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RESEARCH ARTICLE

Brain Epileptic Seizure Detection Using Joint CNN and Exhaustive Feature Selection With RNN-BLSTM Classifier

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ABSTRACT Brain Epilepsy seizure is a critical disorder, which is an uncontrolled burst of electrical activity of brain. The early detection of brain seizure can save the life of humans. The electroencephalogram (EEG) signals may be used to automatically identify brain seizures, which is one of the most prominent solutions for this issue. However, the conventional methods are failed to classify the brain seizure effectively. So, this work implemented the Brain Epilepsy Seizure-Detection-Network (BESD-Net) using deep learning, recurrent learning properties. Initially, the dataset pre-processing is performed, which eliminates the noise, unwanted data from EEG dataset. Then, the deep learning based customized convolution neural network (CCNN) is trained on the pre-processed EEG data for precise extraction of disease correlated features. The machine learning based exhaustive random forest (ERF) feature selection is used to optimize the features obtained from the CCNN, which are highly correlated with disease dependent properties. In conclusion, the recurrent neural network (RNN) based bi-directional long short-term memory (BLSTM) is used in order to detect brain seizures from the chosen ERF features. Training and testing of suggested methodology had made use of CHB-MIT Scalp EEG Database. The aforementioned model has achieved the values of 98.36%, 97.54%, 97.91%, 98% and 95.08% respectively for precision, sensitivity, F1-Score, accuracy and specificity. The findings of the simulations demonstrate that the suggested BESD-Net led to superior performance when compared to the technologies that are already in use.

INDEX TERMS Electroencephalogram, epilepsy, brain seizure detection, convolution neural network, exhaustive random forest, recurrent neural network, seizure.

I. INTRODUCTION

Epilepsy is a neurological condition that affects millions of individuals all over the globe. It is characterized by seizures that occur repeatedly and unprovoked [1]. It is essential to detect and classify the seizures quickly and precisely for successful medical treatments and for enhancing the quality of life for people who have epilepsy. The EEG is a non-invasive approach that may record the electrical impulses that are produced by the brain during seizures. Figure 1 shows the EEG signals that are generated during the epilepsy seizure of brain. It has become an invaluable tool for monitoring and evaluating brain activity in recent years [2]. Analysis of intricate temporal and spatial patterns of brain activity is required for both the identification of seizure types and their categorization when utilizing EEG recordings. Voltage fluctuations obtained from multiple electrodes that are placed on the scalp are traced with respect to time. This gives the EEG recording of the brain. These fluctuations reflect the electrical activity that is summed up from hundreds of neurons in the brain [3]. However, because of the presence of numerous artifacts, noise, and inter-individual variability

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in the raw EEG data, it is difficult to differentiate between normal brain activity and seizure occurrences. Researchers have developed sophisticated methods of signal processing and machine learning to overcome these problems [4]. These methods extract significant information from EEG data and identify them as belonging to one of many distinct kinds of seizures. Signal pre-processing techniques such noise reduction, artifact removal, and feature extraction are used [5] for improvement in the EEG data quality and quantity that can be derived. The terms statistical measurements, spectrum analysis, time-frequency representations, and higher-order statistics are examples of characteristics that are often used.

The EEG is especially helpful in the identification of many forms of brain illnesses, was first developed by Hans Berger. When neurologists investigate the changes that take place at the time of epileptic seizures occurrence in brain, the use of such a technological tool is of great assistance to them [6]. The investigation of these variances has the potential to aid in the correct discrimination between the healthy capacities of the brain and the pathological capabilities of the brain. In order to perform an accurate analysis of epileptic seizures, it is important to gather long-term EEG data that spans over a period that lasts for days, weeks, and even months. This involves a significant amount of time and effort from a person [7], but it is necessary in order to get reliable results. Seizure prediction refers to a model's ability to accurately estimate the likelihood of a patient experiencing an epileptic seizure in the near future. Seizures may be caused by epilepsy. Predicting seizures is accomplished by recognizing the preictal state of the patient. Classification of seizures and phases refers to the process through which a model can divide seizures and seizure phases into distinct categories. The development of a robust and efficient brain seizure detection system using EEG has several potential benefits. Automated seizure detection can assist healthcare providers in making accurate and timely diagnoses [8]. It can help differentiate between seizure and non-seizure activity, as well as classify different seizure types. This can reduce the time and uncertainty associated with manual analysis, leading to faster and more effective treatment decisions. Seizure detection systems can provide valuable information for treatment planning [9]. By accurately detecting the onset, duration, and frequency of seizures, medical professionals can adjust medication regimens, explore alternative therapies, or recommend surgical interventions. This personalized approach can optimize treatment outcomes and minimize side effects.

Real-time seizure detection systems can provide immediate alerts or triggers when a seizure occurs. This enables caregivers or medical professionals to intervene promptly, potentially preventing or minimizing the impact of seizures. Early intervention [10] can help reduce the risk of injury, improve patient safety, and enhance overall quality of life. Automated seizure detection can facilitate long-term monitoring of patients with seizure disorders. By continuously analyzing EEG signals, it becomes possible to track seizure patterns, evaluate treatment efficacy, and identify potential triggers or correlations with other physiological or environmental factors. This longitudinal data can aid in refining treatment plans and developing personalized interventions. Developing accurate and efficient seizure detection algorithms can contribute to advancements in epilepsy research. By analyzing large-scale EEG datasets, researchers can uncover new insights into seizure dynamics, identify biomarkers, or discover novel patterns, that can improve our understanding of epilepsy and can provide guidance for future treatment strategies.

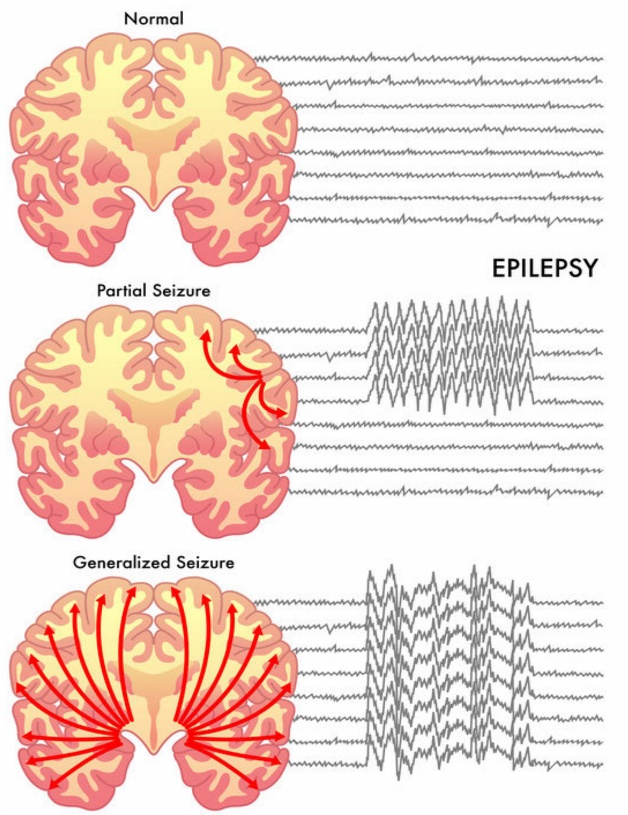

FIGURE 1. Normal vs seizure related EEG patterns.

