Maximum Overlap Discrete Transform (MODT)—Gaussian Kernel Radial Network (GKRN) Model for Epileptic Seizure Detection from EEG Signals

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***Abstract*—One of the most severe neurological conditions that abruptly changes a person's way of life is epileptic seizures. Recent diagnostic approaches have concentrated on creating Electroencephalogram (EEG) methods based on machine/deep learning model, with the goal of creating new and efficient technologies for managing epileptic seizures. It is a challenging task to identify the seizure and seizure-free states of an epileptic patient by classifying EEG signals into ictal and interictal classes. Many machines learning-based approaches to analyzing and interpreting EEG signals for the aim of accurate categorization were previously introduced. Still, it is challenging to obtain comprehensive information on these dynamic biological signals, nevertheless, due to the non-linear and non-stationary nature of EEG data. This paper aims to develop an automated epileptic seizure diagnosis system with the use of advanced feature extraction and classification techniques. Here, the Maximum Overlap Discrete Transform (MODT) approach is used to extract the epileptic seizure-related features that are most valuable. The Redone Butterfly Optimization (RBO) technique is used to reduce the dimensionality of features in order to increase classification accuracy. The Gaussian Kernel Radial Network (GKRN) is used to precisely forecast the seizure and classify its proper class. To compare and validate the outcomes of the MODT-GKRN framework, a variety of measures and benchmark datasets have been used in this study.**

***Keywords*—Electroencephalogram (EEG), machine learning, Maximum Overlap Discrete Transform (MODT), Redone Butterfly Optimization (RBO), Gaussian Kernel Radial Network (GKRN)**

I. INTRODUCTION

The recent statistical report indicates that a common neurological condition known as epilepsy affects roughly 50 million people worldwide. Frequent seizures [1], caused by an excessive electrical discharge in a number of brain cells, are its key characteristic. Patients with epilepsy [2, 3] struggle because seizures are unexpected. According to World Health Organization research, 70% of epilepsy patients react to medication and can completely manage their seizures. Consequently, seizure forecasting could enhance the quality of life for many epilepsy patients by allowing them to prepare for the seizure's potentially harmful effects. The Electroencephalography (EEG) [4, 5] is still one of the best and most reliable methods for identifying epilepsy. Moreover, it is affordable, quasi, and quite accurate, and also it has been proven to be an essential tool for medical professionals and those who struggle with epilepsy. The pre-ictal, ictal, post-ictal, and inter-ictal are the different states of epilepsy [6, 7]. Moreover, it is common practice to categorize the EEG data into ictal or interictal stages in order to detect seizures. It takes a long time to visually examine EEG recordings for peaks and seizures in order to detect epilepsy, especially when the recordings are lengthy. Epilepsy [8] represents the most prevalent neurological disorder that affects individuals of all ages.

EEG [9] can also be utilized to make a clinical diagnosis for certain neurological problems, such as a tumor or brain damages incurred by a head injury. Typically, the high pass and low pass filters with operating frequencies of 0.5 to 1 Hz and 35 to 70 Hz can be used to filter the EEG signal. The Brain imaging signal is comprised up of radio frequencies including delta, theta, beta, and gamma waves. Delta waves have a frequency range of less than 4 and signify the state of deep sleep [10]. Alpha waves with wavelengths ranging from 8 to 12 Hz symbolize fatigue in adults and teenagers. Beta waves have a bandwidth of 13 to 24 Hz as well as reflect the relaxation position. Gamma waves have a frequency band of 24 to 45 Hz and comprise human's strong consciousness and effective thinking. One of the components of the human brain's cerebral cortex is the parietal lobe. Its primary job is to gather and process data from all parts of the body. Occipital lobe is responsible to analyze shape, color and movement [11, 12]. There are various lobes in the nervous system. The area of the brain that controls emotion expression is called the medial

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temporal lobe. The discrete wavelet transforms to detect the faults and also to decompose signal with respect to different frequencies. From the standpoint of machine learning, seizure prediction may be thought of as a binary classification between inter-ictal and pre-ictal states. For seizure prediction, categorizing EEG data into pre-ictal or inter-ictal states is frequently used. The majority of seizure prediction algorithms are patient-specific because EEG signals vary between patients due to differences in seizure characteristics and patterns.

