EEG signals. [1] Model is designed to describe non-Gaussianity that often appears in EEG data due to various physiological factors such as scalp potential or signal cross-correlation. The model uses the Laplacian distribution to capture the non-Gaussianity in a multivariate manner. To demonstrate the efficacy of the model, it was tested on EEG datasets from six epileptic patients. The outcomes presented that model could accurately detect non-Gaussianity in brain signals. Furthermore, model was also able to identify seizure onset and termination more accurately than a traditional Gaussian-based approach

Different sleep disorders were studied by Loretta Giuliano. Giuliano [10] used polysomnography to assess a sample of 30 patients with focal epilepsy in order to evaluate frequency of arousals, presence of sleep disordered breathing events and sleep variants. Giuliano realized that meaningfully developed arousal frequency in epileptic persons is always present. In addition, Giuliano found that Periodic Limb Movements (PLM) in sleep were also present in greater frequency among those with focal epilepsy. Giuliano also noted that physiological sleep variants, such as obstructive sleep apnea-hypopnea, were present in much higher frequency in these patients.

A prospective controlled study conducted by Melanie Bergmann explored the disruption of sleep patterns in drug resistant epilepsy (DRE). The study had two phases: a pre-intervention phase in which baseline data was captured and a post-intervention phase in which measures of sleep disturbance were assessed after an intervention. The study targeted 54 participants with DRE, of which 26 being part of intervention cluster and the rest being part of control cluster. First cluster participated in five-week sleep hygiene program, which involved education about healthy sleep habits and utilizing sleep diaries to facilitate improvements in sleeping and also the assessment of influence of sleep disturbance. [9] Results indicated that intervention group had an overall improvement in consideration with sleep disorders. That the intervention had a positive effect. The study concluded that a sleep hygiene intervention program was effective in reducing harshness of sleep disorders for DRE patients and it improved their quality of life.

Continuous Positive Airway Pressure (CPAP) treatment is normal treatment for OSA that can also help to control seizures in people who have epilepsy and OSA. In this, [19] Martina V examined CPAP treatment consequences in adults affected with OSA and epilepsy. Review found that CPAP was generally seen to be effective in controlling seizures in co-morbid OSA and epilepsy. Seizure Freedom rate increased with CPAP treatment from 40-100%. Additionally, CPAP therapy showed positive effects in patients' life. Early CPAP treatment proved as important task for achieving seizure freedom and improving symptoms. The study suggested that further research could be conducted to investigate the exact mechanisms by which CPAP improves seizure control. CPAP can lead to improved seizure control.

Marine Predators Algorithm (MPA) is a nature-inspired metaheuristic optimization algorithm introduced by Afshin Faramarzi. It is based on the social foraging behavior of marine predators and interaction between the predators and their environment. The main idea behind MPA is that a predator's search area is determined by mixture of both environmental factors present, as well as the internal knowledge acquired from past experiences. Like real-life predators, the MPA algorithm herds multiple individuals within its own group to explore new areas in search of prey. [30] The parameters of MPA can be set to simulate varying levels of aggressiveness, which will affect the exploration rate. As such, MPA always strives to balance exploration and exploitation in order to locate and target the most relevant prey in an efficient and effective manner. Each predator operates using a local search strategy focused on exploring its vicinity. The predators use a mechanism called 'inter-predator communication' which enables them to synchronize their search behavior in between them. This mechanism allows the predators to adjust their search efforts so as to avoid hunting the same prey twice and to maximize their overall hunting success. MPA is tested and tested for various benchmark problems like the Traveler Salesman Problem and bi-objective optimization. It seems to be relatively new algorithm, so additional investigation is required to further expand upon its potential applications.

3. METHODOLOGY

The data input utilized in this research is gathered from Cyclic Alternating Pattern (CAP) dataset (DT) [46], which is referred as a persistent action of EEG signal that appears in non-rapid eye movement sleep, which is separated into cerebral activating and non-activating periods in less than a minute, as well as real-time DT, that is gathered from Smt. Kashibai Navale Medical College and General Hospital with epilepsy(figure 3.2) and the frequency sampling which ranges from 256 Hz and band pass filtered (BPF) within 0.53 to 70 Hz with 24 and 32 channel full band data, which is acquired simultaneously as well as EEG contemporary capability of digital video with an average age of 20.63% to 24.76%, and CHB MIT DT [47] with the EEG record gathering of 22 pediatrist subjects with unmanageable captures and annotation of 182 captures..

Figure 1 shows the steps used in this research work. There is possibility of adding any unwanted signals known as artifacts while acquiring EEG. So, first task is to remove artifacts from acquired EEG using different pre-processing techniques such as band pass filtering, notch filtering. [7]

During the data collection, it is significant to verify whether gained data are artifacts less to avoid the difficulty during investigation of EEG, which determines that gained data retrieves only value of human brain electrics, thus extracting the artifacts in the data. EEG signal processing is significant for the effective detection of the human brain disorders. The process includes the under-sampling of the fresh EEG signals and then BPF is utilized to remove unnecessary noises and other EEG signal artifacts, in addition, the prevalence range that is less than 0.05 Hz and more than 75 Hz is reduced from data input in order to produce even functioning of EEG signals.

