IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 25 April 2023, accepted 24 May 2023, date of publication 30 May 2023, date of current version 7 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3281450

RESEARCH ARTICLE

Efficient Seizure Prediction and EEG Channel Selection Based on Multi-Objective Optimization

RANJAN JANA [1,2] **AND IMON MUKHERJEE** [1]

[1]Department of CSE, Indian Institute of Information Technology Kalyani, Kalyani, West Bengal 741235, India
[2]Department of IT, RCC Institute of Information Technology, Kolkata 700015, India

Corresponding author: Ranjan Jana (ranjan.rcciit@gmail.com)

ABSTRACT Epileptic seizures are unpredictable events due to sudden abnormal electrical activities in the brain of epilepsy patients. A seizure can be predicted by analyzing the EEG signals to prevent unwanted life risks. The goal of this paper is to implement a method that will apply to design a lightweight, wearable, and efficient seizure prediction device. The proposed method will satisfy two objectives. The first objective is relevant feature extraction for the classification of EEG signals with excellent accuracy. The second objective is the use of fewer EEG channels. In this paper, one 1D-CNN is applied for feature extraction and classification of raw EEG signals for early prediction of seizure events. The 1D-CNN is faster compared to 2D-CNN, which uses fewer trainable parameters. Hence, it is suitable to implement a low-power energy-efficient seizure prediction device. In this paper, the NSGA-II algorithm is applied to get the optimum set of EEG channels for seizure prediction. The NSGA-II algorithm identifies a set of three EEG channels from twenty-two channels as the optimum channel set. The proposed method optimizes the EEG channels from 22 to 3, i.e., 86.36% channel reduction. It provides the classification accuracy, sensitivity, and specificity of 0.9651, 0.9655, and 0.9647, respectively. The proposed method is better than the state-of-the-art works under the condition of using three channels. The proposed method provides excellent performance using only three EEG channels, which will be applicable to design a lightweight, low-power, and wearable seizure prediction device.

INDEX TERMS Channel selection, EEG signals, multi-objective optimization, NSGA-II algorithm, seizure prediction, 1D-CNN.

I. INTRODUCTION

Epileptic seizure in recurrent is a neurological disorder of epilepsy patients [1], [2]. Seizures occur due to excessive electrical impulses inside the brain. These electrical impulses can be measured by placing metal electrodes on the scalp. The recording of these impulses is called an electroencephalogram (EEG). The seizure is usually detected by analysis of EEG signals [1], [2], [3]. The occurrences of seizure events are violent shaking, loss of control, and loss of consciousness. Hence, seizures reduce the quality of life of epilepsy patients. There are 65 million epilepsy patients worldwide [4]. It is required to predict the seizure events in advance to avoid the life risks of these patients. The states of epilepsy patients are classified into four [5], [6]. The state during the seizure event is called the ictal state. The states before and after the seizure event are called pre-ictal and post-ictal states, respectively. The normal state of the epilepsy patient is called the inter-ictal state. Identification of the pre-ictal state is the main task of seizure prediction in advance [3]. Hence, the seizure prediction method is a classification task of inter-ictal and pre-ictal states. The EEG signal patterns of these four states are different, as shown in Fig. 1. The inter-ictal and pre-ictal states can be classified based on the unique features of EEG signals. The unique features need to be extracted from EEG signals very carefully due to unique patterns for individual epilepsy patients.

In the beginning, researchers extracted various handcrafted features from EEG signals for seizure prediction. The most commonly used handcrafted features were spectral features

The associate editor coordinating the review of this manuscript and approving it for publication was Md. Kafiul Islam.

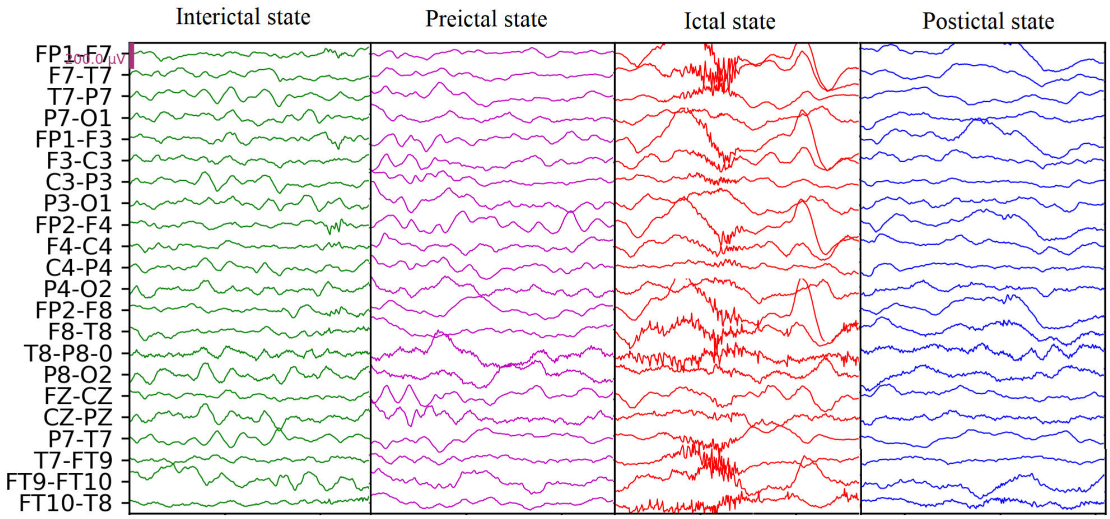

FIGURE 1. Sample pattern of EEG signals from patient CHB01 (22 channels).

[7], [8], wavelet transform features [9], [10], zero crossing rate [11], [12], spatial features [3], [13], fuzzy entropy features [14], and correlation features [15] of EEG signals. They exhibited the performance of their seizure prediction model based on the classification of handcrafted features using some machine learning algorithms. The most commonly used machine learning algorithms were Multilayer perceptron [7], [15], Support vector machine [8], [10], k-nearest neighbor [16], [17], and linear discriminant analysis [18]. Although, it was very difficult to prove which features provided good performance for all epilepsy patients. Hence, most of the researchers used deep learning techniques, which were used to extract the most relevant features from the EEG signals for the classification of pre-ictal and inter-ictal states to predict seizures in advance. The most commonly used deep learning techniques are Convolution neural networks [19], [20], [21], LSTM [22], [23], [24], DenseNet [24], [25], Self-Organizing Maps [26], and Long-term recurrent convolutional networks [27]. It was found that the use of deep learning techniques provided better accuracy for seizure prediction. Few researchers used deep learning techniques for feature extractions from some transformed EEG signals though DL has the capability to extract relevant features from raw EEG signals. The most commonly used transformations are discrete wavelet transforms [26], [27], continuous wavelet transforms [28], and short-term Fourier transforms [4], [29]. All channels of EEG are not relevant for seizure prediction [20], [30], [31]. Hence, one channel selection technique can be applied to identify the relevant channels. A few researchers used channel selection algorithms to find the optimized channel set for efficient seizure prediction [32], [33], [34], [35].