To learn the patient-specific properties that distinguish the pre-ictal and inter-ictal states [13], these algorithms employ supervised learning techniques utilizing data previously obtained from each patient. To detect the potential onset of a seizure, data collected from the patient is online analyzed using the trained classifier [14]. The time required for extracting necessary features can be reduced with the help of classifiers. Moreover, the feature selection and feature extraction are the two basic approaches mainly used for dimensionality reduction. Recently, both supervised and unsupervised learning models are increasingly used in the existing works for feature extraction and selection [15]. Many of the literature works used the principal component analysis and linear discriminant analysis models for extracting features from the EEG signals. they key contributions of this paper are as follows:

- To extract the most useful features associated to the epileptic seizure, the Maximum Overlap Discrete Transform (MODT) technique is applied.
- To squeeze the dimensionality of features for improving the classification accuracy, the Redone Butterfly Optimization (RBO) algorithm is utilized.
- To accurately predict the seizure and, categorize its appropriate class, the Gaussian Kernel Radial Network (GKRN) is employed.
- To validate and compare the results of the proposed MODT-GKRN framework using various performance network.

The other portions of this paper structured into the following units: the literature review of some of the recent state-of-the-art model approaches is presented in Section II with the advantages and problems. Section III provides the complete explanation for the MODT-GKRN based epileptic seizure detection framework. Then, the validation and comparative results are presented with several datasets and performance parameters in Section IV. Finally, the overall paper is summarized with the new idea that is going to be implemented in future in Section V.

II. Literature Review

Here, some of the recent state-of-the-art model approaches used for epileptic seizure detection and classification are reviewed with the pros and cons.

Emara *et al.* [16] developed an efficient framework for detecting epileptic seizure from EEG signals. In this framework, the scale invariant feature transformation incorporated with Fast Fourier Transform (FFT) has been used to predict the seizure. Action potentials are widely assessed in terms of amplitude and phase representations using extraction and classification procedures. The wavelet packet transform and the time domain transform are two-line conversion techniques that can take a noisy signal and transform it into a processed signal. The wavelet decomposition method produces approximation and detail coefficients through a down sampling operation. Ahmad *et al*. [17] investigated several machine learning and deep learning techniques used for EEG based epileptic seizure detection. Typically, the seizure is categorized into the following types: partial, generalized, simple partial, complex partial, generalized conclusive and generalized non-conclusive. Moreover, the seizure detection system comprises the following operations: data collection, feature extraction, and seizure detection. Here, the different types of features such as time domain, frequency domain, polynomial based, principal component analysis, and embedding have been used to extract the features from the given dataset. Hossain *et al.* [18] applied a deep learning based detection methodology for detecting epileptic seizure according to the brain visualization features obtained from the EEG signal. Given that EEG recordings have a poor signal-to-noise ratio and exhibit significant sensitivity to noise, the model can use these attributes to learn the overall structure of a seizure that is less susceptible to fluctuations. A CNN-based deep learning method is used because, the artefacts can also interfere with EEG recording and feature extraction.

Boonyakitanont *et al*. [19] conducted a comprehensive review to investigate the different types of feature extraction models for EEG monitoring and seizure detection. In order to eliminate contradictions in several complex feature definitions that have been reported in the literature, the authors gave detailed mathematical descriptions and computations of the characteristics. Chen *et al.* [20] introduced a unified framework for the diagnosis of epileptic seizure from EEG signals. Here, an Auto-Regressive Moving Average (ARMA) model has been used to analyze the dynamic behavior of EEG signals. Although, the auto-regression analysis-based seizure detection may be performed quickly, it requires a post-processing technique to distinguish epilepsy from other illnesses. The popular usage of the sliding-window technique for continuous EEG diagnosis is constrained by the necessity for accurate and efficient feature extraction, which provides correct diagnosis but requires a lot of computation time. Siddiqui *et al.* [21] presented a survey on various machine learning based classification techniques used for the identification and classification of epileptic seizures. Typically, monitoring brain signals is one of the most tedious jobs, hence most of the medical experts prefer EEG signals for seizure prediction. The classification techniques investigated in this work are Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), decision tree and forest.

Vidyaratne *et al.* [22] employed a Harmonic Wavelet Packet Transform (HWPT) technique for the real time prediction and classification of EEG signals. Here, the FT technique is also used to analyze the similar patterns of the EEG signal. Moreover, the Ruby Version Manager (RVM) based machine learning model is used to efficiently categorize the type of disease with its accurate class. Likewise, harmonic wavelet packet transform, a subset of wavelet packet transform, is used in this work to extract features from EEG data. Recursive calculations are necessary for systematic signal decomposition into succeeding levels in generic discrete wavelet packet transform algorithms. Wang *et al*. [23] deployed a multi-domain feature extraction model for detecting epileptic seizure from the EEG signals. Here, the non-linear analysis is also performed to analyze the multi-domain features, which helps to increase the accuracy of seizure detection.