Once the filtered signal is obtained, for each EEG signal various features are extracted. EEG signal revels some of the features in frequency domain too. So, time domain and frequency domain analysis are done so as to extract features like mean. variance, entropy, band power, skewness. The features that are extracted are Kurtosis, Wavelet features, Skewness, Hjorth features, Spectral features, Statistical features, Tsallis entropy, Common spatial pattern and Band power.

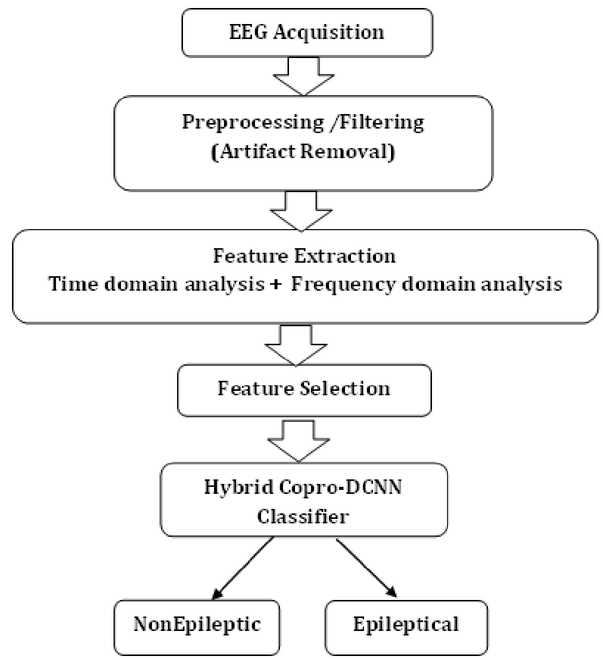

Figure 1. Methodology

A. *Feature Extraction and selection*

Following features have been extracted from each recorded EEG signal. EEG signal is decomposed in to frequency bands and features are calculated for each sub band.

- Mean: Mean of each frequency band is calculated and tabulated.
- Variance: Variance represents typical grade to which individual point varies as compared to mean.
- Kurtosis:

Kurtosis estimates the level of indisposed information in the data distribution, which computes to identify whether the input information is distributed strongly or weakly in a usual distribution, which is arithmetically presented as

$$Kurtosis = \frac{M_4[x(n)]}{M_2^2[x(n)]} \quad (1)$$

- Skewness:

The skewness transfers the aligned signal curve present in DT and estimates the similarity in the data through calculating whether input data is behaving strongly or weakly, which is expressed as, It donates asymmetric form that diverges from symmetric curvature.

$$Skewness = \frac{E[(x(n)-\mu)^3]}{\sigma^3} \quad (2)$$

- Dispersion:

  It is calculated as second root of the variance.

- Band power:

Power of each EEG sub band is calculated using periodogram. The estimation of power spectral mass as well as power in a certain bandwidth medium is referred as band power. The signals of EEG are the collection of varied types of subsets for discovering the alterations in the human brain in the means of different levels of prevalence theta from 4–8 Hz, delta from 0.5–4 Hz, beta from 12–30 Hz, gamma from 30–100 Hz and alpha from 8–12 Hz.

- Entropy:

The tsallis entropy exhibits a presiding part in the limited analytical automation as well as multi-fractal latitude period controls, extended impacts of evocation or extended level of communications are strongly demonstrated by the tsallis entropy. As EEG signals contain an extended communication range, it is relevant to utilize the limited estimation to demonstrate the impacts of the extended communication.

- Spectral features:

The spectral features are majorly dependent on the constituents of prevalence, which is obtained by transferring the period stand of the waveforms into the domain of prevalence by establishing the examination of Fourier such as spectral roll-off, spectral crest factor, spectral flatness and spectral centric which are estimated by the functioning of automation signals.

- Hjorth features

The variables of Hjorth are usually utilized for the analytical elements present in the functioning of EEG signal in the time period, which is utilized largely for estimating the signals of EEG in the extraction of features.

$$HV = \mathrm{var}(x) \quad (3)$$

where, HV is referred to as Hjorth variables.

B. *Hybrid COPRO-DCNN classifier*

In order to, predict changes in brain activity that are helpful for identifying a neurological disorder, EEG signals are used. A highly developed system assists to visualize the variation in brain. To eliminate noises from the electrodes, the EEG machine and outside sources, the EEG signals from given database are extracted as well as processed.