So, the motivation behind the research on brain seizure detection using EEG is to improve the diagnosis, treatment, and quality of life for individuals with seizure disorders. By leveraging automated algorithms and real-time monitoring, this research has the potential to revolutionize the field of neurology and have a positive impact on countless lives. Many approaches have been proposed in the literature for detecting the seizures. However, the fusion of the necessary algorithms overcome the limitations of using single algorithm that eventually results in better performance. The novel contributions of this work are as follows:

1. The BESD-Net (Brain Epilepsy Seizure-Detection-Network) combines multiple deep learning techniques to create a comprehensive framework for accurate seizure detection.

2. The deep learning CCNN (Customized Convolution Neural Network) is designed to extract disease-specific features from pre-processed EEG data.

3. Machine learning-based ERF (Exhaustive Random Forest) feature selection is used to identify highly correlated features related to the disease.

4. The integration of a RNN (Recurrent Neural Network) based BLSTM (Bi-directional Long Short-term Memory) network enhances the classification of brain seizures and non-seizures. The approach that has been developed has the ability to identify seizures in real time, so that the concerned clinician will immediately intervene which finally improves patient safety.

The remaining parts of the paper are structured as follows: The complete analysis of the literature review can be found in section II, and the thorough analysis of BESD-Net using CCNN, ERF, and RNN-BLSTM approaches can be found in section III. The findings of the simulation are reported in the last part IV, and the concluding section V discusses potential future scope.

II. LITERATURE SURVEY

An intelligent model for the epileptic seizures identification and categorization with the help of a deep canonical sparse autoencoder (DCSAE-ESDC) was proposed by Hilal et al. [11] using EEG data. The DCSAE-ESDC approach that has been presented incorporates two fundamental procedures, namely, the selection of features and the categorization of data. The DCSAE-ESDC methodology creates a new feature selection method that is based on the coyote optimization algorithm (COA). This method is used to pick feature subsets in the most effective way possible. In addition, a classifier incorporating DCSAE was developed with the purpose of recognizing and classifying the epileptic seizures. This was done so that we could make a diagnosis. In conclusion, an algorithm known as the krill herd algorithm (KHA) is used in order to maximize the parameters of the DSCAE model. Liu et al. [12] developed a method for the diagnosis of epileptic seizures by combining variational modal decomposition (VMD) with a deep forest (DF) model. In order to determine the EEG signal's distribution in time and frequency, the EEG recordings are put through variational modal decomposition. The first three acquired VMF's are the ones that are chosen for use in the development of the time–frequency distribution. This choice was made since these VMFs provide the most information. After that, the log-Euclidean covariance matrix (LECM) is constructed to establish EEG features and to reflect the properties of the EEG. For EEG signal categorization, the deep forest model is used successfully. It learns features by using the forest as a training ground. This model is characterized by the fact that it is used with the intention of achieving the objective of classification in its entirety. Escorcia-Gutierrez et al. [13] devised the ADLBSC-ESD (Automated Deep Learning-Enabled Brain Signal Classification for Epileptic Seizure Detection) approach. It was considered since its primary purpose is to classify the signals emanating from the brain in order to determine the presence or absence of seizures. The model that was presented also includes the development of a method for picking features from EEG data.

Zhang et al. [14] suggested a technique regarding the integration of the techniques of signal decomposition and statistical analysis. This approach is referred to as the integrated signal decomposition and statistical analysis (ISDAS) strategy. In the very first step of the process, the method of variational mode decomposition (VMD) is applied for the EEG signals in order to deconstruct them and for the intrinsic mode functions (IMFs) extraction. This is done in preparation for the subsequent stages of the procedure. An automated categorization of EEG data was described by Daftari et al. [15], for the purpose of identifying epileptic episodes. This was done by using wavelet transformation, machine learning and deep learning strategies. In order to accomplish this objective, the use of wavelet transforms will be required. Data pre-processing, extracting features with the incorporation of wavelet transformations, and classification through the use of ML and DL classifiers are the three components that make up the model. The process of quadratic classification requires all three of these components to be present. Anuragi et al. [16] developed a technique for categorizing epileptic seizures by using ensemble learners and a phase-space representation of FBSE-EWT based EEG sub-band data. This allowed for the classification of the data. The empirical wavelet transforms (EWT), also known as the Fourier Bessel series expansion empirical wavelet transforms (FBSE-EWT), is used initially for the partition of the EEG signals into sub bands. These sub bands are built on top of the FBSE, which acts as their base. Following this step, the three-dimensional (3D) PSR is rebuilt using these sub-bands as the fundamental building blocks of the structure. After that, features based on entropy such as line-length (LL), log-energy-entropy (LEEnt), and norm-entropy (NEnt) are derived.

Saminu et al. [17] proposed an approach for the automated diagnosis of epileptic seizures by using EEG signals as the primary data source. The primary objective of the authors of this review is to explore the basics, applications, and advancement of AI-based approaches that are utilized in CAD systems for the detection and characterization of epileptic seizures. It would aid in the actualization and realization of smart wireless wearable medical devices so that individuals with epilepsy may monitor their condition prior to the onset of seizures and assist physicians in the diagnosis and treatment of those episodes. Qui et al. [18] came up with the idea of development of ResNet-LSTM network, which is also known as DARLNet. The residual neural network, also known as ResNet, and the long short-term memory network, commonly known as LSTM, are both used in the model that is proposed, in order to obtain spatial correlations and temporal dependencies. Both of these networks have their own abbreviations. In addition to that, a difference layer is built so that the further data on epileptic seizures may be mined in an automated fashion.