This paper implemented both online and offline prediction systems with the ensemble of classifiers such as Latent Dirichlet Allocation (LDA), Naive Bayes (NB), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Logistic Regression (LR). In addition to that, the Analysis of Variance (ANOVA) statistical test also conducted to examine the efficacy of prediction. However, the major complexities of this paper are high error, false positives, and complexity in feature extraction. Bajaj *et al.* [24] utilized an Empirical Mode Decomposition (EMD) method for developing an effective epileptic seizure diagnosing system. In this study, localized temporal lobe epilepsy was identified using intracranial EEG waves. The suggested approach makes advantage of the Intrinsic Mode Functions (IMFs), which are represented analytically by signals due to the EMD process, and their Hilbert transformation. The Support Vector Machine (SVM) is one of the widely used classification approach for EEG signal prediction.

With the help of signal processing algorithms, the EEG signal is split into various levels such as delta, alpha, theta, beta, and gamma sub-bands. These quantities are the classifier's outputs with a performance index of 80% because emotional states are conceptualized as combos of physiological constituents like arousal, valence, and dominance. Typically, the SVM classifier with combination of wavelet techniques of each spectral domain, the EEG signal is labelled as being either various scenarios mental functioning or not. The raw signal has been processed to generate characteristics that were used to classify the focus state. Because it is more efficacious in training and categorization of complex data. An impactful classifier-SVM can make a distinction Perception States by tracing the data to a greater dimension.

III. Materials and Methods

This section provides the complete explanation for the proposed epileptic seizure diagnosis system. In order to detect an epileptic patient's seizure state, the enhanced model for the automatic detection of epileptic seizures proposed in this research that classifies input EEG recordings into ictal and interictal classes, as illustrated in Fig. 1. At first, the single-channel and multi-channel EEG recordings are both forms of EEG signals that are examined. These signals were obtained from the Bonn dataset, the CHB-MIT dataset, and the Freiburg dataset, three benchmark datasets. The CHB-MIT [25, 26] dataset consists of lengthy interictal and ictal EEG recordings, in contrast to the Bonn dataset [27, 28], which includes normal, interictal, and ictal EEG signals. Then, the signal decomposition is performed and Maximum Overlap Discrete Transformation (MODT) is applied to get the set of most relevant EEG features. Consequently, the Redone Butterfly Optimization (RBO) algorithm is employed to squeeze the dimensionality of features for improving the accuracy of seizure diagnosis framework. Moreover, the Gaussian Kernel Radial Network (GKRN) is utilized to categorize the type of signal as normal (i.e., healthy), interictal or ictal.

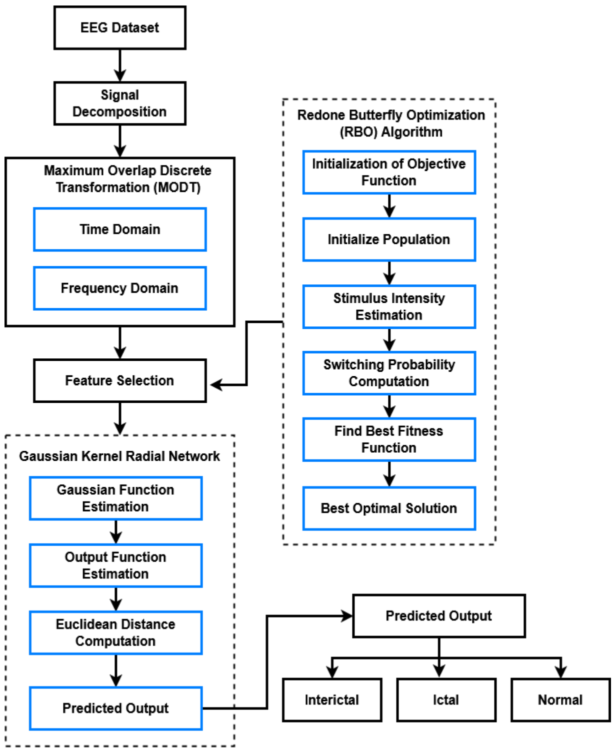

Figure 1. Workflow of the proposed framework.