The accuracy in seizure prediction is not only the most important factor for the development of a wearable headband. The other two factors are the required computational power and the number of EEG channels. Hence, our aim is to decrease the computational cost and optimize the number of channels for the implementation of a lightweight, low-power, and wearable seizure prediction device. In this work, one 1D-CNN is used for automatic feature extraction from EEG signals for seizure prediction. The non-dominated sorting genetic algorithm (NSGA-II) is also used to optimize the number of EEG channels, which will help to implement wearable seizure prediction devices. The remaining part of the paper is organized as follows. The proposed methodology is described in section II. In this section, the pre-processing of EEG data, the architecture of the deep learning model, and the optimization algorithm for channel selection are discussed. The experimental results are shown in section III. The detailed results are discussed in section IV. The comparison study of the proposed work with the state-of-the-art works is also shown in this section. Finally, the conclusion of the proposed work and the direction of future works are mentioned in section V.

II. PROPOSED METHODOLOGY

In this paper, we have proposed a patient-dependent seizure prediction method. Most of the state-of-the-art works on seizure prediction have used the standard CHB-MIT database [36]. This database is a collection of EEG recordings from 23 patients. It consists of two types of EEG recordings: seizure and non-seizure. The seizure recordings have at least one seizure event, whereas the non-seizure recordings were recorded during the normal situation of the epilepsy patients. The EEG signals were recorded at 256 Hz. The position of electrodes on the scalp was based on the international 10-20 systems. All recordings were captured using at least 23 channels, where each channel consists of two different electrodes. In this section, the pre-processing of EEG signals has been mentioned in the first part. The proposed deep learning approach is mentioned in the next part, which is used for feature extraction and classification of pre-ictal and inter-ictal states for seizure prediction. Finally, one channel optimization technique is applied to use less number

TABLE 1. Names of 22 unique channels.

Id	Name	Id	Name
1	FP1-F7	12	P4-O2
2	F7-T7	13	FP2-F8
3	T7-P7	14	F8-T8
4	P7-O1	15	T8-P8
5	FP1-F3	16	P8-O2
6	F3-C3	17	FZ-CZ
7	C3-P3	18	CZ-PZ
8	P3-O1	19	P7-T7
9	FP2-F4	20	T7-FT9
10	F4-C4	21	FT9-FT10
11	C4-P4	22	FT10-T8

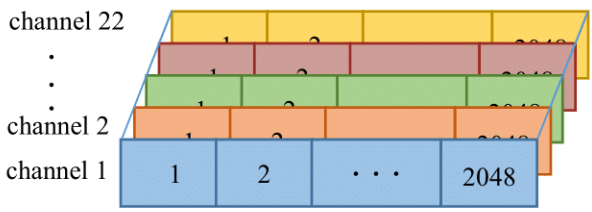

FIGURE 2. Representation of 8-s EEG data with 22 channels.

of channels to implement lightweight, low-power, and wearable seizure prediction devices.

A. DATA PRE-PROCESSING

In this work, we have used EEG recordings of 23 patients. The classification of pre-ictal and inter-ictal states is the main task of seizure prediction. The duration of pre-ictal states is unique for each seizure event. It was found that the pre-ictal state lasts at least 10 minutes before each seizure event [28]. Hence, we have considered 10 minutes of EEG signals before the seizure as pre-ictal data. The EEG signals of 10 minutes duration from non-seizure recordings are considered for inter-ictal data. It is found that the range of signal intensities in seizure and non-seizure EEG recordings is 110^{-4} volt. Hence, we have multiplied by 10^4 for standardization to get faster convergence during the training of the model. Individual researchers have used different sample duration of EEG signals for seizure prediction. It was found that the sample duration of 8-s EEG signals is sufficient for efficient prediction [20]. Hence, we have considered 8-s EEG signals as one sample in our proposed method. One 8-s duration of EEG signals consists of $2048(8 \times 256)$ intensities values as the signals were recorded using 256 Hz. In this work, a total of 22 channels has been considered as mentioned in Table 1. These channels are fixed in all EEG recordings of 23 patients. Hence, a sample of 8-s EEG signals for 22 channels is represented by 2048×22, as shown in Fig. 2. These samples are used for training the model.

B. FEATURES EXTRACTION AND CLASSIFICATION

Deep learning is capable to extract relevant features from EEG signals for seizure prediction [37]. Recently, CNN is the most commonly used deep learning technique for seizure prediction [19], [38], [39]. Most of the researchers have used 2D-CNN and 3D-CNN for feature extraction. 2D-CNN and 3D-CNN can extract the most relevant features which provide excellent performance. Although, they use millions of parameters. The limitation of 2D-CNN and 3D-CNN is the high computational complexity. Hence, 2D-CNN and 3D-CNN will not be suitable to implement low-power/low-memory devices. The 1D-CNN can achieve excellent performance in several applications [21], [40]. Our main aim is to implement a seizure prediction device which will be low-cost hardware. Hence, it is better to use the 1D-CNN for feature extraction from EEG signals.

We have used one 1D-CNN model for automatic feature extraction from EEG signals and classification of features for seizure prediction, as shown in Fig. 3. The proposed 1D-CNN model consists of six convolution layers. The convolution layers are the most important part of CNN, which is required for feature extraction from input data using a set of filters. The size of 1D filters is 3. The Rectified Linear Unit (ReLU) is applied in all convolution layers for non-linearity in the output. The proposed 1D-CNN model consists of six pooling layers. The pooling layer is also important in CNN which reduces the computational cost of the model by reducing the number of parameters using down-sampling. We have used the max-pool operation which is one of the most commonly used pooling operations in CNN. The size of the max-pool region is 3. Hence, the number of parameters reduces by 3 times in every max-pool operation which reduces a huge computation cost. Finally, the fully connected layers are used for feature classification. The proposed 1D-CNN model consists of two fully connected layers. A total of 128 nodes is used in the first layer with the ReLU activation function for non-linearity. In this work, pre-ictal and inter-ictal are the two output classes. Hence, the final fully connected layer contains only two nodes. The Softmax activation function is used in the final fully connected layer, which generates the output class probabilities of pre-ictal and inter-ictal classes. In this work, the Binary Cross Entropy measurement is used to calculate the total loss for this two-class classification problem.