Following the feature extraction, the RELIEEF filters the removed features by rating them and sorting them according to the weights calculated. The features chosen are passed to the DCNN classifier, which incorporates a hybrid CoPrO-based algorithm for classifier tuning. The developed research highlights worth of the hybrid CoPrO-based algorithm for fine-tuning the inner model structure like bias and weight of DCNN classifier. This algorithm inherits traits of the long jump and intelligent environment adaptation. Additionally, in aim of improving the detection model's precision, the features are removed to identify brain irregularities.

a) Input : EEG dataset used consists of CAP data collection, CHB-MIT dataset and real time epileptic dataset and then it is forwarded through the pre-processed model for further processing.

b) Pre-processing & Feature extraction: Brain signals are applied to preprocessing which reduces the irregularities present in raw brain signals, moreover processed EEG signals are given to feature extractor, which is used for informative feature extraction such as Statistical features, Hjorth features, Common spatial pattern, Tsallis entropy, Wavelet features, Spectral features and Band power

This segment demonstrates how to categorize pre-processed EEG so that it will identify brain abnormalities. Deep learning techniques are primarily used to diagnose disease, precisely predict variation in the anatomical formation of brain, as well as analyses abnormalities in the brain. An effective machine learning (ML) technique is utilized for categorizing images is the deep CNN. For effective brain abnormality prediction, a hybrid CoPrO-DCNN model is developed.

Using the EEG signals, the developed hybrid optimization-based on DCNN is utilized to calculate brain disorders. The Artificial intelligence network (ANN) is constructed through DL, which is a ML model that is intended for evaluating better quantity of information travel throughout different neuron layers, which are the fundamental component of Artificial Intelligence (AI).

EEG is progressed through a deep CNN model, which are fewer than amount of fake neurons for EEG processing. A mathematical technique known as "convolution" is used to train the classifier using the input EEG signals. The convolutional network's architecture contains four layers named convolution, pooling, ReLU and FC layer (FCL).

To avoid searching for prey in specific areas, the hybrid coyote optimization's decision-making and adaptability traits are combined with characteristics of long jump of the predator, as a result, shows faster convergence and less time spent is attained looking for prey. The growing prevalence of these conditions indeed necessitates novel methodologies to ensure timely and accurate diagnoses.

Hybrid algorithms shown in Table 1 typically combine elements from multiple algorithms or techniques to leverage their respective strengths and mitigate weaknesses. These combinations are often designed to improve overall performance, efficiency, or robustness. In the context of CoPrO-based algorithms, CoPrO may refer to Cooperative Co-evolutionary Optimization, which is a type of optimization technique inspired by biological co-evolution.

Table 1 Hybrid CoPrO-based Algorithm

.

S.NO	Pseudo-code for hybrid CoPrO-based algorithm
1.	Input: Initialization of V_x groups with V_y prairie wolf
2	Output: P_{hyd} with the optimal fitness
3	Initialization
4	Fitness estimation
5	The adaptability checking for prairie wolf
6	When the condition for termination is not attained then,
7	For every V_x group to perform
8	Leaders position updated
9	Cultural tendency generation
10	For every V_x wolf of the group to perform
11	Social behavior updated
12	New communal activities generation
13	New solution's origin
14	End for
15	Target's state updation
16	Search agent's new position
17	End for
18	End while
19	Best solution selection

The developed hybrid CoPrO-DCNN classifier is utilized to assess comparative and experimental findings in order to identify any abnormalities in the brain. The outcomes of the developed system are utilized for the efficiency of the anticipated model. MATLAB is used in the experimental setup to evaluate the efficiency of the developed system. The suggested approach can be quickly and efficiently used with Windows 10 . 64-bit operating systems, 16 GB RAM, a MATLAB tool installed. To evaluate the efficiency of the developed hybrid CoPrO-DCNN model, the sensitivity, specificity, accuracy are measured.

Accuracy:
The performance can be explained in part by accuracy, which is a key parameter. Accuracy is referred as the distance relating the calculated value of the developed form and the correct value.

Sensitivity:
Sensitivity is a necessary component for accurately identifying patients with brain abnormalities

Specificity: Specificity is measured by its accuracy in identify brain abnormality of the proposed method. As a result, the relative amount of true negatives to every real negative case

4. Results and Discussions

Figure 2 represents plots of EEG signal for Nonepileptic and epileptic signals.