A. *Maximum Overlap Discrete Transform (MODT) Based Feature Extraction*

Fig. 2 shows the estimation of the original signal, where the data coefficients of the EEG input signal were estimated using spectral 1-dimensional decomposition. To acquire the data coefficients of the signal, the input data has been modified. The original signal's wavelet coefficients update was obtained using the MODT method. Action potentials are widely assessed in terms of amplitude and phase representations using extraction and classification procedures. The wavelet packet transform and the time domain transform are two-line conversion techniques that can take a noisy signal and transform it into a processed signal. The wavelet decomposition method produces approximation and detail coefficients through a down sampling operation. The wavelet decomposition procedure makes use of lowpass and high pass wavelet decomposed filters. Before demodulating the signal, the approach distorts it using lowpass and high pass filters. In this study, the Daubechies wavelet was used in conjunction with the degradation process to extract the signal variables. Then, the low pass filter and the high pass filter have been concatenated with the EEG signal as represented in below:

$$S(n) = x(n) + \sigma N(n) \tag{1}$$

where, n denotes a symmetrical duration of continuous signal, σ denotes frequency, and $N(n)$ denotes Outliers. Reducing the signal's noise in order to calculate the original signal is the main objective of analysis methods. One kind of noise reduction technique uses a wavelet to break down a signal into N levels. This technique is known as the discrete wavelet transform. The result could be reformed using the interpolating constants as $A(j+1)[k]$ and $D(j+1)[k]$ with N levels, where $l[n-2k]$ and $h[n-2k]$ are the low pass and high pass filters respectively. Consequently, the resampling process is performed based on the following model:

$$A_{j+1}(x) = \sum_i s_j(n) \times l(n-2k) \tag{2}$$

$$D_{j+1}(x) = \sum_m s_j(n) \times h(n-2k) \tag{3}$$

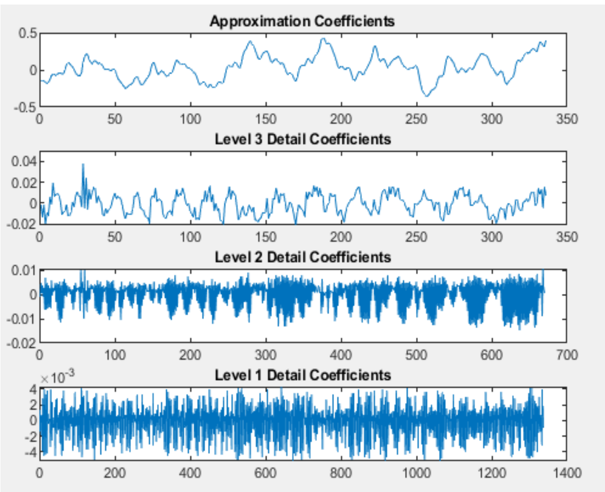

Figure 2. Approximate and detail coefficients.

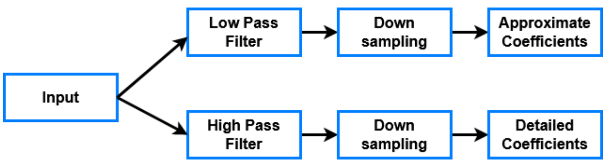

Figure 3. Wavelet decomposition.

Fig. 2 depicts the wavelet-based two different variables, in which the signal's high and low regularity portions were down sampled to obtain the approximate solution and detailed constants. Fig. 3 depicts the wavelet-based transformation algorithm, where various kinds of filters are employed for specific filteration, and the down sampling strategy enables us to procure partial derivatives and indepth indices of the EEG signal. Spectral abilities appear to be useful for attempting to balance the both frequency and time domains. The mother wavelet symbolizes the time domain as represented in the following model:

$$\int_{-\infty}^{\infty} \varphi(t)dt = 0 \tag{4}$$

The mother wavelet with scaling factor is estimated as shown in below:

$$\{\varphi_{s,u}(t) = \frac{1}{\sqrt{s}}\varphi(\frac{t-u}{s})\} \tag{5}$$

A low pass filter is used to extract the high frequency components of the signal; a high pass filter is used when the scaling factor is between 0 and 1. If the scaling factor is greater than 1, the filter is a low pass one. The wavelet must fulfill the regularity property in order to identify the regularities in the input signal. The maximum overlap discrete wavelet transform can generate detail coefficients and scaling coefficients and therefore is useful for decaying time series data. In order to denoise the signal with MODT, the wavelet must be orthogonal. It has the capacity to generate scaling and detail coefficients with lengths twice as long as the exact input signal. By using the threshold selection rule, the noise disturbance is removed in conjunction with the MODT. Then, Eq. (6) demonstrates the joint distribution of the basic functions at different intervals and interpretation, and Eq. (7) proves the thorough variable functions P_j at different intervals as represented in the following models:

$$P(x) = \sum_{i=0}^{M-1} c_i 2^{-J_0/2} \Phi(2^{-J_0}x - Q) + \sum_{i=1}^{i_0} P_i(x)) \tag{6}$$

$$P_j(x) = \sum_{i=0}^{N-1} d_{j,i} 2^{-j/2}\, \Psi(2^{-j}x - Q) \tag{7}$$

As shown in Eq. (8), it is possible to achieve the MODT detailed constants at the j^{th} level, whereas the actual threshold decomposed process's levelling constants that can be determined and the signal's duration is N as represented in below:

$$||z||^2 = \sum_{j=1}^{J_0} ||x_j||^2 + ||y_{J_0}||^2 \tag{8}$$

As shown in Eq. (9), $H(j,k)$ symbolises the wavelet function, and Eq. (10) resembles the coordinates at the j^{th} level.

$$\frac{1}{N}\sum_{K=0}^{N-1} H_{j,k}\, e^{i2\Pi nk/N} \tag{9}$$

$$\frac{1}{N}\sum_{K=0}^{N-1} G_{j,k}\, e^{i2\Pi nk/N} \tag{10}$$

By using this algorithm, the most essential features are extracted from the EEG signal with less computational burden.

B. Redone Butterfly Optimization (RBO) Algorithm

In this work, a brand-new nature inspired optimization technique, named as, RBO algorithm is utilized for optimizing the feature set by squeezing its dimensionality. Naturally, the RBO technique has the better capability to solve global optimization problems, and this algorithm is developed according to the foraging behavior of butterflies. The air fragrance is picked up by butterflies, who then process it to determine where they might find a food source or mate. In order to locate the optima in the hyper-search space, RBO imitates this behavior. In order to locate food and a mate, butterflies employ their senses of smell, perception, feel, sensation, and sound. These senses are also useful for moving from one location to another, avoiding predators, and laying eggs in the right locations. The most crucial sense among these is aroma, which enables butterflies to locate sustenance, typically nectar, even at great distances. Butterflies use odor-sensitive sense receptors, which are dispersed throughout the body parts of butterflies such as the wings, limbs, and palps, to determine the source of nectar. Sensory receptors are nerve cells that act as receptors on the outside of butterflies. The three key terms of sensory modality, stimulus intensity, and power exponent form the foundation of the entire idea of perceiving and processing the modality. Every butterfly is expected to provide some kind of odor that attracts other butterflies. Each butterfly will either migrate at random or in the direction of the butterfly with the strongest smell. The space of the fitness function influences or determines the butterfly's sensory intensity. Typically, the RBO algorithm is composed of three phases: (1) Setup; (2) Iteration; and (3) Final. Each BOA run begins with the initiation step, continues with iterative searching, and ends with the algorithm being terminated when the optimal solution has been identified. The goal function and its solution space are defined by the algorithm at the setup phase. Besides that, the values for the Bayesian Output Analysis (BOA) parameters are specified. The algorithm then creates a starting population of butterflies for optimization after choosing the parameters. A fixed size memory is allotted to store the data for the butterflies because the overall number of butterflies does not fluctuate throughout the Entire simulation. Butterfly places are produced at random in the search area, and fitness and fragrance values are computed and recorded. With the initialization step complete, the method moves on to the iteration phase, where the search is carried out using the produced artificial butterflies.