The possibility of the Hjorth parameter to identify seizures via the use of EEG data was first postulated by Kaushik et al. [19]. The EEG signal is decomposed into its component sub bands at varying intensities using the tunable-Q wavelet transform (TQWT). In the last step, a comparison is made between the method that was presented and the most recent, cutting-edge methods that have been published. The CNN and LSTM are the two components of the model that Jiwani et al. [20] devised for the purpose of identifying seizures. It integrates CNN and LSTM models to concentrate on the extraction of temporal and spatial characteristics. The fundamental advantage of using this automated system is that it is able to extract spatial as well as temporal information from EEG data, while simultaneously maintaining a high degree of accuracy using fewer trainable parameters. A multilayer perceptron neural network classifier was presented by Yousefi et al. [21] as a potential method for the diagnosis of epilepsy. This classifier can identify distinction between normal illness, epilepsy, and even other disorders that are taught in educational instances. This is because of the fact that training on this classifier incorporates both normal data and epileptic data. Additionally, the utility of using an electroencephalogram signal was investigated in two different ways. A concept for an automated seizure indication system that took use of deep learning approaches was given by Sivasaravanababu et al. [22]. Analytical methods such as the tunable Q-factor wavelet transform (TQWT) and the deep convolutional variational autoencoder (DCVAE) were utilized in order to perform an analysis of the seizure characteristics that were gathered from EEG data. This analysis was carried out in order to determine the nature of the seizure. In the pre-processing step, they used the adjustable Q-factor wavelet transform, which is sometimes referred to as TQWT for short. The authors employed EEG signals that were acquired from the CHB-MIT Scalp EEG database for the demonstrated method.

In an attempt to enhance the overall performance of seizure detection, Gao et al. [23] developed an unbalanced deep learning model. This was done in an effort to improve the overall performance. A generative adversarial network (GAN) is a promising method for augmenting data and for generating seizure-period EEG data. After that, this data was put to use in order to construct a more well-rounded training set. This technique is carried out so that the uneven distribution of EEG data may be corrected. Kavitha et al. [24] proposed a different framework for determining whether or not someone is having an epileptic seizure. EEG signals gathered from the University of Bonn in Germany and Senthil Multispecialty Hospital in India are used. By using the discrete wavelet transform (DWT), these signals were segmented into a total of six frequency sub bands, from which a total of twelve statistical functions were produced. Kumar et al. [25] introduced an intelligent system that incorporates the variational mode decomposition (VMD) technique, the Hilbert transform (HT) method, and the stacking neural network (NN) method. In order to detect epileptic episodes, the NN approach is used, whereas the VMD and HT methods are utilized in order to extract important properties from EEG data. After the EEG signals have been decoded using the VMD method into its intrinsic mode functions, the EEG data is next subjected to the HT procedure in order to have features extracted from them. The method known as stacked-NN is used for the process of identifying epileptic seizures by using extracted feature information. Epileptic seizure detection utilizing EEG signals was a concept that was introduced by Khan et al. [26]. After the raw EEG data have been preprocessed, the time and frequency domain features of the EEG are extracted from the signals using a variety of machine learning algorithms, such as Logistic Regression, Decision Tree, Support Vector Machines, and others, with the intention of identifying generalized seizures in the corpus of data from Temple University Hospital (TUH). This was done in order to determine whether or not the data from TUH contained any instances of epileptic activity. In an attempt to identify epileptic seizures, Mohammad and Al-Ahmadi [27] made use of a multi-focus dataset that was constructed on the basis of EEG signals and brain MRI. After the features have been extracted from both streams, feature fusion is used in order to construct a feature vector. This feature vector is then given as input into a support vector machine (SVM) for the purpose of diagnosing epileptic seizures. The most important phases in this study are the feature extraction utilizing two distinct streams, namely, EEG by making use of wavelet transformation together with SVD-Entropy, and MRI by making use of CNN; after the feature extraction from both streams, feature fusion is carried out.

A hybrid model was presented by Varlı and Yılmaz [28] that makes use of the time sequence of EEG data in addition to time-frequency-EEG data transformations. To transform signals into EEG data, CWT and STFT techniques were used. The results of the CWT and STFT approaches were used in different processes to generate two distinct models. An approach for determining the Largest Lyapunov Exponent (LLE) was proposed by Brari and Belghith [29], and it was based on the technique developed by A. Wolf. The LLE is a useful instrument for doing analysis of chaotic signals. The method that has been presented enables the examination of noisy chaotic signals. They were successful in achieving a less error rate in determination of LLE by utilizing the recommended technique (PLLE), which was evaluated by applying a chaotic signal that was created from the Logistic Map. This allowed them to fulfil their goal of achieving a low error rate. This was accomplished by using wide range of values for the bifurcation parameter. The modified binary salp swarm technique was suggested for use in the application of EEG data categorization for the purpose of identifying epileptic episodes by Ghazali et al. [30]. The diagnosis of epileptic seizures might benefit from the use of this approach. The Discrete Wavelet Transform (DWT), which is a part of the multilevel technique has been suggested for division of EEG

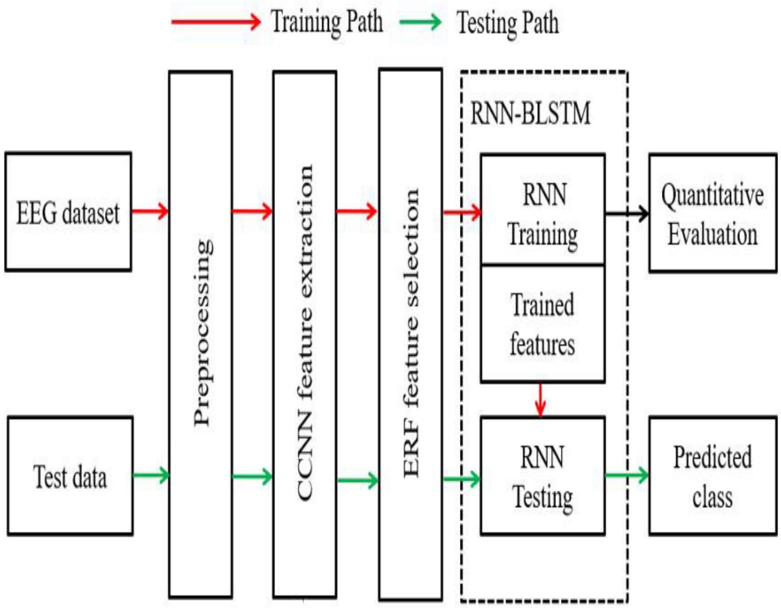

FIGURE 2. Proposed BESD-NET block diagram.

signals into sub band frequency levels. After that, for extraction of time-domain features, it uses a strategy that is based on a population, known as the Modified Binary Swarm technique (MBSSA). A Feed-Forward Neural Network (FFNN) is suggested and it implements the Levenberg-Marquardt (LM) backpropagation classification model.