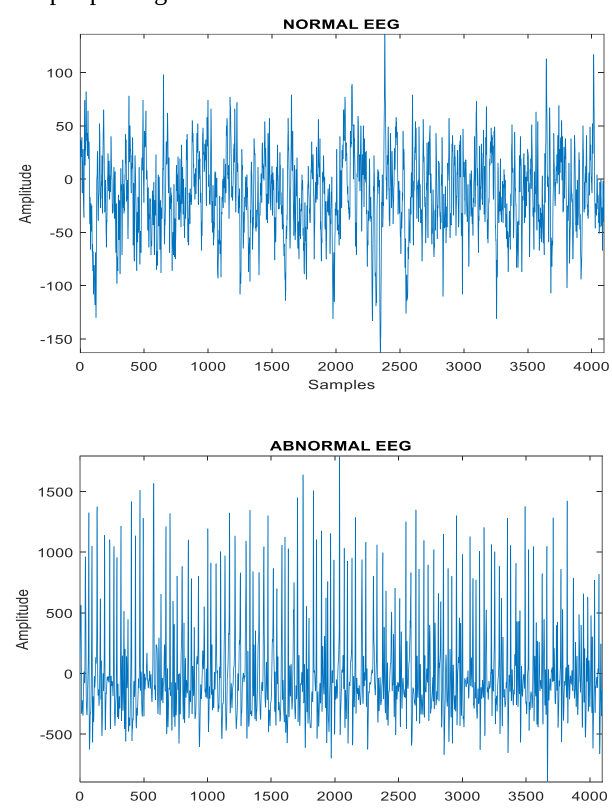

Figure 2. Epileptic & Non-Epileptic EEG

Nonepileptic EEG plot illustrates the brain's electrical activity over time, showcasing different frequency bands. In a normal EEG:

- Delta waves (0.5-4 Hz) dominate during deep sleep.
- Theta waves (4-8 Hz) are associated with drowsiness and light sleep.
- Alpha waves (8-13 Hz) are present during wakeful relaxation with closed eyes.
- Beta waves (13-30 Hz) are associated with active, alert mental activity.

The amplitude varies, generally lower in slower frequencies and higher in faster ones. Recognizable and organized patterns are evident, with clear distinctions between frequency bands. Variations occur based on wakefulness or sleep states

Nonepileptic EEG plot indicate various irregularities:

- Epileptiform activity, such as spike or sharp waves, suggests epilepsy.
- Slow waves, like generalized or focal slowing, indicate potential abnormalities.
- Presence of artifacts from external sources or patient movement distorted the signal.

Figure 3 represents epileptic signal decomposition. Epileptic EEG signal decomposition involves the process of breaking down an EEG recording into its constituent components to better understand the underlying electrical activity. This decomposition analyzes epileptic patterns and events within the EEG signal.

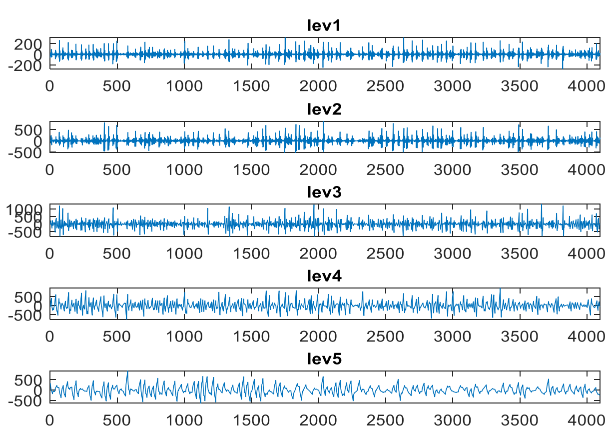

Figure 3. EEG Decomposition

Following tables shows statistical parameters of both signals.

- Mean values indicate the central tendency of the data. In general, mean values for Det1 to Det4 are close to zero for normal conditions but deviate for epileptic conditions.
- Det4 shows a noticeable increase in mean for epileptic conditions, indicating a shift in the baseline. (Table 2)
- Variance measures the spread or dispersion of the data. Variance values are significantly higher in epileptic conditions for all detectors, suggesting increased variability in EEG signals during seizures. (Table 3)

TABLE 2. MEAN

	Mean Values	
	Normal	***Epileptic***
Det1	0.002008	-0.018073022
Det2	-0.00488	0.045201009
Det3	-0.01217	0.029848583
Det4	-0.00539	0.303370375
Aux4	-13.5798	-8.232692563

TABLE 3. VARIANCE

	Variance Values	
	Normal	***Epileptic***
Det1	14.97847436	1996.396026
Det2	71.93736903	13709.51105
Det3	189.6150768	40100.41058
Det4	313.4355867	41782.07346
Aux4	886.0344246	33438.78538

- Standard deviation values further confirm the increased dispersion in epileptic conditions for all detectors and the auxiliary signal, highlighting the variability and volatility of EEG signals during seizures. (Table 4)

TABLE 4. DISPERSION

	Dispersion Values	
	Normal	***Epileptic***
Det1	3.870203	44.68105
Det2	8.48159	117.0876
Det3	13.77008	200.2509
Det4	17.70411	204.4066
Aux4	29.76633	182.8628

- Band power represents the distribution of power in different frequency bands. There is a substantial increase in band power for epileptic conditions across all detectors, reinforcing the notion of altered frequency characteristics during seizures. (Table 5)

TABLE 5. BAND POWER

	Band Power Values	
	Normal	***Epileptic***
Det1	14.97482	1995.909
Det2	71.91983	13706.17
Det3	189.5689	40090.62
Det4	313.3591	41771.97
Aux4	1070.228	33498.4