The method goes through several iterations in the second part, which is known as the iteration phase. All butterflies travel to new positions in solution space during each iteration, after which their optimum values are calculated. The procedure begins by determining the fitness values for each butterfly at various locations in the solution space. These butterflies will then produce fragrance where they are located. The method contains two essential phases such as global and local searching. During global search, the fittest function is updated by using the following model:

$$s_i^{k+1} = s_i^k + (rnd^2 \times cb^* - s_i^k) \times q_i \tag{11}$$

where, s_i^k represents the solution vector of i^{th} butterfly at k^{th} iteration, rnd is the random number, cb^* denotes the current best value, and q_i represents the fragrance of i^{th} butterfly. Similarly, the local search is also carried out by using the following model

$$s_i^{k+1} = s_i^k + (rnd^2 \times s_j^k - s_h^k) \times q_i \tag{12}$$

where, s_j^k and s_h^k indicates the solution space of j and h butterflies. Then, the switching probability is computed to perform switching between local and global searching operations. This iterative process can be continued until reaching the stopping criterion. According to this process, the best optimal solution is obtained as the output, which can be used to choose the features with reduced dimensionality.

C. Gaussian Kernel Radial Network (GKRN)

After squeezing the feature set, the GKRN technique is implemented to categorize the EEG signal as interictal, ictal or normal. In the classic works, several machine learning and deep-learning-based classification algorithms are developed for epileptic seizure identification and type categorization. However, many of the classification methodologies limit with the typical problems of increased overfitting, high computational time for training features, error rate, false positives, and incapable for handling huge datasets. Therefore, the proposed work aims to use simple and efficient classification algorithm for detection and categorization of epileptic seizures. Several hidden layers are active at once in the GKRN methodology, which is the fundamental advantage of this method of use. The input vector is first used as the basis for the overall mapping, which takes into account the total number of neurons, the central region, the neural weights, and the bias function. The Gaussian kernel is used in this classification strategy because it has a high degree of flexibility, and is estimated as shown in below:

$$Gaussian(\partial) = exp\left(-\frac{(\rho-\gamma)^2}{R}\right) \tag{13}$$

where, γ indicates the center, and R is the radius. The centre of each unit is then thought to be the hidden layer of GKRN, which is symbolized by $\gamma_1, \gamma_2, \dots, \gamma_h$. The following illustration shows the hidden layer's output:

$$\partial_i = \partial(\|\rho - \gamma_j\|) = exp\left(-\frac{\|\rho-\gamma_i\|^2}{2\rho_i^2}\right) \tag{14}$$

Consequently, the Euclidean distance is computed according to the distance between the input vector and i^{th} center. As a result, the following formula is used to calculate the standard deviation σ of the ith Gaussian function:

$$\sigma = Q_{mx}/\sqrt{num_\gamma} \tag{15}$$

where, Q_{mx} indicates the maximum distance between the centers and output of network, and num_γ represents the number of centers. Finally, the output of network k is produced based on the following model:

$$k = \sum_{i=1}^{n} \omega_i \cdot \partial(\|\rho - \gamma_i\|) \tag{16}$$

where, ω_i defines the updated weight value of i^{th} hidden unit. The set of waveform features is used as the input during classifier training, and the output model parameter is the result.

Following that, classifier testing is carried out to produce the classified label based on the testing data and model parameter.

The classifier produces the expected output with its related label based on the weight value and bias vector. Finally, the resultant label is obtained as normal, interictal or ictal.

IV. Result and Discussion

The seizure detection performance and efficiency of the classic and proposed diagnosing frameworks are validated and compared in this part. Here, three different datasets such as Bonn, CHB-MIT, and Freiburg have been used to assess the results of the proposed MODT-GKRN model. The Epileptology Department of Bonn University in Germany generated the freely accessible Bonn dataset, a benchmark dataset. There are five single channel EEG signal subsets in this dataset: A, B, C, D, and E. A and B are made up of normal EEG signals, C and D are interictal EEG samples, and E is made up of ictal EEG recordings taken while the patient was having seizures. Similar to the Bonn dataset, the Children's Hospital Boston-Massachusetts Institute of Technology dataset is a publicly accessible benchmark of EEG data (CHB-MIT). It includes the EEG records of 24 patients with various demographics. It offers lengthy interictal and ictal recordings of epileptic patients for several hours. This dataset has a sampling rate of 256 Hz. As the Bonn dataset was produced from 5 patients, just a small portion of the complete dataset, made up of five patients, is used in this paper for examination. Moreover, several performance metrics have been used to validate the results, which includes the followings:

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_p+F_N} \times 100\% \tag{17}$$

$$Precision = \frac{T_P}{T_P+F_P} \times 100\% \tag{18}$$

$$F1-score = \frac{2 \times Pre \times Sen}{Pre+Sen} \times 100\% \tag{19}$$

$$Recall = \frac{T_P}{T_P+F_N} \times 100\% \tag{20}$$

$$Sensitivity = \frac{T_P}{T_P+F_N} \times 100\% \tag{21}$$

$$Specificity = \frac{T_N}{T_N+F_P} \times 100\% \tag{22}$$

where, T_P—true positives, T_N—true negatives, F_P—false positives, and F_N—false negatives. Table I and Fig. 4 presents the comparative analysis among the classic [29] and proposed seizure diagnosing frameworks using Bonn dataset. For this evaluation, some of the most popular and standard machine learning techniques are compared with the proposed model. According to the observation, it is indicated that the MODT-GKRN overwhelms the other classifiers with highly improved results. The suggested model is contrasted with some of the most well-known and widely used machine learning techniques for this evaluation. The finding suggests that the MODT-GKRN outperforms the other classifiers with significantly better outcomes.

TABLE I. Comparative Analysis Using Bonn Dataset

Methods	Sensitivity	Specificity	Accuracy
SVM	93	93.5	92
RF	93	92	91
BLDA	94	93	93
DF	99	98	98
KNN	96	97	97
Proposed	99	99.2	99.5

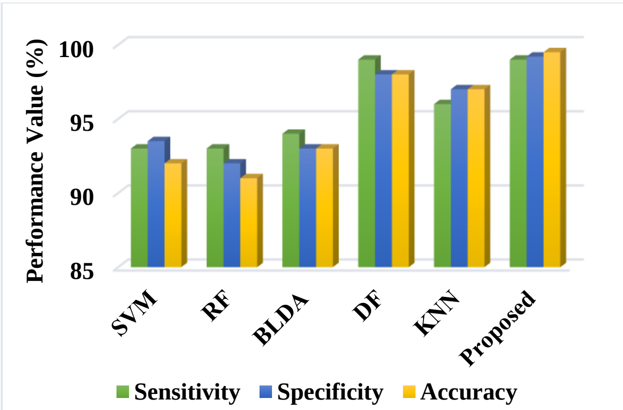

Figure 4. Comparative analysis among the classic and proposed models using Bonn dataset.

Fig. 5 presents the performance of traditional machine learning, fuzzy based classifiers, and proposed MODT-GKRN approaches using CHB-MIT dataset.

The goal of this research is to determine the length of an EEG segment that boosts the classification accuracy by improving signal interpretation. It has been noted that among conventional machine learning methods, MODT-GKRN has the highest classification accuracy for EEG recordings from the Bonn and CHB-MIT datasets. With the inclusion of discrete transformation and feature selection processes, the overall performance of the proposed MODT-GKRN model is effectively increased, when contrast to the other seizure prediction methodologies.

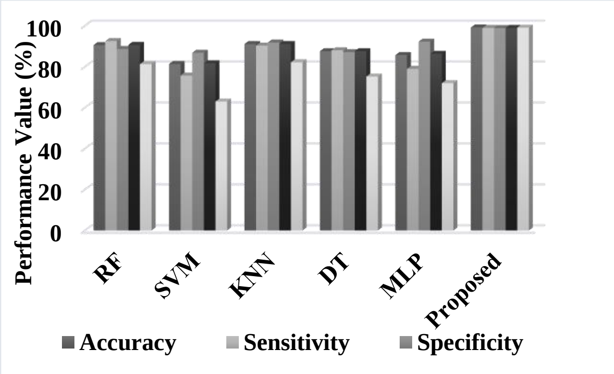

Figure 5. Performance analysis using CHB-MIT dataset.

Fig. 6 and Table II presents the overall comparative analysis among the baseline [30] and proposed MODT-GKRN methodologies by using Freiburg dataset. The obtained outcomes indicate that the proposed prediction method overwhelms the other classic approaches with highly improved results. Specifically, the proper training and testing of signal features with reduced dimensionality helps to obtain a better classification result.