III. PROPOSED METHODOLOGY

The BESD-Net approach has the potential for real-time seizure detection, which is a crucial and challenging aspect of seizure management. By leveraging the efficiency and computational capabilities of deep learning models, the proposed framework can process EEG data in real-time, enabling timely intervention and improving patient safety. Figure 2 shows the proposed BESD-Net block diagram. The proposed approach integrates multiple deep learning techniques, including CCNN, ERF feature selection, and BLSTM network, to form a comprehensive and synergistic framework for seizure detection. By combining these techniques, the model can leverage the strengths of each component, leading to a more accurate and robust seizure detection system. Initially, the dataset preprocessing is performed to normalize the dataset with uniform nature. Further, the noises presented in EEG dataset are removed by analyzing the characteristics. The preprocessing is further explained in detail in the next part of this section. CNN architecture is used as it effectively learns different feature representations from the input data by grouping different convolution and pooling layers. The utilization of a tailored CCNN specifically for extracting disease-specific features from pre-processed EEG data is a novel contribution. The model can learn and capture intricate patterns and characteristics associated with seizures, potentially leading to improved accuracy. Then a machine learning-based exhaustive random forest feature selection is applied on the extracted CCNN features. The ERF offers a comprehensive approach to select optimal features that are highly correlated with disease-dependent properties. This technique helps to identify the most relevant and informative features, enhancing the efficiency and effectiveness of the subsequent classification process. The use of RNN-BLSTM architecture for seizure classification is well-suited for sequential data analysis, as they can capture dependencies in both forward and backward directions and also the discriminative power of the classifier can be enhanced.

A. PREPROCESSING

The EEG is an example of a nonlinear and nonstationary signal that can be better analyzed and handled using variational modal decomposition (VMD). It decomposes the original signal, $f(t)$, in an adaptive manner into non-recursive modes represented by u_k where k is an integer value. In order to take into consideration, the fact that the EEG signal is both dynamic and nonstationary, the data from every channel is categorized into epochs of four seconds using a moving window that does not overlap. This is done so that the results may be more accurately interpreted. This window has the potential to distinguish EEG data and record epilepsy activity effectively, all while preserving the stationary nature of the signals. The pre-processing stage of our work mostly consists of two steps. The first thing that must be done is VMD [12], which will help locate the primary low-frequency zone where the seizures are occurring. Variational mode functions, or VMF for short, are assigned to each mode and its corresponding equation is written as follows:

$$u_k = A_k \cos(\phi_k) \tag{1}$$

In this case, the envelope of the VMFs is denoted by A_k, and the phase is denoted by k. Each VMF is centered on the central frequency, which can be determined by taking the envelope of the VMFs derivative and computing the result. The central frequency is the frequency at where the envelopes of the VMFs intersect, which is denoted by the symbol, k. When VMD is dealing with variational issues, it first applies the Hilbert transform to each mode, u_k, in order to produce the unilateral spectrum $\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)$, and then it adds $e^{-jw_k t}$ to each mode, u_k, in order to change the center frequency, w_k. This process is repeated until the problem has been solved. Finally, we have arrived at a limited variational issue as a result of the application of the Gaussian smoothing operation, as shown by Equation (2).

$$\min_{\{u_k\},\{w_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right)^* u_k(t) \right] e^{-jw_k t} \right\|_2^2 \right\}$$
$$s.t.\ \sum_{k=1}^{k} u_k = f(t) \tag{2}$$

$f(t)$ represents the original signal, the aggregation of all modes. The confined variational problem is changed into an unconstrained variational problem when an improved Lagrangian (L) is constructed by combining the limited variational problem with the data fidelity constraint factor, α and the Lagrangian multiplier, $\lambda(t)$.

$$\begin{aligned} &L(\{u_k, \{w_k\}, \lambda) \\ &= \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u(t) \right] e^{-jw_k t} \right\|_2^2 \\ &\quad + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(T) - \sum_K u_k(t) \right\rangle \end{aligned} \tag{3}$$

An algorithm known as the alternate direction technique of multipliers is used in order to bring about the necessary changes to the sequence, which is used to handle different issues that occur during the decomposition process. In this algorithm, the following constitutes an update to the mode, u_k, with center frequency, k.

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq ku_i} (\omega + \hat{\lambda}(\omega)/2)}{1 + 2\alpha(\omega - \omega_k)^2} \tag{4}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega} \tag{5}$$

The time–frequency information of the EEG signal is obtained by original signal decomposition $f(t)$ into modal functions u_k.

B. CCNN FEATURE EXTRACTION

In order to acquire the features from pre-processed EEG data, the CCNN architecture had to be developed from the ground up by adjusting the values of number of hyperparameters that were included inside the design. The hyperparameters, included are count of convolutional layers and fully connected layers, as well as the number of filters, stride, pooling locations, and the number of units contained inside the fully connected layers. In addition, the number of filters varied depending on the size of the pooling sites. Because there is no formal framework for the determination of optimal parameters for a particular dataset, it was necessary to manually go through a process of trial and error in order to choose the hyperparameters. Figure 3 provides a visual representation of the entire computational architecture of the proposed customized CCNN system. The design includes a Softmax layer on top of convolutional layers, activation layers, max-pooling layers, and fully connected layers [2], [22]. Two convolution layers are employed with application of 3 × 3 kernel, and ReLU (Rectified Linear Unit) activation function and Max-pooling with desired pooling size. Then two fully connected layers are enclosed at the end of architecture with the final layer using softmax function. These layers primary function is to improve the performance of the model, extracting valuable features, lowering the dimensionality of the input and adding nonlinearity. The spatial invariance property was improved by using the convolutional layers in blocks, which helped in the detection of essential characteristics in the input EEG data. This was accomplished by using the layers to create blocks. To train, the architecture of a CCNN relies on either the spatial or sequential properties of the input. The capacity for the network to learn is severely hindered when the data that it receives as input is very limited. In the research that has been done on this topic, there are reports of potential solutions to this issue. On the other hand, the study that was offered made use of an Adam optimizer as an adaptive learning-rate strategy to deal with sparse input

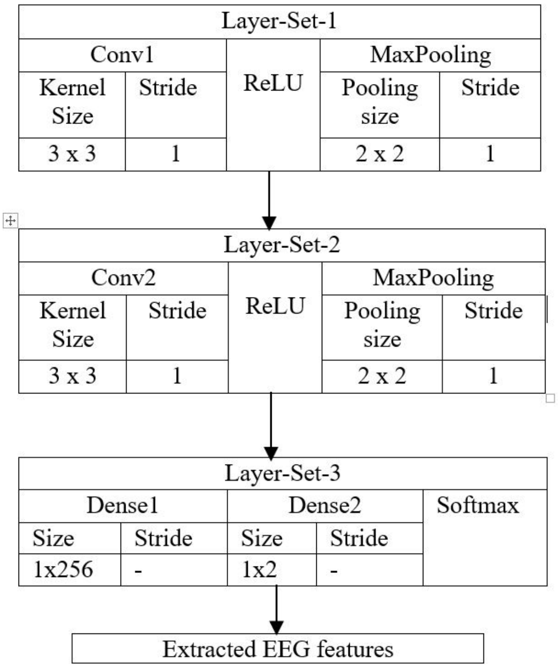

FIGURE 3. CCNN feature extraction architecture.

data. Although RMSprop, Adadelta, and Adam are all comparable algorithms, the idea for choosing "Adam" was that it performs well at the end of the optimization process when the gradients get sparser. This was the reasoning behind the adoption of "Adam."