- Entropy measures the disorder or unpredictability in the signals. There is a notable increase in negative entropy values for epileptic conditions, indicating a higher degree of disorder and complexity during seizures. (Table 6)

TABLE 6. ENTROPY

	Entropy Values	
	Normal	***Epileptic***
Det1	-218417	-7.6E+07
Det2	-1585715	-6.3E+08
Det3	-4914076	-2E+09
Det4	-8635938	-2E+09
Aux4	-3.4E+07	-1.6E+09

- Kurtosis describes the shape of the distribution. Higher kurtosis in epileptic conditions, especially for Det1 to Det3, suggests a more peaked and heavy-tailed distribution, potentially reflecting abnormal EEG patterns during seizures. (Table 7)

TABLE 7. KURTOSIS

	Kurtosis Values	
	Normal	***Seizure EEG / Abnormal***
Det1	3.638981	11.62455
Det2	5.158707	10.92533
Det3	5.592646	8.197364
Det4	4.685814	4.561308
Aux4	3.797553	4.019348

- Skewness measures the asymmetry of the distribution. Positive skewness in both normal and epileptic conditions for most detectors suggests a right-skewed distribution. The higher magnitude in epileptic conditions indicates a more pronounced skewness. (Table 8)

TABLE 8. SKEWNESS

	Skewness Values	
	Normal	***Epileptic***
Det1	0.036866	0.702951
Det2	0.033372	0.88553
Det3	0.037513	0.683605
Det4	0.125821	0.421174
Aux4	-0.17635	0.338782

Results are analyzed depending on performance parameters like specificity, accuracy, sensitivity, in which developed method accuracy seems to be improved by integrating the extended run and flexible elements which instructs the algorithm and states that the EEG signals consist many information about the brain waves. Thus, the result shows that the developed hybrid CoPrO-DCNN classifier achieved an accuracy rate of 97.50% and 94.56% respectively depending on Training Percentage and K Fold, which is comparatively higher than the existing techniques for Real time dataset.

RATIO INDICES

Different EEG indices calculated for real time dataset are listed below in Table 9

Table 9 Ratio Indices

Indices	**Epileptic**	**Normal**	**Percentage change**
δ/θ (Mean)	0.215656	0.130671	65.03
α/δ (Mean)	0.522481	0.816094	-35.97
θ/δ (Variance)	28.66238	10.44697	174.36
θ/α	3259.564	284.2535	1046.71

(Skewness)			
α/θ (ApEntropy)	0.01823	0.015837	15.10
$\beta/(\alpha+\theta)$ (Variance)	0.2671	0.3288	-18.76

Increased percentage of δ/θ (Mean) represent patient is to be epileptic one. Percentage decrease in α/δ (Mean) represent low alertness. Increased θ/α (Skewness) ratio shows anxiety, stress.

Conclusions

Brain signal can be analyzed for spotting brain ailments. In this research work EEG signals of normal and Seizure patients have been recorded. By using 4 level decomposition of acquired and filtered signals various features are extracted. Further these features are used for predicting the normal persons EEG from seizure EEG. Simple classifiers are used for classifying the signals. There is large difference between power calculated for each type of signals. EEG capturing around the ear is an evolving field which gives more accuracy in findings. In this work accuracy obtained is around 97.35 %. The research effectively tests and implements the suggested model technique, training the DCNN's hyper parameter with the coyote predator algorithm. The coyote predator algorithm is linked to the outcomes of this study. Thus, the result shows that the developed hybrid CoPrO-DCNN classifier achieved an accuracy rate of 97.50% and 94.56% respectively depending on Training Percentage and K Fold, which is comparatively higher than the existing techniques for Real time DT. Finally, it is settled that brain signals can be analyzed properly and fed to the classifier to predict the abnormal signals easily. In turn, patient's condition can be known earlier so as to avoid any future consequences by early prediction and treatment.

Acknowledgment

It will be our honor to give our thanks to Dr. Uma B., MS, IEC, SKNMCGHP for supporting this research effort.

References

[1] A. Furui, R. Onishi, A. Takeuchi, T. Akiyama and T. Tsuji, "Non-Gaussianity Detection of EEG Signals Based on a Multivariate Scale Mixture Model for Diagnosis of Epileptic Seizures," *IEEE Transactions on Biomedical Engineering*, vol. 68, no. 2, pp. 515-525, 2021.

[2] Y. Lin *et al*., "Identifying Refractory Epilepsy without Structural Abnormalities by Fusing the Common Spatial Patterns of Functional and Effective EEG Networks," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 708-717, 2021.

[3] Guo, J., Li, H., Sun, X., Qi, L., Qiao, H., Pan, Y., Ji, R., "Detecting High Frequency Oscillations for Stereo electroencephalography in Epilepsy via Hypergraph Learning," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 587–596, 2021.

[4] D. Hu, J. Cao, X. Lai, Y. Wang, S. Wang and Y. Ding, "Epileptic State Classification by Fusing Hand-Crafted and Deep Learning EEG Features," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 68, no. 4, pp. 1542-1546, 2021.