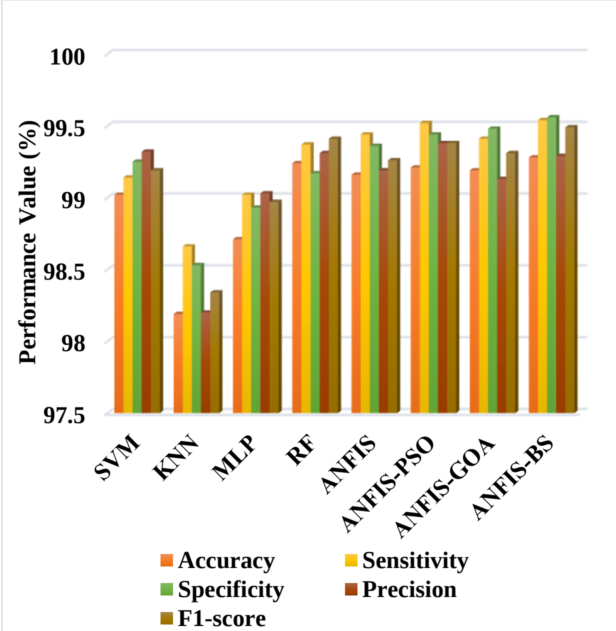

Figure 6. Overall performance analysis using Freiburg dataset.

TABLE II. COMPARATIVE ANALYSIS USING FREIBURG DATASET

Methods	Accuracy	Sensitivity	Specificity	Precision	F1-score
SVM	99.02	99.14	99.25	99.32	99.19
KNN	98.19	98.66	98.53	98.20	98.34
MLP	98.71	99.02	98.93	99.03	98.97
RF	99.24	99.37	99.17	99.31	99.41
ANFIS	99.16	99.44	99.36	99.19	99.26
ANFIS-PSO	99.21	99.52	99.44	99.38	99.38
ANFIS-GOA	99.19	99.41	99.48	99.13	99.31
ANFIS-BS	99.28	99.54	99.56	99.29	99.49

V. DIFFERENCE FROM PRIOR WORK

In comparison to prior work in the field of automated epileptic seizure diagnosis using EEG signals, the proposed MODT-GKRN framework offers several important differences and advancements.

Feature Extraction: The use of the Maximum Overlap Discrete Transform (MODT) for feature extraction sets this framework apart from previous approaches. The MODT approach is specifically tailored to extract epileptic seizure-related features that are most valuable. By focusing on the unique characteristics of seizures, it is expected to enhance the discriminative power of the extracted features and improve the accuracy of subsequent classification.

Dimensionality Reduction: The Redone Butterfly Optimization (RBO) technique is introduced in this work to address the dimensionality reduction of the extracted features. Dimensionality reduction is crucial to eliminate irrelevant or redundant features and enhance classification accuracy. The novelty lies in the application of RBO to select the optimal subset of features, considering their relevance to seizure diagnosis. This approach is likely to enhance the efficiency and performance of the overall system.

Classification Model: The Gaussian Kernel Radial Network (GKRN) is employed as the classification model in this framework. GKRN utilizes a Gaussian kernel function for non-linear mapping, which allows for more accurate forecasting of seizures and classification into proper classes. The use of GKRN presents a departure from previous studies that may have employed different classification algorithms. The novelty lies in the application of GKRN specifically to the task of epileptic seizure diagnosis.

VI. CONCLUSION

Seizures put on by epilepsy affect a patient's ability to maintain both their normal physical and mental health. The classification of EEG signals using machine learning-based methods has been widely used in the literature to identify epileptic seizures. Several machine learning-based techniques for examining and classifying EEG data with the aim of accuracy have already been introduced. However, EEG data is non-linear and non-stationary, it is difficult to gather full information on these dynamic biological signals. This study uses sophisticated feature extraction and classification methods to create an automated epileptic seizure diagnosis system. The most important features associated with epileptic seizures are extracted in this case using the

MODT method. In order to improve classification accuracy, the dimensionality of features is reduced using the RBO method. To accurately predict the seizure and assign it to the appropriate class, the GKRN is used. The input vector is first used as the basis for the overall mapping, which takes into account the total number of neurons, the central region, the neural weights, and the bias function. The Gaussian Kernel is used in this classification strategy because it has a high degree of flexibility. Here, three different datasets such as Bonn, CHB-MIT, and Freiburg have been used to assess the results of the proposed MODT-GKRN model. With the inclusion of discrete transformation and feature selection processes, the overall performance of the proposed MODT-GKRN model is effectively increased, when contrast to the other seizure prediction methodologies. The research presented in this paper addresses the challenge of automated epileptic seizure diagnosis using EEG signals. The proposed MODT-GKRN framework offers advancements in feature extraction, dimensionality reduction, and classification techniques, with the goal of improving the accuracy and efficiency of seizure detection and classification.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Sandhya Kumari Golla collected and analyzed the data, wrote the manuscript, and developed the concept for the study. Suman Maloji supervised the research project and revised the manuscript. All authors had approved the final version.

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