C. CHANNEL OPTIMIZATION

The main aim is to implement a lightweight wearable seizure prediction device using less number of EEG channels. The EEG signals are recorded using many channels. It was found that all the channels are not relevant for seizure prediction [20], [30], [31]. Hence, it is required to select a set of relevant channels for efficient seizure prediction. There will be a total of $2^n - 1$ number of unique sets using n channels by selecting the set of $1, 2, 3, \ldots, n-1$, and n channels, as shown in (1). It is an NP-Hard problem. For 22 EEG channels, there is a $(2^{22} - 1)$ combination of sets. It will require a huge amount of time to find the optimized channel set.

$$Number\ of\ combinations = \sum_{i=1}^{n} {}^{n}C_i \tag{1}$$

The accuracy decreases if we remove further channels after the reduction of non-relevant channels [20]. The problem is

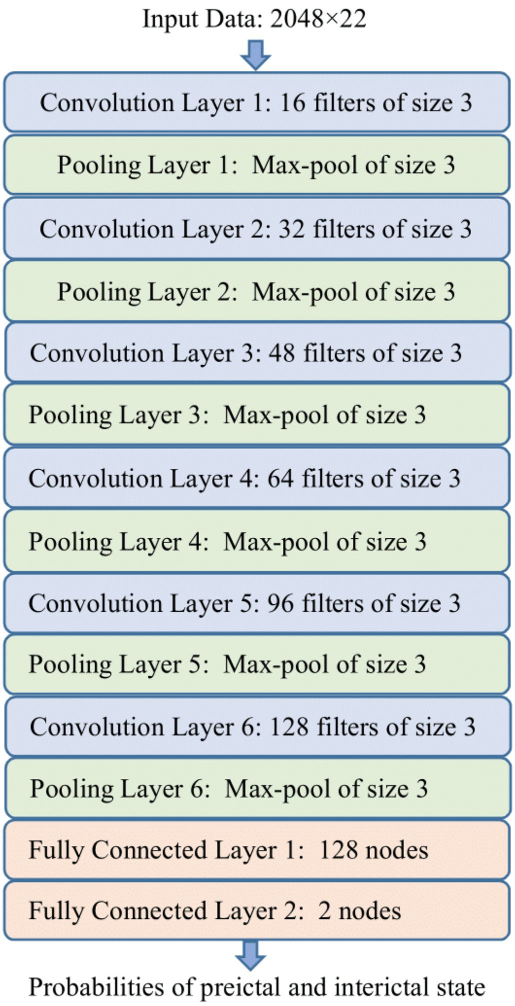

FIGURE 3. Architecture of proposed 1D-CNN.

a two objectives optimization problem. The first objective is to increase the classification accuracy and the second objective is to use less number of EEG channels for seizure prediction. Hence, it is required to apply a multi-objective optimization algorithm to find the optimized channel set. The optimized channel set will provide high classification accuracy using less number of EEG channels. NSGA-II is a fast and elitist multi-objective optimization algorithm [41]. A few researchers applied the NSGA-II optimization algorithm for channel reduction in seizure prediction [42], [43]. In this paper, we have used the NSGA-II optimization algorithm to find the optimal channel sets. The working procedure of the NSGA-II algorithm is mentioned in Algorithm 1.

The problem is defined as the minimization of the number of EEG channels and the maximization of the classification accuracy. The problem is converted into the minimization of two objective functions f_1 and f_2, where f_1 is represented as the number of EEG channels and f_2 is represented as the classification error rate. The error rate is defined as shown in (2).

$$Error\ Rate = 1 - ClassificationAccuracy \tag{2}$$

Algorithm 1 NSGA-II Algorithm

Initialize all parameters and randomly generate the initial population with size N.
Fitness functions evaluation for the initial population.
while *generation* $\leq$ *MaxGeneration* **do**
    Parent selections for next-generation using tournament selection with size 2.
    Perform one-point crossover and random mutation operations to generate new offspring with size N.
    Evaluate fitness function for offspring.
    Combine parent and offspring population that makes the population size $2N$.
    Select N Chromosomes from the combined population using the crowding distance method to keep again N chromosomes for the next generation.
end while
Identify all solutions of the Pareto optimal front.

Algorithm 2 Crowding Distance Measure

Input a non-dominate set of points I for a Pareto front.
Find the value of n, where n is the number of points that belong to I.
Initialize the distance $d_i = 0$ for all points, where $i = 1$ to n.
for $j = 1$ to m (where m = number of objectives) **do**
    Sort I according to the objective f_j
    d_1 and $d_n = \infty$
    for $i = 2$ to $n - 1$ **do**
        $d_i = d_i + \frac{(|f_j(I(i+1)) - f_j(I(i-1))|)}{(|f_j^{max} - f_j^{min}|)}$
    end for
end for
Return d

In this work, each binary chromosome is represented using 22 genes. The 22 genes are representing 22 EEG channels. The initial population is chosen randomly and the population size is 12, which is chosen experimentally. The parents are selected for crossover operation using tournament selection of size 2. Here, the single-point crossover operation is used. The random mutation technique is used, where the mutation probability is 0.1. The parents and offspring populations are combined after crossover and mutation operations. After that, the selection operations are applied based on crowding distance to keep the fixed population size for the next generation. The crowding distance is used to measure the distance with its neighbors as mentioned in Algorithm 2. Finally, all solutions of the Pareto optimal front are reported after a fixed number of generations.

III. RESULT

The proposed 1D-CNN is trained using two seizure and two non-seizure recordings from each patient. The EEG signals with a duration of 10 minutes are considered from each seizure and non-seizure recording. The EEG signals with a

