



Epilepsy Identification using Hybrid CoPro-DCNN Classifier

Ganesh Basawaraj Birajadar¹, Altaf Osman Mulani¹, Osamah Ibrahim Khalaf², Nasren Farhah³, Pravin G. Gawande⁴, Kishor Kinage⁵ and Abdulsattar Abdullah Hamad⁶

¹Electronics and Telecommunication, SKN Sinhgad College of Engineering, Pandharpur, Maharashtra, India

²Department of Solar, Al-Nahrain Research Center for Renewable Energy, Al-Nahrain University, Jadriya, Baghdad, Iraq

³Department of Health Informatics, College of Health Sciences, Saudi Electronic University, Riyadh 11673, Saudi Arabia

⁴Electronics and Telecommunication, Vishwakarma Institute of Information Technology, Pune, India

⁵Electronics and Telecommunication, Pimpri Chinchwad College of Engineering, Pune, India

⁶University of Samarra, College of Education, Department of physics, Iraq

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Abstract: The Electroencephalogram (EEG) stands as a burgeoning frontier in the study of neuronal activity, offering a rich tapestry of information crucial for identifying abnormalities and addressing cognitive disorders and irregularities. This paper delves into the examination of EEG from subjects exhibiting abnormalities, contrasting them with those from normal subjects. Various topographical features such as Mean, Entropy, and Wavelet bands are meticulously evaluated and compared. Inspired by the adaptive hunting strategies observed in coyotes, this study introduces a novel hybrid computational model that integrates deep learning architectures, aiming to amplify diagnostic accuracy. The methodology hinges upon the development of a unique computational algorithm inspired by the intricate hunting behaviors of coyotes, seamlessly fused with the potent data-driven capabilities of deep neural networks. This hybrid model is meticulously applied to scrutinize EEG data for the detection of brain disorders, capitalizing on both the biologically-inspired algorithm and the data-centric strengths of deep learning.

The results obtained from this innovative approach are highly promising. The proposed scheme exhibits a remarkable diagnostic accuracy, achieving an impressive rate of 98.65 per for training (True Positive - TP) and 98.82 per utilizing k-fold validation. These preliminary findings underscore the potential efficacy of the hybrid methodology in accurately discerning brain disorders from EEG signals. However, it is essential to acknowledge that these results represent an initial success and form just a fragment of the extensive evaluation process. This study marks a significant stride towards leveraging interdisciplinary insights, blending principles from ethology with advanced computational techniques to tackle complex neurological challenges. By harnessing the sophisticated strategies observed in nature alongside cutting-edge technological advancements, this research endeavors to carve a path towards more nuanced and precise diagnostic tools for understanding and addressing brain disorders. Further exploration and refinement of this hybrid model hold promise for revolutionizing the landscape of neurodiagnostics, offering hope for more effective interventions and treatments in the realm of cognitive health.

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. [1] 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. [2] 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. [3] The primary objective of this study is to investigate the effectiveness of a hybrid CoPrO-Deep Convolutional Neural Network (DCNN) classifier in identifying epilepsy based on EEG data. Existing methods for classification often face limitations in terms of accuracy, efficiency, and robustness. Traditional machine learning classifiers struggle with complex and high-dimensional data where features are not well represented or easily separable. Many classifiers, especially deep neural networks, are prone to overfitting when dealing with small datasets or noisy data, leading to poor generalization performance on unseen data. Class imbalance within the dataset can bias the classifier towards the majority class, leading to poor performance for [4] minority classes. By combining the strengths of convolutional neural networks and probabilistic modeling, the hybrid CoPrO-DCNN classifier aims to overcome the limitations of existing methods and achieve superior performance across various classification tasks. The study aims to address the gap in existing literature by investigating the efficacy of the hybrid CoPrO-DCNN classifier in automating epilepsy detection from [5] EEG signals.