[5] Jayaraj, Rajeswari, and Jagannath Mohan,"Classification of Sleep Apnea Based on Sub-Band Decomposition of EEG Signals," *Diagnostics, vol.* 11, no. 9, pp. 1571, 2021.

[6] Mullins, Anna E., Jong W. Kim, Keith KH Wong, Delwyn J. Bartlett, Andrew Vakulin, Derk-Jan Dijk, Nathaniel S. Marshall, Ronald R. Grunstein, and Angela L. D'Rozario. "Sleep EEG microstructure is associated with neurobehavioural impairment after extended wakefulness in obstructive sleep apnea." Sleep and Breathing, vol. 25, no. 1, pp. 347-354, 2021.

[7] T. Mahmud, I. A. Khan, T. I. Mahmud, S. A. Fattah, W. -P. Zhu and M. O. Ahmad, "Sleep Apnea Detection from Variational Mode Decomposed EEG Signal Using a Hybrid CNN-BiLSTM," *IEEE Access*, vol. 9, pp. 102355-102367, 2021.

[8] Liu, S., Shen, J., Li, Y., Wang, J., Wang, J., Xu, J., Wang, Q., & Chen, R., "EEG Power Spectral Analysis of Abnormal Cortical Activations During REM/NREM Sleep in Obstructive Sleep Apnea," Frontiers in neurology, vol.12, pp. 643855, 2021.

[9] Bergmann, Melanie; Prieschl, Manuela; Stefani, Ambra; Heidbreder, Anna; Walser, Gerald; Frauscher, Birgit; Unterberger, Iris; Hogl, Birgit, "A prospective controlled study about sleep disorders in drug resistant epilepsy," Sleep Medicine, vol. 75, pp. 434–440, 2020.

[10] Giuliano, L., Mainieri, G., Cicero, C. E., Battaglia, G., Guccione, A., Salomone, S., Drago, F., Nicoletti, A., Sofia, V., & Zappia, M., "Parasomnias, sleep-related movement disorders and physiological sleep variants in focal epilepsy: A polysomnographic study," Seizure, vol. 81, pp. 84–90, 2020.

[11] DiLuca, M., Olesen, J., "The cost of brain diseases: a burden or a challenge?" Neuron, vol. 82, no. 6, pp. 1205–1208, 2014.

[12] Ernst, R.L., Hay, J.W., "The US economic and social costs of Alzheimer's disease revisited," American journal of Public Health, vol. 84, pp. 1261–1264, 1994.

[13] Jack, C.R., Petersen, R.C., Xu, Y.C., Waring, S.C., O'Brien, P.C., Tangalos, E.G., Smith, G.E., Ivnik, R.J., Kokmen, E., "Medial temporal atrophy on MRI in normal aging andvery mild Alzheimer's disease," Neurology, vol. 49, pp. 786–794, 1997.

[14] Jafri, M.J., Pearlson, G.D., Stevens, M., Calhoun, V.D., "A method for functional network connectivity among spatially independent resting-state components in schizophrenia. NeuroImage, vol. 39, pp. 1666–1681, 2008.

[15] Lorenzetti, V., Allen, N.B., Fornito, A., Yücel, M., "Structural brain abnormalities in major depressive disorder: a selective review of recent MRI studies," Journal of Affective Disorders, vol. 117, pp. 1–17, 2009.

[16] de Weerd, A., de Haas, S., Otte, A., Trenité, D. K., van Erp, G., Cohen, A., de Kam, M., & van Gerven, J., "Subjective sleep disturbance in patients with partial epilepsy: a questionnaire-based study on prevalence and impact on quality of life," Epilepsia, vol. 45, no.11, pp. 1397–1404, 2004.

[17] Unterberger, I., Gabelia, D., Prieschl, M., Chea, K., Hofer, M., Högl, B., Luef, G., & Frauscher, B., "Sleep disorders and circadian rhythm in epilepsy revisited: a prospective controlled study," Sleep medicine, vol. 16, no.2, pp. 237–242, 2015.

[18] Malow, B. A., Foldvary-Schaefer, N., Vaughn, B. V., Selwa, L. M., Chervin, R. D., Weatherwax, K. J., Wang, L., & Song, Y. (2008). "Treating obstructive sleep apnea in adults with epilepsy:

a randomized pilot trial," Neurology, vol. 71, no. 8, pp. 572–577, 2008.

[19] Vendrame M, Auerbach S, Loddenkemper T, Kothare S, Montouris G., "Effect of continuous positive airway pressure treatment on seizure control in patients with obstructive sleep apnea and epilepsy," Epilepsia, vol. 52, no.11, pp. e168-e171, 2011.

[20] Sujata Roshan, Vinod Puri, Neera Chaudhry, Anu Gupta, Sumit Kumar Rabi, "Sleep abnormalities in juvenile myoclonic epilepsy—A sleep questionnaire and polysomnography-based study," Seizure, Volume 50, Pages 194-201, 2017.