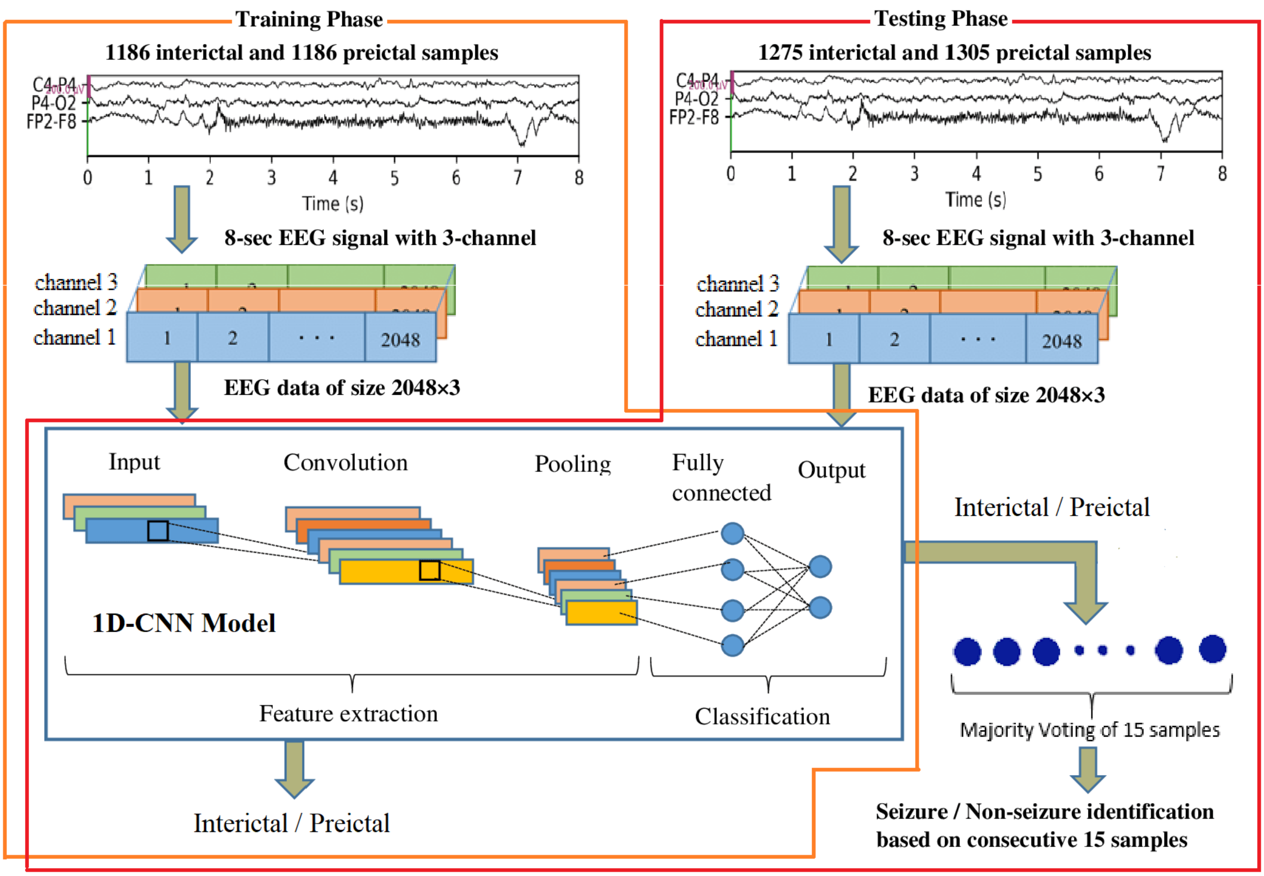

FIGURE 4. **Schematic representation of the proposed seizure prediction method.**

duration of 10 minutes consist of 593 training samples of 8-s duration each by considering a gap of 1-s. Hence, a total of 1186 pre-ictal and 1186 inter-ictal samples are taken from two seizure and two non-seizure recordings for training and validation checking as mentioned in Fig. 4. The training and validation data samples are divided into an 80:20 ratio. The performances are measured using classification accuracy (Acc), precision (Prec), sensitivity (Sen), specificity (Spec), and F1-score which are calculated using (3), (4), (5), (6), and (7), respectively. Here, *TP* stands for true prediction and *FP* stands for false prediction.

$$Acc = \frac{TP \text{ of pre-ictal and inter-ictal states}}{\text{Total no. of samples}} \tag{3}$$

$$Prec = \frac{TP \text{ of pre-ictal state}}{TP \text{ of pre-ictal state} + FP \text{ of pre-ictal state}} \tag{4}$$

$$Sen = \frac{TP \text{ of pre-ictal state}}{TP \text{ of pre-ictal state} + FP \text{ of inter-ictal state}} \tag{5}$$

$$Spec = \frac{TP \text{ of inter-ictal state}}{TP \text{ of inter-ictal state} + FP \text{ of pre-ictal state}} \tag{6}$$

$$F1 - Score = \frac{2 \times Prec \times Sen}{Prec + Sen} \tag{7}$$

Initially, the classification accuracies of the 2D-CNN model and 1D-CNN model using 22 EEG channels are mentioned in Table 2. It is observed that the average accuracy for 23 patients is 0.9963 using 2D-CNN and 0.9950 using 1D-CNN. The average classification accuracy of 1D-CNN is reduced by 0.13%, which is negligible. The 1D-CNN is 10 times faster compared to the 2D-CNN for testing a sample. Hence, 1D-CNN is proposed which consists of a very less number of parameters as shown in Table 3 and will be applicable to design lightweight, low-power, and wearable seizure prediction devices. The NSGA-II algorithm is applied for 100 generations to get the optimal channel set. It is found that after 80 generations our NSGA-II model is converged, as shown in Fig. 5. We have considered only five patients(Chb01 to Chb05) to calculate the classification error rate during 100 generations of the NSGA-II algorithm due to huge computational time. The hypervolume (HV) indicator is a widely recognized measure for performance evaluation in multi-objective optimization [44]. It is a unary value that measures the quality of the solutions to the optimal set. The HV indicator is calculated using (8). We have considered only two objectives (channel minimization and error rate minimization) for optimization. Hence, the HV

TABLE 2. Classification accuracy using 22 channels.

Patient ID	2D-CNN	1D-CNN
Chb01	1.0000	1.0000
Chb02	0.9970	0.9970
Chb03	0.9996	0.9996
Chb04	0.9983	0.9949
Chb05	0.9970	0.9932
Chb06	0.9992	0.9949
Chb07	0.9996	0.9983
Chb08	1.0000	0.9996
Chb09	1.0000	0.9996
Chb10	0.9992	0.9966
Chb11	0.9890	0.9970
Chb12	0.9996	0.9970
Chb13	0.9992	0.9954
Chb14	0.9869	0.9751
Chb15	0.9979	0.9987
Chb16	0.9920	0.9949
Chb17	0.9958	0.9924
Chb18	0.9903	0.9937
Chb19	0.9983	1.0000
Chb20	1.0000	1.0000
Chb21	0.9890	0.9857
Chb22	0.9941	0.9954
Chb23	0.9924	0.9861
Mean	**0.9963**	**0.9950**

TABLE 3. Comparison of 2D-CNN vs. 1D-CNN.