2. LITERATURE SURVEY

Several studies have explored diverse methodologies for epilepsy identification, ranging from traditional signal processing techniques to advanced machine [6] 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 [7] lack consistency. The need for automated and objective methods has led to a surge in research exploring various computational techniques. Dinghan Hu et al. [8] explores opportunity of combining traditional hand-crafted features with DL designs to identify epilepsy states from EEG recordings. Paper is highly relevant to the current study as it introduces a fusion framework that combines traditional hand-crafted features with deep learning designs. This method directly addresses the challenge of improving the accuracy and efficiency of epilepsy detection from EEG signals. 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 [9] EEG signals. 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. By highlighting the prevalence of sleep disorders in epilepsy patients and their impact on overall health, this study contributes to the broader understanding of epilepsy management. 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 [11] sleep disturbance. 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, [12] 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 per. 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 [13] of prey. 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 study utilizes EEG data collected from individuals with and without epilepsy. This data undergoes preprocessing to enhance signal quality and remove noise. Feature extraction techniques is then applied to capture relevant characteristics indicative of epileptic activity from the EEG signals. These features will serve as input to the hybrid CoPro-DCNN classifier, [14] which combines convolutional neural networks with probabilistic modeling. The classifier is trained on labeled EEG datasets to distinguish between epileptic and non-epileptic patterns. Performance evaluation will involve metrics such as accuracy, sensitivity, and specificity. Finally, the performance of the hybrid classifier is compared with existing methods for epilepsy detection. The data input utilized in this research is gathered from Cyclic Alternating Pattern (CAP) dataset (DT) [15], 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. The collected dataset includes Normal data from 26 males and 16 females having an average age of 20.63 and Epileptic data from 21 males and 21 females

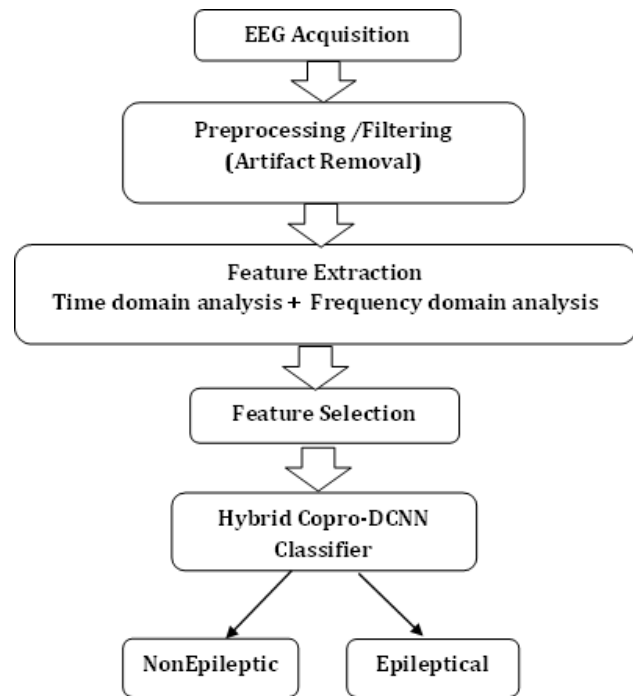


Figure 1. Methodology

with an average age of 24.76. This data, sampled at 256 Hz and band-pass filtered between 0.53 to 70 Hz, is likely used for epilepsy monitoring or diagnosis. Recordings are made using 24 or 32 channels, providing comprehensive coverage of brain activity. CHB MIT DT [16] with the EEG record gathering of 22 pediatric subjects with unmanageable captures and annotation of 182 captures is also studied. 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. [17], [18] 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 [19] 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, [20] 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 [21], [22] EEG signals. The preprocessing steps, including under-sampling, BPF, and removal of frequencies outside the prevalence range, collectively contribute to the removal of artifacts and enhancement of EEG [23] signal quality. Frequencies outside the prevalence range (less than 0.05 Hz and more than 75 Hz) are reduced to enhance the functionality of EEG signals. BPF is employed to remove unnecessary noises

and EEG signal artifacts while retaining the frequencies [24] of interest. Once the filtered signal is obtained, for each EEG signal various features are extracted. EEG signal reveals some of the features in frequency [25] domain too. So, time domain and frequency domain analysis are done so as to extract features like mean, variance, entropy, band [26] power, skewness. The features that are extracted are Kurtosis, Wavelet features, Skewness, Hjorth features, Spectral features, Statistical features, Tsallis entropy, Common spatial pattern and [27], [28] Band power.

A. Feature Extraction and selection: Following features have been extracted from each recorded EEG signal. EEG signal is decomposed into frequency bands and features are calculated for each [29] sub band.

Mean: Mean of each frequency band is calculated and tabulated.