The first layer receives input as EEG data which is preprocessed and then it reduces the size of the EEG data by passing it through several convolutional and max pooling layers. The fully connected layer receives the final feature vector, after its journey through the convolutional layers with filter application, max-pooling operation and ReLU activation functions. This vector is then used as an input into the softmax layer for predicting the output class.

1) CONVOLUTIONAL LAYER

The primary responsibility of the convolutional layer is to pull out the useful features by locating resident networks among the data samples that are sent down from the layer below it, which is presented in Equation (6).

$$C_{out} = \sum (I_{kxk} + W_{k\times k}) + B \tag{6}$$

The convolutional operation was carried out between the pre-processed EEG input data (I_{kxk}), and the weight-based kernel (w_{kxk}), which in turn resulted in the output feature map C_{out}. The W, B of the convolutional layer operation are referred to as filter weights and filter bias respectively. In the convolutional layer, the feature vector is created by convolving the filter across the EEG data pixels and then adding the pixels together. This is done to get the feature vector. It is important to note that the resulting feature maps are not consistent across the various convolutional kernels. The ultimate feature vector that was created is then sent into the activation layer, which is known as Rectified Linear Unit (ReLU).

2) ReLU ACTIVATION LAYER

Through the execution of an elementwise operation as presented in Equation (7), the ReLU brings all the nonnegative values that were received from the convolutional layer to a value of zero. By injecting nonlinearity, this layer ensures that the feature maps that were produced by the convolutional layer are usable. It is usual practice to utilize the activation layer, also known as the ReLU, because of its superior computing speed compared to that of other activation functions, such as the sigmoid and the tanh.

$$\sigma(I) = \max(0, C_{out}) \tag{7}$$

3) MAX-POOLING LAYER

At this stage, the value of each kernel that is considered to be the greatest possible value is passed on to the succeeding layer. The following is a list of the major duties that are carried out in the various max-pooling layers: (1) taking smaller samples of the data that was sent down from the layer before it, in order to reduce the overall dimensionality of the data; and (2) reducing the total number of parameters in the model, which results in reduction in the amount of computing time required and an improvement in the generalizability of the model.

4) FULLY CONNECTED LAYER

It is possible to think of the fully connected layer as an old-fashioned neural network that is responsible for logical reasoning. Using a complete convolution operation, the completely linked layer in the proposed system is responsible for converting the three-dimensional matrix into a one-dimensional vector after receiving it from the levels that came before it. This matrix was collected from the layers that came before it. The following is an expression of the mathematical procedure that underlies the completely linked layer.

$$Zv_{ox1} = W * V_o * V_i * V_{ox1} \tag{8}$$

In this case, V_i and V_o stand for the input and output vector sizes, respectively, whereas Z denotes the output of the layer that is completely connected.

5) SOFTMAX LAYER

SoftMax layer is positioned as the last layer in CCNN construction, and its purpose is to compute the normalized class probabilities, $P(y^i = n^i x^i; W)$ for each period n^i, where there is a total of n classes. Equation (9) is utilized to do this calculation.

$$\left(y^i = n^i|x^i; W\right) = \begin{bmatrix} y^i = 1|x^i; W \\ y^i = 2|x^i; W \\ \vdots \\ y^i = n|x^i; W \end{bmatrix} = \frac{1}{\sum_{j=1}^{n} e^{W_j^T} x^i} \begin{bmatrix} e^{W_1^T x^i} \\ e^{W_2^T x^i} \\ \vdots \\ e^{W_n^T x^i} \end{bmatrix} \tag{9}$$

Here, m refers to the total number of data samples, and i might range anywhere from 1 to m. The symbol W stands for the weights, while the input that goes into the classifier is indicated by the notation $e^{W_n^T x^i}$. The input for Equation (9) is a vector containing arbitrary real-valued scores, while the Equation's output is a vector containing values that range from 0 to 1.

C. ERF FEATURE SELECTION

Figure 4 shows the ERF feature selection flow chart, which provides optimal performance with low complexity as compared to other methods. If we take a closer look at one individual tree in the forest, we can define the i^{th} partition of samples (M_i) and features (N_i) using the notation , $P_i \in \mathbb{R}^{M_i \times N_i}$. $P_i$is chosen randomly from the data that were originally collected ($X \in \mathbb{R}^{M_i \times N_i}$) via the process of producing random samples with replacement. At each node, the features that are part of the subset N_i are evaluated to see whether

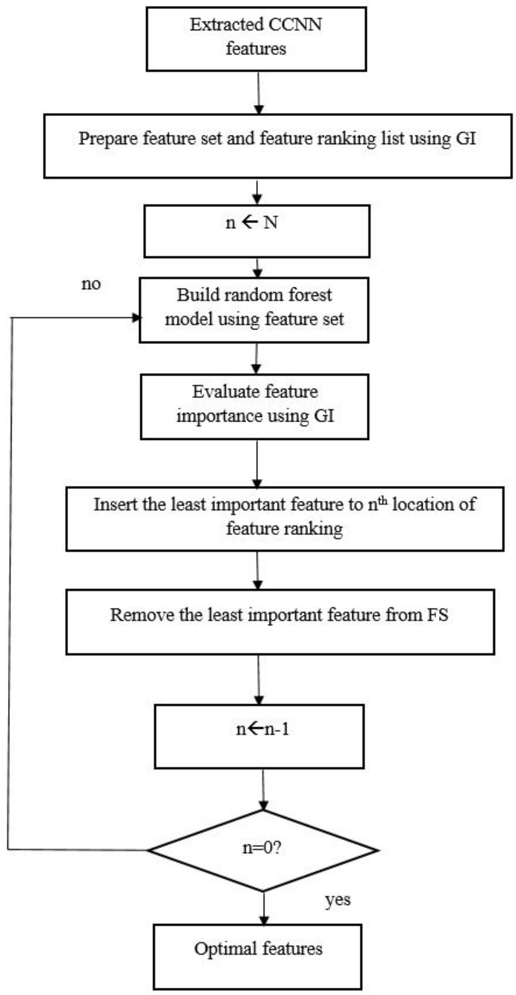

FIGURE 4. **ERF Feature selection flow chart.**

or not they are suitable candidates for splitting the available samples, M_i. The Gini Index, often known as the GI, is used in order to locate the optimal dividing feature and cut-off point. If the sample's values are lower than the cut-off point for the specified feature, then it will be sent to the left node (v_L), but if they are higher, then they will be routed to the right node (v_r). Following a series of splitting operations, the samples have been transferred from the root node (v_R) to the terminal nodes, also known as terminal leaves, which are responsible for providing the sample predictions. The ensemble prediction ($\hat{Y} \in \mathbb{R}^{M_i \times N_i}$) provided by a forest is derived as a mixture of the outcomes of the individual trees; traditionally, the majority vote method is used for classification problems, while the average is used for regression issues. The feature selection-based classification problem is defined as follows:

$$\hat{Y}_i = mode_{n=1} \ldots N_{trees} \hat{Y}_n \tag{10}$$

The feature selection-based regression problem is defined as follows:

$$\hat{Y}_i = \frac{1}{N_{trees}} \sum_{n=1}^{N_{trees}} \hat{Y}_n \tag{11}$$

Here, N_{trees} is the complete count of all trees that were considered for inclusion in the ERF. When trying to optimize an ERF, it is crucial to pay special attention to two parameters: the number of features that will be evaluated as split candidates (also referred to as the size of the N_i subset), and the number of trees that will be deployed in the ensemble. Both of these factors are essential in order to achieve optimal performance. Both factors are vital in determining how well an ERF will perform, while doing the classification. The former is often adjusted so that it equals sqrt(n), and while performing regression, it is typically adjusted so that it equals N/3. Where N refers to the total number of characteristics that X has. Because increasing the number of trees does not always lead to a gain in performance, the latter is often set to be comparable to a few hundred trees and instead merely slow down the processing time. Consequently, this setting is usually considered to be appropriate. K-fold cross-validation is one of the additional criteria that is used in the process of determining the values that should be used for these parameters.

The significance of each characteristic is determined by ERF, which is used to determine the characteristics that are most important to a certain problem, as well as to provide a technique for selecting the features to employ. The significance of characteristic x_j is given as:

$$Importance_j = \frac{1}{N_{tree}} \sum_{v \in S} G\left(X_j, v\right) \tag{12}$$

Here, S is the set of nodes where X_j is used to split the samples, and $G(x_j, v)$ is so-called the RF gain of x_j. Therefore, gain is determined by the measurements (impure) that are computed after the samples have been divided at each node. There were a few different impurity criteria that were used to partition the data and, as a result, to assess the relevance of the feature. For the purpose of improving the selection of attributes when they are correlated, measures such as permutation significance or alternative implementations of ERF such as Boruta or subsample without replacement were created. This is due to the fact that regularization serves as the cornerstone of ERF. The GI is a straightforward statistic that can be computed in a short amount of time. It reduces the risk of incorrect classification by using the formula, $GI = 1 - \sum_{i=1}^{n_c} (p_i)^2$, where n_c is the total number of classes and p_i is the chance of belonging to class i. Following is an equation that may be used to get the value of the function G.

$$G\left(x_j, v\right) = GI\left(x_j, v\right) - \omega_R GI\left(x_j, v_R\right) - \omega_L GI(x_j, v_L \tag{13}$$

Here, ω_R and ω_L represent the percentages of the total samples that can be found in each node. In regression, the split principles are often the measurements taken from the Residual Sum Squares (RSS): $RSS = \sum_{i=1}^{N_i} \left(y_i - \hat{y}_i\right)^2$. G is acquired by doing the following:

$$G\left(x_j, v\right) = RSS(RSS_L + RSS_R) \tag{14}$$

The RSS in the right node is denoted by S_R, while the RSS in the left node is denoted by RSS_L. The ERF generates

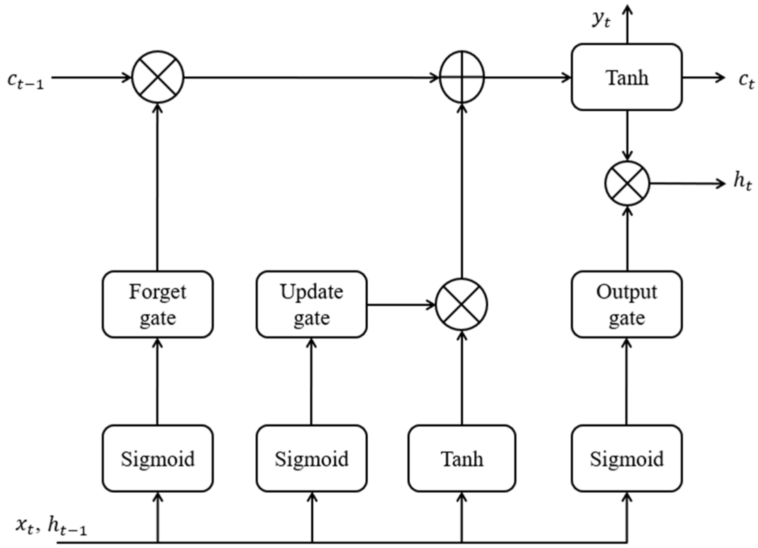

FIGURE 5. **Architecture of LSTM in the proposed method.**

feature subsets of high quality, and it results in a decrease in the number of features used for classification and regression tasks. Given that F is the subset of features that has been picked (which was previously empty), and x_j is the value of each feature, the gain of the ERF is computed as:

$$G_{ERF}\left(x_j, v\right) = \begin{cases} G(x_j, v) & if\ j \in F \\ \lambda G(x_j, v) & if\ j \notin F \end{cases} \tag{15}$$

Here, G is the selected features, F is the subset of features that were selected to split the samples in the node that came before it, and the range [0, 1] is a penalty factor for the features that were not selected in the nodes that came before them. It is essential to bear in mind that the advantage of a feature will be diminished if it is selected, so the feature should have a high priority value in order to be selected. On the other hand, if a feature has already been selected, the gain of that feature will be the same as the gain of the ERF that is set as the default. The features whose G_{ERF} values are equal to zero are not included in the group that is selected. The features that are chosen by ERF are the ones that do not include any redundant information. This is because the irrelevant features have a very low important value.

D. RNN-BLSTM CLASSIFICATION

The extracted features from ERF are inputted into the RNN-BLSTM layer for classification. RNNs have the concept of memory that helps them store the states or information of previous inputs to generate the next output of the sequence. LSTM networks are a variant of RNN that handles vanishing and exploding gradient problem of RNN by introducing new gates, such as input and forget gates, which account for a better control over the gradient flow [7]. In addition, this sort of network is better than other types when it comes to maintaining long-range connections since it comprehends how values at the beginning and end of a series are connected. Figure 5 shows the architecture of LSTM cell. It has three different types of gates, which are as follows: The forget gate is responsible for controlling the amount of data that should move to another memory cell from its previous one. The input gate of the memory cell, also known as the update input is responsible for deciding whether the cell will be updated or not. In addition to this, it controls the amount of information that a potential new memory cell may transmit to the one that is now being used. The output gate decides the transmission of most recent cell output using sigmoid activation function and the final state is obtained using tanh function. The value that is stored in the subsequent concealed state is decided by the output gate.