Learning Model	Number of parameters	Acc	Training time	Testing time
2D-CNN	245650	0.9963	3850-s	9.8600-ms
1D-CNN	105250	0.9950	200-s	0.9511-ms

indicator calculates the area of the objectives space covered by members of the Pareto optimal solutions with respect to a reference point (r1, r2). In our optimization problem, r1 is the maximum number of channels which is 22 and r2 is the maximum error rate which is 1. The HV indicator values are calculated for Pareto optimal front in every generation. It is observed that our optimization technique is acceptable and provides an HV indicator value of 0.9522 after 100 generations, as shown in Fig. 6.

$$H(S, r) = \Lambda\left(\bigcup_{p\in S \text{ and } p\leq r}[p, r]\right) \tag{8}$$

where $\Lambda(\cdot)$ denotes the Lebesgue measure and $[p, r] = \{q \in \mathbb{R}^d \mid p \leq q \text{ and } q \leq r\}$ denotes the box delimited below $p \in S$ and above by r [44].

The fitness value of a channel set is considered based on the average classification accuracy of five patients (Chb01 to Chb05). Only seven sets are identified as optimal sets of channels after 100 generations. The accuracies of these seven sets of channels are shown in Table 4. These are validation accuracies during the training of the CNN model. Here, 20% of samples are considered as validation data. The overall performance of seven sets of channels is also measured using 23 patients, as shown in Table 5.

A. PERFORMANCES USING SAMPLE DURATION OF 8-S

The performance of our proposed method is measured by testing our prediction model using unknown EEG signals. A total

TABLE 4. Accuracy of 7 sets of channels by considering 5 patients.

Channel IDs	Number of channels	Acc
13	1	0.9830
12,13	2	0.9947
11,12,13	3	0.9956
9,12,13,17	4	0.9969
4,9,12,13,17	5	0.9983
1,2,3,7,9,11,12,13,18,21	10	0.9987
2,4,7,8,14,16,17,18,19,21,22	11	0.9988

of 87 seizure recordings and 85 non-seizure recordings are used for testing. The EEG signals of 2 minutes duration are selected randomly from each non-seizure recording. The main aim of this paper is to alert epilepsy patients before the seizure event to take necessary precautions. Hence, the EEG signals of 2 minutes duration before ten minutes of the seizure event are selected from each seizure recording for testing. A total of 1305 pre-ictal samples and 1275 inter-ictal samples are used to calculate the testing accuracy of our proposed model. The overall performances of the seven sets of channels are shown in Table 6.

B. PERFORMANCES USING MAJORITY VOTING TECHNIQUE

In our proposed method, EEG signals with an 8-s duration are considered as one sample for training and testing the CNN model. Medical experts suggest that EEG signals with long duration should be considered for efficient seizure prediction. Here, we have not increased the duration of the samples of EEG signals due to the implementation of a simple 1D-CNN model with less number of parameters and layers. A majority voting technique is considered here which increases the performance of the proposed 1D-CNN model. The majority of 15 consecutive samples are considered for the correct prediction of seizure events. The overall performance using the majority voting technique is shown in Table 7.

IV. DISCUSSION

In this work, a seizure prediction method is proposed which will be applicable to implement a lightweight, low-power, and wearable seizure prediction device. Jana et al. [20] used 2D-CNN for seizure prediction, which has a large number of parameters. Here, one 1D-CNN is used, which has a very less number of parameters, as shown in Table 3. Hence, the computational cost is reduced in our proposed method. The 1D-CNN is 10 times faster compared to the 2D-CNN for testing a sample. Although, the classification accuracy is reduced by 0.13%, which is acceptable to implement a seizure prediction device with low computational cost.

In this work, the NSGA-II algorithm is applied to find several optimal channel sets for efficient seizure prediction. A total number of 7 optimal channel sets are selected after 100 generations as shown in Fig. 5. It is found that the accuracy, precision, sensitivity, specificity, and F1-Score are better using a set of ten channels as mentioned in Table 7. Although, it will be a very challenging task to design a less-power consumable and lightweight wearable seizure

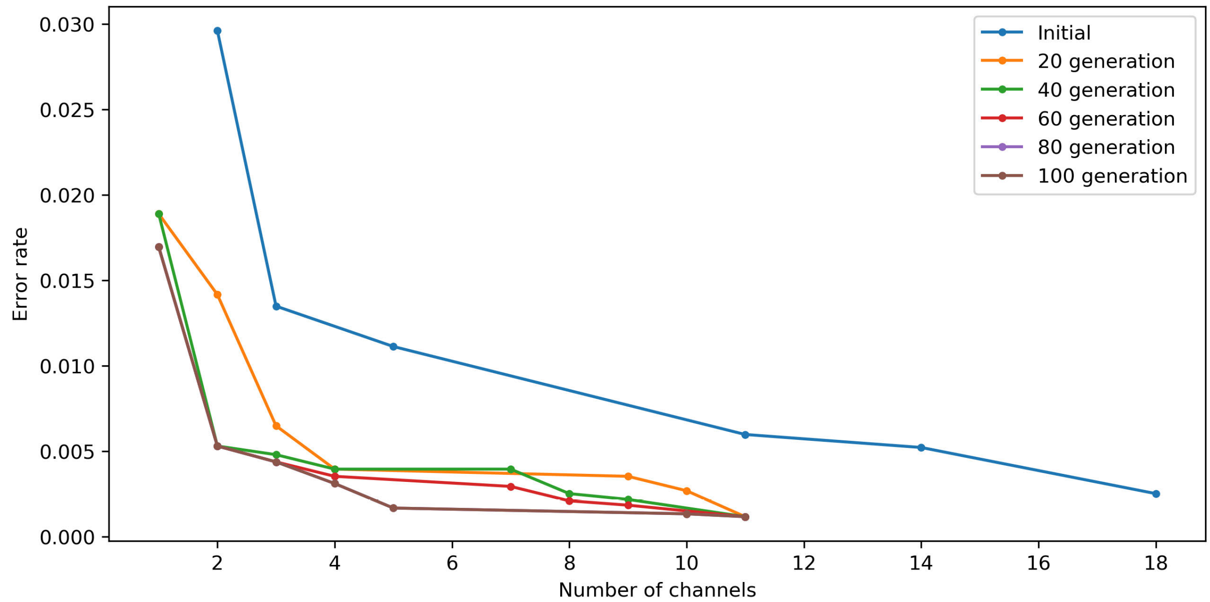

FIGURE 5. Number of channels vs. error rate in different generations of NSGA-II.