Variance: Variance represents typical grade to which individual point varies as compared [30] 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 [31] presented as $Kurtosis = (M_4[x(n)])/(M_2^2[x(n)])(1)$

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 [32], [33] symmetric curvature. $Skewness = (E[(x(n) - (U + 03BC))^3])/(U + 03C3)^3(2)$

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 [34], [35] 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 [36] tsallis entropy. As EEG signals contain an extended communication range, it is relevant to utilize the limited estimation to demonstrate the impacts of the [37] extended communication.

Spectral features: The spectral features are majorly dependent on the constituents of prevalence, which is obtained by transferring the period stand [38] 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 [39], [40] 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 [41], [42] of

features. $HV = \text{var}(x)$ (3) where, HV is referred to as Hjorth variables.

Hybrid COPRO-DCNN classifier In order to, predict changes in brain activity that are helpful for identifying a neurological disorder, [43] EEG signals [44] 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. The proposed hybrid CoPrO-DCNN classifier combines the strengths of CNNs with probabilistic modeling to further refine epilepsy detection from [45] EEG signals. CNNs excel at extracting intricate features from complex data, while probabilistic modeling offers a mechanism for quantifying uncertainty in predictions, enhancing the classifier's robustness and interpretability. Following the feature extraction, the RELIEF [46], [47] 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 [48], [49] 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 [50] 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 [51] further processing.

b) Pre-processing and 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, [52] Hjorth features, Common spatial pattern, Tsallis entropy, Wavelet features, Spectral features and [53] 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, [54] 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 [55], [56] 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, [57] which is a ML model that is intended for evaluating better quantity of information travel throughout different neuron layers, [58] 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 [59], [60] EEG signals. The convolutional network's architecture contains four lay-

ers named convolution, pooling, ReLU and FC layer (FCL). To avoid searching for prey in specific areas, [61] the hybrid coyote optimization's decision-making and adaptability traits are combined with characteristics of long jump of the predator,[62] 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 [63], [64] accurate diagnoses. Hybrid algorithm shown in Table 1 typically combine elements from multiple algorithms or techniques to leverage their respective strengths and [65] 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 [68], [69] biological co-evolution.

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[70] 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 [71], [72] 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 [73] correct value.

Sensitivity: Sensitivity is a necessary component for accurately identifying patients with [74] 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 [75], [76] negative case.

4. RESULTS AND DISCUSSIONS

Figure 2 illustrates the characteristic patterns observed in epileptic and non-epileptic EEG signals. Key findings include the presence of sharp waves, spike-and-wave complexes, and high-frequency [77], [78] oscillations in epileptic EEGs, whereas non-epileptic EEGs exhibit smoother, more regular waveforms.

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

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

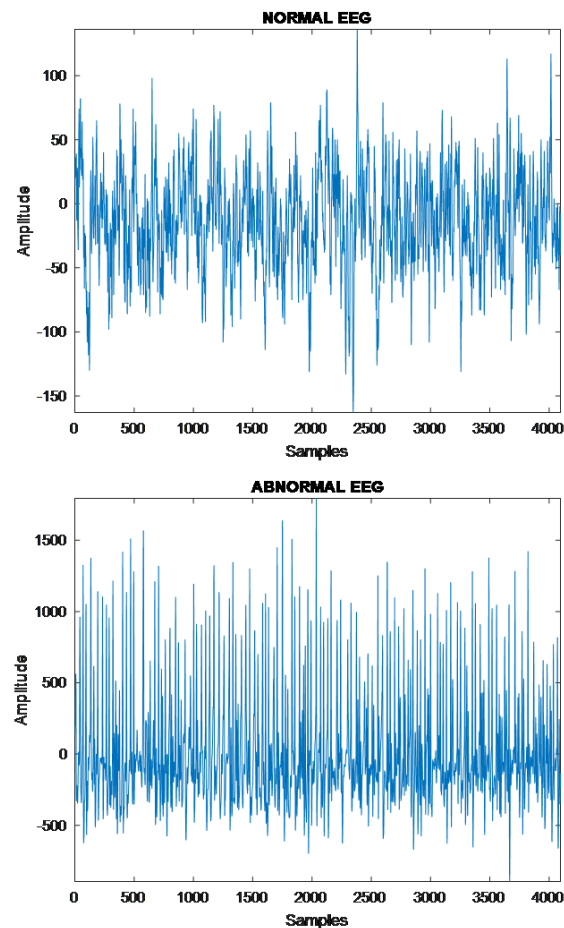


Figure 2. Epileptic and Non-Epileptic EEG

The amplitude varies, generally lower in slower frequencies and higher in faster ones. Recognizable and organized patterns are evident, with clear distinctions between [79] frequency bands. Variations occur based on wakefulness or sleep states

Nonepileptic EEG plots indicate various irregularities:

- 1) Epileptiform activity, such as spike or sharp waves, [80] suggests epilepsy.
- 2) Slow waves, like generalized or focal slowing, indicate potential abnormalities.
- 3) Presence of artifacts from external sources or patient movement distorted [81] 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 [82], [83] EEG signal.