This work used bidirectional LSTM (BLSTM), a special RNN that models each sequence in both the forward and backward directions, whereas in normal LSTM the data flows in forward direction only. BLSTM effectively deals with long-term dependencies of time series data, since each token encoding contains context information from the past and the future. Figure 6 shows the proposed architecture of RNN-BLSTM. The BLSTM network has been shown to be trustworthy and efficient, for sequences having extensive dependencies. This network has input flow in both directions to preserve the future and the past information. This has been demonstrated by several studies. Because the gathered EEG signals are organized in a time-sequence based form, the current state is greatly impacted by the settings that the subject was exposed to in the past. When it comes to solving this issue, the BLSTM model is the most effective instrument that anybody has at their disposal. Along with the BLSTM layer, two dropout layers were deployed between the BLSTM layers to combat the issue of overfitting. These dropout layers were placed between each BLSTM layer. Using these dropout layers, RNN-BLSTM can circumvent the issue of overfitting. The main aim of involving dropout layer is to reduce the error

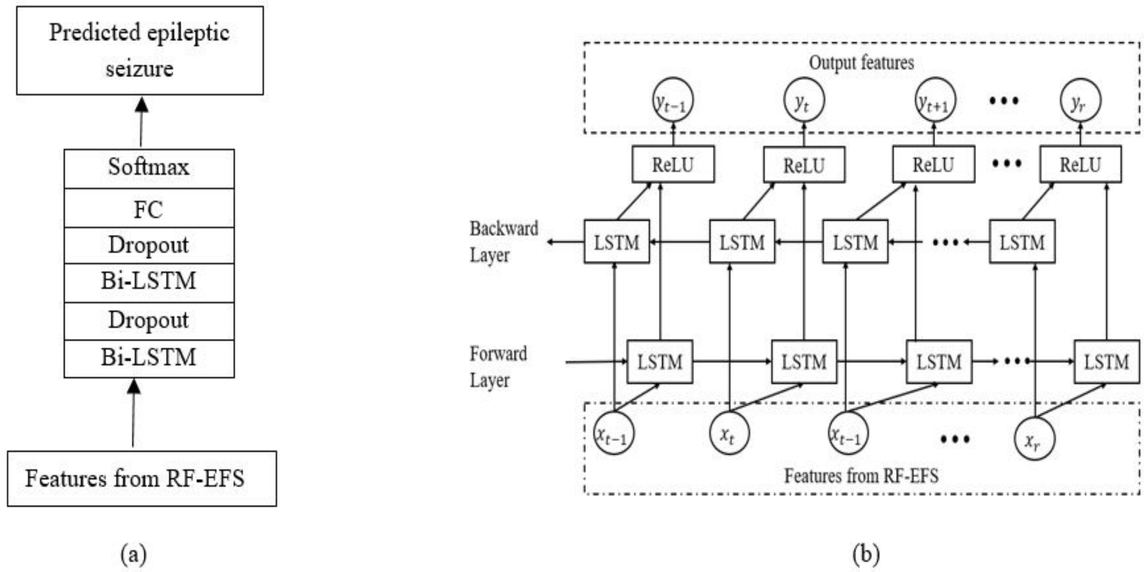

FIGURE 6. (a) RNN-BLSTM structure (b) Architecture of BLSTM (often called as Bi-LSTM) framework used.

of generalization, which is being sought in combination with the rise in the number of layers that are included inside neural networks. The full connected layer follows the BLSTM layer, which uses a Softmax function that detects the presence of epileptic seizure.

IV. RESULTS AND DISCUSION

This part presents a comprehensive analysis of the findings, which are implemented using python software simulation. The Epileptic Seizure related dataset is used to test the performance of the proposed BESD-Net based on deep learning techniques.

A. DATASET

The CHB-MIT Scalp EEG Database is a collection of data that is often used in the investigation of epilepsy as well as the diagnosis of brain seizures. The Children's Hospital Boston (CHB) and the Massachusetts Institute of Technology (MIT) collaborated in its creation at various points along the process. The recordings were made on the scalps of children who were diagnosed with epilepsy and for extended periods of time. The most important aspects and features of the CHB-MIT Scalp EEG Database:

- Patients: Recordings from 23 juvenile epilepsy patients with the condition are included in the collection. Each patient's data is identified by a unique code, such as chb01, chb02, etc.
- Recording Duration: The recordings span varying durations for each patient, typically ranging from several hours to a few days. Some patients have multiple recordings over different periods.
- Seizure Annotations: Each recording is annotated considering periods of seizure onset and seizure offset, as fine as additional seizure-related information, such as seizure type and clinical observations. These annotations are crucial for training and evaluating seizure detection algorithms.
- Non-Seizure Annotations: Alongside the seizure data, the dataset also includes segments of interictal (non-seizure) EEG signals. These segments are useful for training algorithms to distinguish between seizure and non-seizure patterns.
- EEG Channels and Sampling Rate: The EEG recordings in the dataset are obtained from multiple scalp electrodes, typically ranging from 19 to 26 channels. The sampler rate of the EEG signals is 256 Hz.
- Data Format: The information is offered in what is known as the European Data Format (EDF), which is a standardized file format for the storage of multichannel biological signals. Each patient's data is organized into individual EDF files.

It has been determined that the CHB-MIT Scalp EEG Database is widely utilized for developing and evaluating seizure detection algorithms, studying seizure patterns, and exploring various signal processing and machine learning techniques for epilepsy research.

B. ABLATION STUDY

Ablation study, in the context of machine learning and data analysis, refers to a systematic process of evaluating the contribution or impact of individual components or features of a model or system. It involves selectively removing or disabling certain components or features to assess their effect on the overall performance or behavior of the system. The term "ablation" in this context is borrowed from medical science, where it refers to the removal or destruction of a body part or tissue, often performed in a controlled experimental setting to study its function or impact on the organism. In the field of machine learning, an ablation study is typically conducted to understand the importance or effectiveness of different model components, feature sets, or algorithms. By selectively disabling or removing specific elements, researchers can observe how the system's performance changes and gain insights into the contribution of each component. Ablation studies can help researchers identify critical components that significantly affect the system's performance and determine which parts can be improved or eliminated. They also provide a deeper understanding of the inner workings and dependencies within the system, aiding in the development of more efficient and effective models or algorithms. Studies of ablations are used often in different fields such as natural language processing, computer vision and bioinformatics, to analyze the impact of different factors and drive improvements in model design and architecture.

Table 1 shows the ablation study of proposed BESD-Net. Here, the proposed BESD-Net resulted in improved performance as compared to only CCNN, only RNN-LSTM, and BESD-Net without ERF feature selection properties. Figure 7 shows the graphical representation of ablation study of proposed BESD-Net. The Proposed BESD-Net outperforms the Only CCNN method with a percentage improvement of approximately 4.31% in precision, 3.63% in sensitivity, 4.95% in F1-Score, 4.26% in accuracy. However, there is no improvement in specificity when compared to Only CCNN. Compared to the Only RNN-LSTM approach, the Proposed BESD-Net shows remarkable advancements, achieving a substantial percentage improvement of 272.58% in precision, 95.08% in sensitivity, 183.74% in F1-Score, and 86.33% in accuracy. The Proposed BESD-Net significantly outperforms Only RNN-LSTM in all metrics. When compared to BESD-Net without ERF, the Proposed BESD-Net demonstrates a modest percentage improvement of approximately 2.44% in precision, 2.85% in sensitivity, 2.79% in F1-Score, 2.70% in accuracy, and 6.13% in specificity. The Proposed BESD-Net achieves slightly higher values in all these metrics, showcasing its enhanced performance.