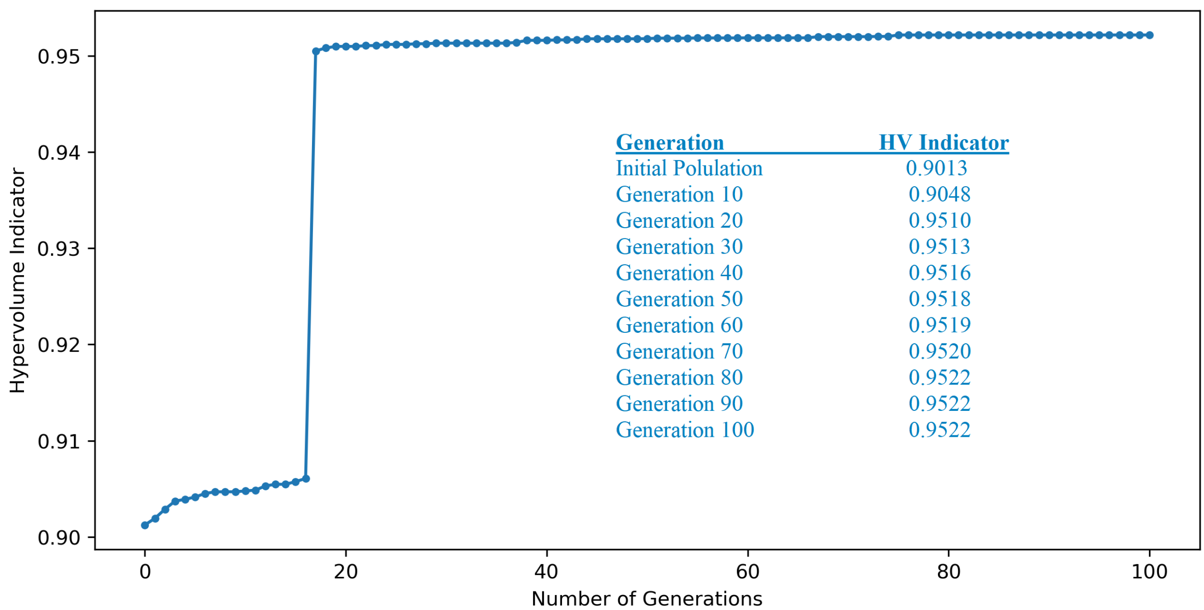

FIGURE 6. Generation-wise hypervolume indicator values.

TABLE 5. Performance measures by considering 23 patients during training.

Channel IDs	Number of channels	Acc	Prec	Sen	Spec	F1-Score
13	1	0.9432	0.9457	0.9404	0.9462	0.9428
12,13	2	0.9640	0.9658	0.9621	0.9659	0.9638
11,12,13	3	0.9715	0.9738	0.9690	0.9740	0.9713
9,12,13,17	4	0.9748	0.9761	0.9737	0.9760	0.9748
4,9,12,13,17	5	0.9795	0.9807	0.9784	0.9804	0.9794
1,2,3,7,9,11,12,13,18,21	10	0.9906	0.9915	0.9898	0.9915	0.9906
2,4,7,8,14,16,17,18,19,21,22	11	0.9922	0.9936	0.9908	0.9937	0.9921

prediction device using ten channels. Hence, we have considered the optimized channel set with three channels, which provides better results compared to optimized channel sets with one channel, two channels, four channels, and five channels for accuracy, precision, sensitivity, specificity, and F1-Score. The proposed method provides the average sensitivity and specificity of 0.9655 and 0.9647, respectively, using only 3 EEG channels, as shown in Table 7. A comparison

TABLE 6. Performance measures by considering 23 patients during testing.

Channel IDs	Number of channels	Acc	Prec	Sen	Spec	F1-Score
13	1	0.8395	0.8607	0.8146	0.8651	0.8370
12,13	2	0.8717	0.9052	0.8337	0.9106	0.8680
11,12,13	3	0.8942	0.9135	0.8736	0.9153	0.8931
9,12,13,17	4	0.9089	0.9246	0.8927	0.9255	0.9084
4,9,12,13,17	5	0.9198	0.9223	0.9188	0.9208	0.9205
1,2,3,7,9,11,12,13,18,21	10	0.9120	0.9256	0.8981	0.9263	0.9117
2,4,7,8,14,16,17,18,19,21,22	11	0.9182	0.9221	0.9157	0.9208	0.9189

TABLE 7. Performance measures by considering 23 patients using majority voting technique.

Channel IDs	Number of channels	Acc	Prec	Sen	Spec	F1-Score
13	1	0.8895	0.8953	0.8851	0.8941	0.8902
12,13	2	0.9244	0.9625	0.8851	0.9647	0.9222
11,12,13	3	0.9651	0.9655	0.9655	0.9647	0.9655
9,12,13,17	4	0.9651	0.9655	0.9655	0.9647	0.9655
4,9,12,13,17	5	0.9709	0.9556	0.9885	0.9529	0.9718
1,2,3,7,9,11,12,13,18,21	10	0.9767	0.9770	0.9770	0.9765	0.9770
2,4,7,8,14,16,17,18,19,21,22	11	0.9651	0.9655	0.9655	0.9647	0.9655

TABLE 8. Performance of proposed work and state-of-the-art works on CHB-MIT database.

Research work	Year	Pre-processing / Feature extraction	Learning technique	Number of channels	Number of patients	Sen	Spec
Usman *et al.* [4]	2020	STFT	SVM	23	24	0.9270	0.9080
Zhang *et al.* [38]	2020	WPD and CSP	CNN	18	23	0.9220	0.8800
Yao *et al.* [22]	2021	Raw EEG data	Bi-LSTM	17	24	0.8730	0.8830
Jana *et al.* [20]	2021	Raw EEG data	2D-CNN	06	23	0.9783	0.9236
Ryu *et al.* [24]	2021	DWT	DenseNet and LSTM	22	24	0.9292	0.9365
Usman *et al.* [39]	2021	EMD + CNN	SVM + CNN + LSTM	23	22	0.9628	0.9565
Guo *et al.* [27]	2022	DWT	EasyEnsemble	18	24	0.9555	0.9257
Zhao *et al.* [45]	2022	Raw EEG data	AddNet-SCL	23	19	0.9490	0.9230
Shen *et al.* [46]	2023	Tunable-Q wavelet transform	CNN	8	16	0.9890	0.9790
Kapoor *et al.* [47]	2023	Statistical features	Ensemble classifier	22	23	0.9467	0.9136
Proposed method	2023	Raw EEG data	1D-CNN	**03**	23	**0.9655**	0.9647

table with our proposed method and the state-of-the-art works is shown in Table 8. All the state-of-the-art works mentioned in Table 8 used the same database i.e. CHB-MIT database. It is observed that our proposed method is more efficient compared to others under the condition of using three channels. The proposed method demonstrates that it is capable to learn the patterns of EEG signals using only a few electrodes for efficient seizure prediction. Hence, it will be applicable to implement a wearable seizure prediction device that will be low computational cost and energy efficiency.