[21] Bazil C. W., "Seizure modulation by sleep and sleep state," Brain research, vol. 1703, pp. 13-17, 2019.

[22] Bazil CW, Walczak TS., "Effects of sleep and sleep stage on epileptic and nonepileptic Seizures," Epilepsia, vol. 38, pp. 56–62, 1997.

[23] Grigg-Damberger, M. M., & Foldvary-Schaefer, N., "Primary sleep disorders in people with epilepsy: clinical questions and answers," Child and adolescent psychiatric clinics of North America, vol. 24, no. 1, pp. 145–176, 2015.

[24] Quigg, M., Gharai, S., Ruland, J., Schroeder, C., Hodges, M., Ingersoll, K. S., Thorndike, F. P., Yan, G., & Ritterband, L. M., "Insomnia in epilepsy is associated with continuing seizures and worse quality of life," Epilepsy research, vol. 122, pp. 91–96, 2016.

[25] An, X.; Kuang, D.; Guo, X.; Zhao, Y.; He, L., "A deep learning method for classification of EEG data based on motor imagery," International Conference on Intelligent Computing, Taiyuan, China, 3–6 August 2014; Springer: Cham, Switzerland, vol. 2014; pp. 203–210, 2014.

[26] Tabar, Y. R., & Halici, U., "A novel deep learning approach for classification of EEG motor imagery signals," Journal of neural engineering, vol. 14, no. 1, pp.016003, 2017.

[27] Ren, Y.; Wu, Y. Convolutional Deep Belief Networks for Feature Extraction of EEG Signal. In Proceedings of the Neural Networks (IJCNN), Beijing, China, 6–11 July 2014; pp. 2850–2853.

[28] Cui, Z., Zheng, X., Shao, X., & Cui, L., "Automatic Sleep Stage Classification Based on Convolutional Neural Network and Fine-Grained Segments," Complexity, vol. 2018, pp. 1–13, 2018.

[29] Ganesh Birajadar, Channappa Bhyri, "Epilepsy Identification using EEG signal monitoring", Turkish Journal of Computer and Mathematics Education, Vol 12 No.2 (2021) 2366-2371.

[30] Afshin Faramarzi, Mohammad Heidarinejad, Seyedali Mirjalili, and Amir H.Gandomi, " Marine Predators Algorithm: A nature-inspired metaheuristic", Expert Systems with Applications, vol.152, no.113377, 15 August 2020.

[31] Ganesh Birajadar, Channappa Bhyri, "Comparative survey on EEG analyss for detecting brain disorders", International journal of Future Generation Communication and Networking, Vol 13 No. 3s (2020) pp. 1253-1257.

[32] Ganesh Birajadar, Channappa Bhyri, "Comparative Analysis on Brain Disorder detection using EEG", International Journal of Innovations in Scientific & Engineering Research , Vol 6, Issue 6, June 2019.

[33] S. Vani, G. R. Suresh, "EEG Signal Analysis for Automated Epilepsy Seizure Detection Using Wavelet Transform and Artificial Neural Network". Journal of Medical Imaging and Health Informatics, Vol 9, 1301-1306, 2019.

[34] P. B. Mane and A. O. Mulani, "High throughput and area efficient FPGA implementation of AES algorithm", International Journal of Engineering and Advanced Technology, Vol. 8, Issue 4, April 2019.

[35] Shitanshu Kusmakar, Chandan K. Karmakar, "Automated Detection of Convulsive Seizures Usinga Single Wrist-Worn Accelerometer Device", EEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, 2019.

[36] Ganesh Shinde and Altaf Mulani, "A Robust Digital Image Watermarking using DWT-PCA", International Journal of Innovations in Engineering Research and Technology (IJIERT), Vol. 6 Issue 4 April 2019.

[37] Muhammad Sohaib J. Solaija, Sajid Saleem, "Dynamic Mode Decomposition Based Epileptic Seizure Detection from Scalp EEG", IEEE Access, 2018.

[38] Mulani Altaf O. and P. B. Mane, "Watermarking and Cryptography based Image Authentication on reconfigurable platform", Bulletin of Electrical Engineering and Informatics, June 2017.

[39] Swami S. S. and Mulani A. O., "An efficient FPGA implementation of discrete wavelet transform for image compression", 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS 2017), 2018, pp. 3385–3389.

[40] Mulani Altaf O. and P. B. Mane, "An Efficient implementation of DWT for image compression on reconfigurable platform", International Journal of Control Theory and Applications, Jan. 2017.

[41] Prabhapreet Kaur, Anurag Sharma, "Epilepsy Seizure Detection Using Wavelet Support Vector Machine Classifier", International Journal of Bio science & Bio technology, Vol. 8 No. 2, 2016.