The statistical parameters presents parameters calculated from EEG signals, such as mean amplitude, frequency

TABLE I. Hybrid CoPrO-based Algorithm [66], [67]

S.NO	Pseudo-code for hybrid CoPrO-based algorithm
1	Input: Initialization of groups with prairie wolf
2	Output: 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 group to perform
8	Leaders position updated
9	Cultural tendency generation
10	For every 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

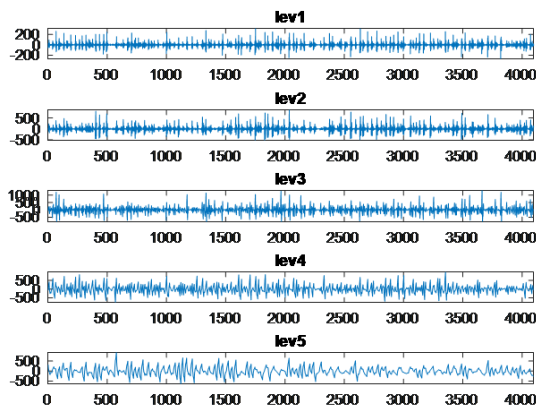


Figure 3. EEG Decomposition

distribution, and [84] signal variability. 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 [85] epileptic conditions. Det4 shows a noticeable increase in mean for epileptic conditions, indicating a shift [86] in the baseline.

TABLE II. Mean

Coeff	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

Variance measures the spread or dispersion of [87], [88] the data. Variance values are significantly higher in epileptic conditions for all detectors, suggesting increased variability in EEG signals during seizures. Standard deviation values further confirm the increased dispersion [89] in epileptic conditions for all detectors and the auxiliary signal, [90] highlighting the variability and volatility of EEG signals during seizures.

TABLE III. Variance

Coeff	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

TABLE IV. Dispersion

Coeff	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 [91], [92] frequency bands. There is a substantial increase in band power for epileptic conditions across all detectors, reinforcing the notion of altered frequency characteristics [93] during seizures. Entropy measures the disorder or unpredictability in [94] the signals. There is a notable increase in negative entropy values for epileptic conditions, indicating a higher degree of disorder [95] and complexity during seizures.



TABLE V. Band Power

Coeff	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

Kurtosis describes the shape of [96] the distribution. Higher kurtosis in epileptic conditions, especially for Det1 to Det3, [97], [98] suggests a more peaked and heavy-tailed distribution, potentially reflecting abnormal EEG patterns during seizures.

TABLE VI. Entropy

Coeff	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

TABLE VII. Kurtosis

Coeff	Normal	Epileptic
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 [99], [100] the distribution. Positive skewness in both normal and epileptic conditions for most detectors suggests a [101], [102] right-skewed distribution. The higher magnitude in epileptic conditions indicates a more pronounced skewness.

TABLE VIII. Skewness

Coeff	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 [103], [104] 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 [105] brain waves. This approach aligns with the research objectives by providing a holistic and innovative solution to the challenges of epilepsy identification from EEG signals. By combining biological-inspired optimization strategies [106], [107] with deep learning architectures, the hybrid CoPrO-DCNN classifier offers a powerful tool for accurately detecting epileptic patterns in EEG data, ultimately improving diagnostic accuracy [108] and patient outcomes in epilepsy management. Thus, the result shows that the developed hybrid CoPrO-DCNN classifier achieved an accuracy rate of 97.50 per and

94.56 per respectively [109], [110] depending on Training Percentage and K Fold, which is comparatively higher than the existing techniques for Real [111] time dataset.

Ratio Indices

Different EEG indices calculated for real time dataset are listed below in Table 9. The ratio indices presented in Table 9 provide insights into [112], [113] various aspects of EEG signal characteristics and their relevance for epilepsy diagnosis [114] or classification.