V. CONCLUSION

This paper presents an optimal seizure prediction method using raw EEG signals. The 1D-CNN is more applicable for designing low-power/low-memory seizure prediction devices. Hence, one 1D-CNN is applied here for automatic feature extraction and classification of EEG signals. The NSGA-II multi-objective optimization algorithm is applied to find the optimal channel set for seizure prediction. The EEG recordings of 23 patients from the CHB-MIT database are used during training and testing to measure the performance of our proposed method. It provides an average sensitivity and specificity of 0.9655 and 0.9647, respectively. The proposed method optimizes the EEG channels from 22 to 3, i.e., 86.36% channel reduction. The proposed method provides excellent performance using only three EEG channels, which is better than the state-of-the-art works. Hence, it will be applicable to implement a lightweight, low-power, and wearable seizure prediction device. However, this is a patient-dependent seizure prediction method. Hence, the future scope of this work is to develop a patient-independent seizure prediction method with excellent performance for all epilepsy patients.

REFERENCES

[1] L. D. Iasemidis, "Epileptic seizure prediction and control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 5, pp. 549–558, May 2003.

[2] A. Gardner, A. Krieger, G. Vachtsevanos, and B. Litt, "One-class novelty detection for seizure analysis from intracranial EEG," *J. Mach. Learn. Res.*, vol. 7, pp. 1025–1044, Jun. 2006.

[3] J. R. Williamson, D. W. Bliss, D. W. Browne, and J. T. Narayanan, "Seizure prediction using EEG spatiotemporal correlation structure," *Epilepsy Behav.*, vol. 25, no. 2, pp. 230–238, Oct. 2012.

[4] S. M. Usman, S. Khalid, and M. H. Aslam, "Epileptic seizures prediction using deep learning techniques," *IEEE Access*, vol. 8, pp. 39998–40007, 2020.

[5] J. Rasekhi, M. R. Mollaei, M. Bandarabadi, C. A. Teixeira, and A. Dourado, "Epileptic seizure prediction based on ratio and differential linear univariate features," *J. Med. Signals Sensors*, vol. 5, pp. 1–11, Jan. 2015.

[6] S. M. Usman, M. Usman, and S. Fong, "Epileptic seizures prediction using machine learning methods," *Comput. Math. Methods Med.*, vol. 2017, pp. 1–10, Dec. 2017.

[7] L. Huang, Q. Sun, J. Cheng, and Y. Huang, "Prediction of epileptic seizures using bispectrum analysis of electroencephalograms and artificial neural network," in *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Mar. 2003, pp. 2947–2949.

[8] Z. Zhang and K. K. Parhi, "Low-complexity seizure prediction from iEEG/sEEG using spectral power and ratios of spectral power," *IEEE Trans. Biomed. Circuits Syst.*, vol. 10, no. 3, pp. 693–706, Jun. 2016.

[9] S. Nasehi and H. Pourghassem, "Automatic prediction of epileptic seizure using kernel Fisher discriminant classifiers," in *Proc. Int. Conf. Intell. Comput. Bio-Med. Instrum.*, Dec. 2011, pp. 200–203.

[10] S. Janjarasjitt, "Epileptic seizure classifications of single-channel scalp EEG data using wavelet-based features and SVM," *Med. Biol. Eng. Comput.*, vol. 55, no. 10, pp. 1743–1761, Oct. 2017.

[11] A. S. Zandi, G. A. Dumont, M. Javidan, and R. Tafreshi, "An entropy-based approach to predict seizures in temporal lobe epilepsy using scalp EEG," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Sep. 2009, pp. 228–231.

[12] S. Elgohary, S. Eldawlatly, and M. I. Khalil, "Epileptic seizure prediction using zero-crossings analysis of EEG wavelet detail coefficients," in *Proc. IEEE Conf. Comput. Intell. Bioinf. Comput. Biol. (CIBCB)*, Oct. 2016, pp. 1–6.

[13] A. Shoeb and J. Guttag, "Application of machine learning to epileptic seizure detection," in *Proc. 27th Int. Conf. Int. Conf. Mach. Learn.*, 2010, pp. 975–982.

[14] W. Hussain, B. Wang, Y. Niu, Y. Gao, X. Wang, J. Sun, Q. Zhan, R. Cao, Z. Mengni, M. S. Iqbal, and J. Xiang, "Epileptic seizure detection with permutation fuzzy entropy using robust machine learning techniques," *IEEE Access*, vol. 7, pp. 182238–182258, 2019.

[15] A. Ventura, J. M. Franco, J. P. Ramos, B. Direito, and A. Dourado, "Epileptic seizure prediction and the dimensionality reduction problem," in *Artificial Neural Networks—ICANN* (Lecture Notes in Computer Science), vol. 5769. Berlin, Germany: Springer, 2009, pp. 202–206.

[16] S. Wang, W. A. Chaovalitwongse, and S. Wong, "Online seizure prediction using an adaptive learning approach," *IEEE Trans. Knowl. Data Eng.*, vol. 25, no. 12, pp. 2854–2866, Dec. 2013.

[17] A. Ahmadi and H. Soltanian-Zadeh, "Epileptic seizure prediction using spectral entropy-based features of EEG," in *Proc. 4th Int. Conf. Pattern Recognit. Image Anal. (IPRIA)*, Mar. 2019, pp. 124–129.

[18] T. N. Alotaiby, S. A. Alshebeili, F. M. Alotaibi, and S. R. Alrshoud, "Epileptic seizure prediction using CSP and LDA for scalp EEG signals," *Comput. Intell. Neurosci.*, vol. 2017, pp. 1–11, Oct. 2017.

[19] R. Jana and I. Mukherjee, "Epileptic seizure prediction from raw EEG signal using convolutional neural network," in *Machine Vision and Augmented Intelligence—Theory and Applications* (Lecture Notes in Electrical Engineering), vol. 796. Singapore: Springer, 2021, pp. 235–244.

[20] R. Jana and I. Mukherjee, "Deep learning based efficient epileptic seizure prediction with EEG channel optimization," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102767.

[21] X. Wang, C. Zhang, T. Kärkkäinen, Z. Chang, and F. Cong, "Channel increment strategy-based 1D convolutional neural networks for seizure prediction using intracranial EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 316–325, 2023.

[22] X. Yao, X. Li, Q. Ye, Y. Huang, Q. Cheng, and G.-Q. Zhang, "A robust deep learning approach for automatic classification of seizures against non-seizures," *Biomed. Signal Process. Control*, vol. 64, Feb. 2021, Art. no. 102215.

[23] M. Ma, Y. Cheng, Y. Wang, X. Li, Q. Mao, Z. Zhang, Z. Chen, and Y. Zhou, "Early prediction of epileptic seizure based on the BNLSTM-CASA model," *IEEE Access*, vol. 9, pp. 79600–79610, 2021.