[42] Amruta Mandwale and A. O. Mulani, "Implementation of High Speed Viterbi Decoder using FPGA", International Journal of Engineering Research & Technology (IJERT), Feb. 2016.

[43] Easwaramoorthy & R. Uthayakumar, "Analysis of Biomedical EEG Signals using Wavelet Transforms and multiultifractal Analysis", IEEE, 2010.

[44] Bhyri et. al., G. B. . (2021). Epilepsy Identification using EEG signal monitoring. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(2), 2366–2371. Retrieved from https://turcomat.org/index.php/turkbilmat/article/view/2022

[45] Birajadar, G., & Bhyri, C. (2020). Comparative survey on EEG analysis for detecting brain disorders. International journal of Future Generation Communication and Networking, 13(3s), 1253-1257.

[46] Akshay G Masa, Shital P Mundlik, Rutuparna R Lawand, & Ganesh B Birajadar (2022), "Smart Parking Management System" (Based on IOT Modules). Journal of Electronics, Computer Networking and Applied Mathematics (JECNAM) ISSN: 2799-1156, 2(06), 8–12. https://doi.org/10.55529/jecnam.26.8.12

[47] Ghodake, R.G., Mulani, A.O. (2018). Microcontroller Based Automatic Drip Irrigation System. In: Pawar, P., Ronge, B., Balasubramaniam, R., Seshabhattar, S. (eds) Techno-Societal 2016. ICATSA 2016. Springer, Cham. https://doi.org/10.1007/978-3-319-53556-2_12

[48] Aasawari Boxey, Anushri Jadhav, Pradnya Gade, Priyanka Ghanti, & Dr. A.O. Mulani. (2022). Face Recognition using Raspberry Pi. Journal of Image Processing and Intelligent Remote Sensing(JIPIRS) ISSN 2815-0953, 2(04), 15–23. https://doi.org/10.55529/jipirs.24.15.23

[49] Korake, D. M., & Mulani, A. O. (2016), "Design of Computer/Laptop Independent Data transfer system from one USB flash drive to another using ARM11 processor", International Journal of Science, Engineering and Technology Research.

[50] Yogita Maske, Mr. A. B. Jagadale, Dr. Altaf O. Mulani & Mrs. A. C. Pise. (2023). Implementation of BIOBOT System for COVID Patient and Caretakers Assistant using IOT. International Journal of Information Technology &Amp; Computer Engineering (IJITC) ISSN : 2455-5290, 2(01), 30–43. https://doi.org/10.55529/ijitc.21.30.43

[51] Mandwale, A. & Mulani, A. O. (2015, January). Different Approaches For Implementation of Viterbi decoder. In IEEE International Conference on Pervasive Computing (ICPC).

[52] Swapnil Takale, & Dr. Altaaf Mulani, (2022). DWT-PCA based Video Watermarking. Journal of Electronics, Computer Networking and Applied Mathematics (JECNAM) ISSN : 2799-1156, 2(06), 1–7. https://doi.org/10.55529/jecnam.26.1.7

[53] Shinde, Ganesh and Altaaf Mulani. "A Robust Digital Image Watermarking Using Dwt -Pca." International Journal of Innovations in Engineering Research and Technology, vol. 6, no. 4, 2019, pp. 1-7.

[54] H. S. Deshpande, K. J. Karande and A. O. Mulani, "Efficient implementation of AES algorithm on FPGA," 2014 International Conference on Communication and Signal Processing, Melmaruvathur, India, 2014, pp. 1895-1899, doi: 10.1109/ICCSP.2014.6950174.

[55] Mulani, A.O., Birajadar, G., Ivković, N., Salah, B., Darlis, A.R. (2023). Deep learning based detection of dermatological diseases using convolutional neural networks and decision trees. Traitement du Signal, Vol. 40, No. 6, pp. 2819-2825. https://doi.org/10.18280/ts.400642

[56] Dr. Pravin G. Gawande, Dr. Rajendra S. Talware, Dr. Shailesh V. Kulkarni, Dr. Anup W. Ingle, Milind S. Patil , Gajanan H. Chavhan, “A REVIEW ON AD-HOC NETWORK IN PERVASIVE ENVIRONMENT”, Eur. Chem. Bull. 2023, 12 (S3), 95 – 102, DOI: 10.31838/ecb/2023.12.s3.012

[57] Pravin G. Gawande and Ashok M. Sapkal, “Quality-dependent fusion system using no-reference image quality metrics for multimodal biometrics”, Periodicals of Engineering and Natural Sciences, 2018, Vol.6, No.1, pp. 260-273, ISSN:2303-4521.

[58] Pravin G. Gawande and Dr. Ashok M. Sapkal, “Quality Based Effective Fusion Mechanism for Multimodal Biometrics System using Palmprint, Iris and Fingerprint", IETE National Journal of Innovation and Research, IETE-NJIR, ISSN: 2320-8961, Volume 5, Issue 1 June 2017, pp25-30

Author 1 Name and a short biography …

Author N Name and a short biography …