TABLE IX. Ratio Indices

Indices	Epileptic	Normal	Per change
delta/theta	0.215656	0.130671	65.03
alpha/delta	0.522481	0.816094	-35.97
theta/delta	28.66238	10.44697	174.36
theta/alpha	3259.564	284.2535	1046.71
alpha/theta	0.01823	0.015837	15.10
beta/(alpha + theta)	0.2671	0.3288	-18.76

An increase in delta/theta ratio indicates heightened slow-wave activity relative to theta activity, which is often associated with abnormal brain states such as [115] epileptic seizures. A decrease in alpha/delta ratio suggests reduced alpha activity relative to slow-wave delta activity, [116] which may be indicative of abnormal cortical functioning observed in epilepsy. An increase in theta/delta variance suggests [117] greater variability in the balance between theta and delta activity, which could reflect dynamic changes in brain states associated with epileptic activity. A high positive skewness in theta/alpha ratio indicates an asymmetric distribution [118], [119] with a longer tail towards higher values, suggesting dominance of theta activity over alpha activity. An increase in alpha/theta ApEntropy suggests [120] greater irregularity or unpredictability in the relative balance between alpha and theta activity. A decrease in beta/(alpha + theta) variance suggests reduced [121], [122] variability in the balance between beta activity and the combined alpha and theta activity, [123], [124] which reflects altered cortical excitability observed in epilepsy.

5. 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. The study likely identified specific patterns or features within EEG signals that distinguish between epileptic and non-epileptic activity. The study addresses limitations in current diagnostic methods for epilepsy, such as subjectivity and time-consuming manual interpretation of EEG signals. Automated approaches, like the proposed hybrid CoPrO-DCNN classifier, offer potential benefits such as improved objectivity, efficiency, and scalability in epilepsy detection. By automating the analysis process, these approaches can enhance diagnostic accuracy, reduce the burden on healthcare professionals, and facilitate earlier detection and



intervention for individuals with epilepsy. By analyzing EEG signals associated with epilepsy, the study provides valuable insights into the pathological mechanisms underlying seizure generation and propagation. For example, the presence of specific spectral or temporal patterns in epileptic EEGs may reflect aberrant synchronization of neuronal networks or hyperexcitability within certain brain regions. 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 per and 94.5 per 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. Moving forward, the study opens up avenues for further research into EEG-based biomarkers of epilepsy and the development of innovative diagnostic and therapeutic approaches. Future studies may explore novel machine learning algorithms, advanced signal processing techniques, or multimodal imaging methods to enhance the accuracy and reliability of epilepsy identification.

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Dr. Ganesh Basawaraj Birajadar is a dedicated professional with a Ph.D. in Electrical and Electronics Engineering Sciences. With a strong background in signal processing and expertise in EEG signal analysis, he is committed to advancing knowledge in the field of brain abnormality detection. His career objective is to excel across all domains of life, upholding principles of diligence to manifest aspirations into tangible achievements. Dr. Ganesh Basawaraj Birajadar's dedication to research, coupled with his expertise in signal processing, positions him as a valuable contributor in the field of electrical and electronics engineering.



Dr. Altaf Osman Mulani is a highly accomplished Professor in Electronics and Telecommunication Engineering at SKN Sinhgad College of Engineering, Pandharpur, India. He obtained his Ph.D. in Electronics and Telecommunication Engineering from Savitribai Phule Pune University (SPPU). With extensive expertise in digital design, VLSI design, and embedded system design, Dr. Mulani has made significant contributions to the field.

Throughout his career, Dr. Mulani has held various leadership roles, including Dean (IQAC and NAAC Coordinator), Head of Electronics and Telecommunication Department, and Coordinator for AICTE Margadarshan scheme. He has been actively involved in organizing international conferences, conducting faculty development programs, and contributing to university curriculum development. Dr. Mulani's research interests encompass a wide range of topics, including deep learning, image processing, machine learning, and IoT-based systems. He has published numerous papers in esteemed journals and conferences, and his work has received recognition through patents and awards. In addition to his academic pursuits, Dr. Mulani is dedicated to continuous learning and has completed certifications in machine learning, Google Docs, grammar and punctuation, and Python basics for data science.