[24] S. Ryu and I. Joe, "A hybrid DenseNet-LSTM model for epileptic seizure prediction," *Appl. Sci.*, vol. 11, no. 16, p. 7661, Aug. 2021.

[25] R. Jana, S. Bhattacharyya, and S. Das, "Epileptic seizure prediction from EEG signals using DenseNet," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Dec. 2019, pp. 604–609.

[26] L. A. S. Kitano, M. A. A. Sousa, S. D. Santos, R. Pires, S. Thome-Souza, and A. B. Campo, "Epileptic seizure prediction from EEG signals using unsupervised learning and a polling-based decision process," in *Proc. 27th Int. Conf. Artif. Neural Netw.*, 2018, pp. 117–126.

[27] Y. Guo, X. Jiang, L. Tao, L. Meng, C. Dai, L. Xi, F. Wan, Y. Zhang, J. van Dijk, R. M. Aarts, W. Chen, and C. Chen, "Epileptic seizure detection by cascading isolation forest-based anomaly screening and EasyEnsemble," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 915–924, 2022.

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

[29] N. D. Truong, A. D. Nguyen, L. Kuhlmann, M. R. Bonyadi, J. Yang, S. Ippolito, and O. Kavehei, "Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram," *Neural Netw.*, vol. 105, pp. 104–111, Sep. 2018.

[30] J. Duun-Henriksen, T. W. Kjaer, R. E. Madsen, L. S. Remvig, C. E. Thomsen, and H. B. D. Sorensen, "Channel selection for automatic seizure detection," *Clin. Neurophysiol.*, vol. 123, no. 1, pp. 84–92, Jan. 2012.

[31] J. Yang, H. Singh, E. L. Hines, F. Schlaghecken, D. D. Iliescu, M. S. Leeson, and N. G. Stocks, "Channel selection and classification of electroencephalogram signals: An artificial neural network and genetic algorithm-based approach," *Artif. Intell. Med.*, vol. 55, no. 2, pp. 117–126, Jun. 2012.

[32] A. Temko, G. Lightbody, E. M. Thomas, G. B. Boylan, and W. Marnane, "Instantaneous measure of EEG channel importance for improved patient-adaptive neonatal seizure detection," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 717–727, Mar. 2012.

[33] A. Romney and V. Manian, "Optimizing seizure prediction from reduced scalp EEG channels based on spectral features and MAML," *IEEE Access*, vol. 9, pp. 164348–164357, 2021.

[34] L. D. Iasemidis, D.-S. Shiau, W. Chaovalitwongse, J. C. Sackellares, P. M. Pardalos, J. C. Principe, P. R. Carney, A. Prasad, B. Veeramani, and K. Tsakalis, "Adaptive epileptic seizure prediction system," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 5, pp. 616–627, May 2003.

[35] P. M. Pardalos, W. Chaovalitwongse, L. D. Iasemidis, J. Chris Sackellares, D.-S. Shiau, P. R. Carney, O. A. Prokopyev, and V. A. Yatsenko, "Seizure warning algorithm based on optimization and nonlinear dynamics," *Math. Program.*, vol. 101, no. 2, pp. 365–385, Nov. 2004.

[36] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. 215–220, 1998.

[37] R. Cherian and E. G. Kanaga, "Theoretical and methodological analysis of EEG based seizure detection and prediction: An exhaustive review," *J. Neurosci. Methods*, vol. 369, Mar. 2022, Art. no. 109483.

[38] Y. Zhang, Y. Guo, P. Yang, W. Chen, and B. Lo, "Epilepsy seizure prediction on EEG using common spatial pattern and convolutional neural network," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 2, pp. 465–474, Feb. 2020.

[39] S. M. Usman, S. Khalid, and S. Bashir, "A deep learning based ensemble learning method for epileptic seizure prediction," *Comput. Biol. Med.*, vol. 136, Sep. 2021, Art. no. 104710.

[40] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," *Mech. Syst. Signal Process.*, vol. 151, Apr. 2021, Art. no. 107398.

[41] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.

[42] L. A. Moctezuma and M. Molinas, "EEG channel-selection method for epileptic-seizure classification based on multi-objective optimization," *Frontiers Neurosci.*, vol. 14, p. 593, Jun. 2020.

[43] M. Pinto, T. Coelho, A. Leal, F. Lopes, A. Dourado, P. Martins, and C. Teixeira, "Interpretable EEG seizure prediction using a multi-objective evolutionary algorithm," *Sci. Rep.*, vol. 12, no. 1, p. 4420, Mar. 2022.

[44] A. P. Guerreiro, C. M. Fonseca, and L. Paquete, "The hypervolume indicator: Computational problems and algorithms," *ACM Comput. Surveys*, vol. 54, no. 6, pp. 1–42, Jul. 2022.

[45] Y. Zhao, C. Li, X. Liu, R. Qian, R. Song, and X. Chen, "Patient-specific seizure prediction via adder network and supervised contrastive learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 1536–1547, 2022.

[46] M. Shen, P. Wen, B. Song, and Y. Li, "Real-time epilepsy seizure detection based on EEG using tunable-Q wavelet transform and convolutional neural network," *Biomed. Signal Process. Control*, vol. 82, Apr. 2023, Art. no. 104566.

[47] B. Kapoor, B. Nagpal, P. K. Jain, A. Abraham, and L. A. Gabralla, "Epileptic seizure prediction based on hybrid seek optimization tuned ensemble classifier using EEG signals," *Sensors*, vol. 23, no. 1, p. 423, Dec. 2022.

RANJAN JANA received the M.Tech. degree from Jadavpur University, Kolkata, India, in 2009. Currently, he is an Assistant Professor in the Department of Information Technology, RCC Institute of Information Technology, Kolkata. He is also a Research Fellow in the Department of Computer Science and Engineering, Indian Institute of Information Technology Kalyani (an Institute of National Importance), India. His research interests include biomedical signal processing, pattern recognition, deep learning, and optimization techniques.

IMON MUKHERJEE received Ph.D. degree from Jadavpur University, Kolkata, India, in July 2015. Currently, he is an Assistant Professor in computer science and engineering, Indian Institute of Information Technology Kalyani (an Institute of National Importance), India. He was an Assistant Professor in the Department of Computer Science and Engineering, Institute of Technology and Marine Engineering, India, from August 2006 to December 2011. Then from January 2012, he was an Associated with the Department of Computer Science and Engineering, St. Thomas' College of Engineering and Technology, Kolkata. He is serving as a Reviewer, Associate Editor, General Chair, etc., of reputed journals and conferences. His research focuses on steganography and data analytics. He is the Principal Investigators of Government Funded Projects.