Dr. Osamah Ibrahim Khalaf is Senior Engineering and Telecommunications Lecturer in Al Nahrain University. He has held 17 years of university-level teaching experience in computer science and network technology and has a strong CV about research activities in computer science and information technology projects. He has had many published articles indexed in (ISI or Thomson Reuters) and has also participated and presented at numerous international conferences. He has a patent and has received several medals and awards due to his innovative work and research activities. He has good skills in software engineering including experience with: .Net, SQL development, database management, mobile applications design, mobile techniques, Java development, android development, and IOS mobile development, Cloud system and computations, website design. I am Editor in Chief and main guest editor in many Scopus and SCI index journals. His brilliant personal strengths are in highly self-motivated team player who can work independently with minimum supervision, strong leadership skills, and outgoing personality. He got his B.Sc. in software engineering field from Al Rafidain University College in Iraq. Then he got his M. Sc. in computer engineering field from Belarussian National Technical University. After that, he got his PhD in the field of computer networks from faculty of computer systems and software engineering -University Malaysia, Pahang. He has overseas work experiences in University in Binary University in Malaysia and University Malaysia Pahang.

He has a patent and has received several medals and awards due to his innovative work and research activities. He has good skills in software engineering including experience with: .Net, SQL development, database management, mobile applications design, mobile techniques, Java development, android development, and IOS mobile development, Cloud system and computations, website design. I am Editor in Chief and main guest editor in many Scopus and SCI index journals. His brilliant personal strengths are in highly self-motivated team player who can work independently with minimum supervision, strong leadership skills, and outgoing personality. He got his B.Sc. in software engineering field from Al Rafidain University College in Iraq. Then he got his M. Sc. in computer engineering field from Belarussian National Technical University. After that, he got his PhD in the field of computer networks from faculty of computer systems and software engineering -University Malaysia, Pahang. He has overseas work experiences in University in Binary University in Malaysia and University Malaysia Pahang.



Dr. Nesren Farhah is the Assistant Professor and Dean of Graduate Studies, Research, and Innovation at Saudi Electronic University. She began her academic journey with a Bachelor's degree in Biology from King Khalid University in Saudi Arabia. She then advanced her studies in the United States, earning a Master's degree followed by a PhD in Biomedical Informatics from Nova Southeastern University, Florida, and Rutgers University, New Jersey, respectively. Dr. Farhah's research interests encompass a broad spectrum of critical topics including health informatics, public health, e-health, intelligent systems, clinical decision support, and health data privacy and security. Her expertise and leadership are pivotal in fostering innovation and research in healthcare technology.

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Dr. Pravin G. Gawande received the B.E. degree in electronics and communication engineering from the Govt. College of Engg. Aurangabad, Dr. Babasaheb Ambedkar Marathwada University, in 2001 and the M.E. degree PhD in electronics and telecommunication engg from the Govt. College of Engg. Pune, University of Pune, India, in 2004 and 2020, respectively. He joined Vishwakarma Institute of Information and

Technology in 2004, where he has been an Assistant Professor since June 2009. His research interests include Embedded systems, Image processing, Machine learning and computer vision.



Dr. Kishor Kinage is a distinguished Professor in Electronics and Telecommunication Engineering at Pimpri Chinchwad College of Engineering in Pune, India. With over 33 years of combined teaching and industry experience, he has held various administrative positions such as Head of Department and Principal at engineering colleges. Dr. Kinage holds a PhD from NMIMS University Mumbai and has a keen interest in subjects

like Signal Processing, Image Processing, Machine Learning, Electromagnetics, Antenna and Wave Propagation, and Microwave Engineering. Beyond academia, he advocates for holistic wellness and spiritual discovery, drawing inspiration from the teachings of Shri Mataji Nirmala Devi. Dr. Kinage actively shares his experiences and insights through his website, inviting feedback to enhance its content and engage with visitors effectively.



Dr. Abdulsattar Abdullah Hamad, born in Salah Al-Deen, Iraq, holds a Ph.D. from Madurai Kamaraj University in Mathematics. Currently affiliated with the University of Samarra, his research interests span a wide array of fields including the application of mathematical methods and science technology in healthcare, dynamic systems, big data, and machine learning. With an

impressive publication record of 60 papers in Scopus and WoS, along with 2 books and 3 patents to his credit, Dr. Hamad serves as an Associate Editor for prestigious journals such as the International Journal of Fuzzy System Applications and Frontiers in Applied Mathematics and Statistics. Additionally, he contributes as an Academic Editor for Computational and Mathematical Methods in Medicine, showcasing his expertise and dedication to advancing knowledge at the intersection of mathematics and healthcare.