TABLE 1. Ablation study of proposed BESD-Net.

Model	Only CCNN	Only RNN-LSTM	BESD-Net without ERF	Proposed BESD-Net
Precision	94.37	26.33	96.04	98.36
Sensitivity	94.3	50	94.85	97.54
F1-Score	93.99	34.49	95.24	97.91
Accuracy	94	52.66	95.33	98
Specificity	100	62.5	89.705	95.08

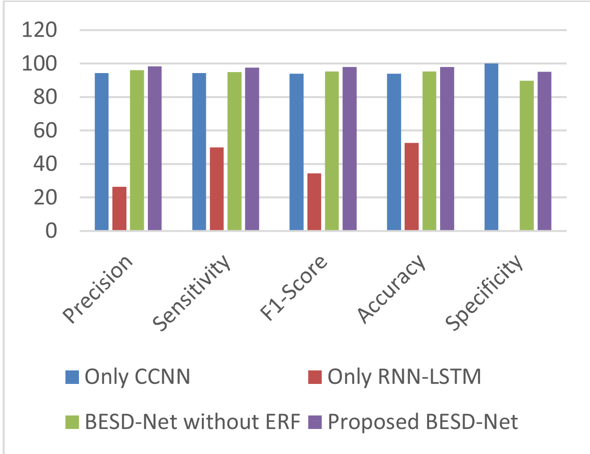

FIGURE 7. Ablation study of proposed BESD-Net.

TABLE 2. Feature extraction performance of proposed CCNN.

Model	DCSAE [11]	ITLBO [13]	FBSE-EWT [16]	Proposed CCNN
Precision	90.92	87.13	92.17	94.37
Sensitivity	87.64	88.43	89.75	94.3
F1-Score	92.08	85.92	91.32	93.99
Accuracy	89.39	92.85	88.66	94
Specificity	92.96	90.21	86.74	100

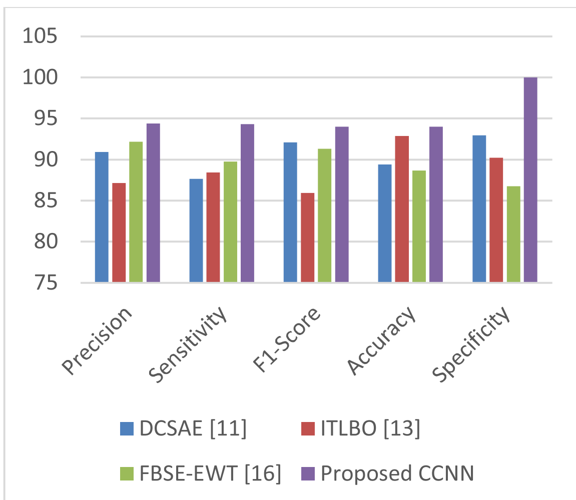

FIGURE 8. Feature extraction performance of proposed CCNN.

C. SIMULATION RESULTS

Table 2 shows the feature extraction presentation of proposed CCNN with existing DCSAE [11], ITLBO [13], and FBSE-EWT [16] methods. Figure 8 shows the graphical representation of feature extraction performance of

TABLE 3. Feature extraction with classification performance of proposed BESD-Net.

Model	ResNet [17]	TQWT [19]	DCVAE [22]	Proposed BESD-Net without ERF
Precision	92.18	89.23	91.62	96.04
Sensitivity	91.84	88.96	92.11	94.85
F1-Score	91.99	90.12	90.95	95.24
Accuracy	93.72	89.91	92.44	95.33
Specificity	88.65	87.92	88.04	89.705

TABLE 4. Performance comparison of proposed BESD-Net with existing methods.

Model	GAN [23]	SVM-CNN [27]	MBSSA [30]	Proposed BESD-Net
Precision	88.26	90.12	89.73	98.36
Sensitivity	91.05	88.96	90.34	97.54
F1-Score	89.57	92.01	88.86	97.91
Accuracy	92.34	89.91	91.12	98
Specificity	91.84	87.92	90.65	95.08

proposed CCNN. Here, the traditional techniques were not successful in learning the precise characteristics from the EEG data. Further, the proposed CCNN method achieves a 3.4% improvement in precision, 0.9% improvement in sensitivity, 1.1% improvement in F1-score, 4.61% improvement in accuracy, and 7.36% improvement in specificity compared to DCSAE [11]. The proposed CCNN method outperforms ITLBO [13] with a 7.17% higher precision, 5.87% higher sensitivity, 0.07% higher F1-score, 1.15% increase in accuracy, and 9.79% higher specificity. Compared to FBSE-EWT [16], the proposed CCNN method demonstrates a 2.2% improvement in precision, 5.55% improvement in sensitivity, 2.67% improvement in F1-score, 5.34% improvement in accuracy, and 13.26% improvement in specificity.

Table 3 shows the feature extraction with classification performance of proposed BESD-Net. Here, the proposed BESD-Net resulted in superior performance as compared to ResNet [17], TQWT [19], and DCVAE [22]. Figure 10 shows the graphical representation of feature extraction with classification performance of proposed BESD-Net. The proposed BESD-Net without ERF achieved an improvement

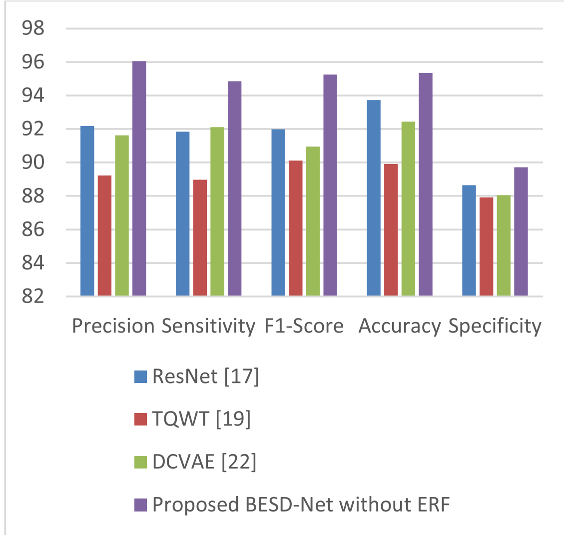

FIGURE 9. Feature extraction with classification performance of proposed BESD-Net.

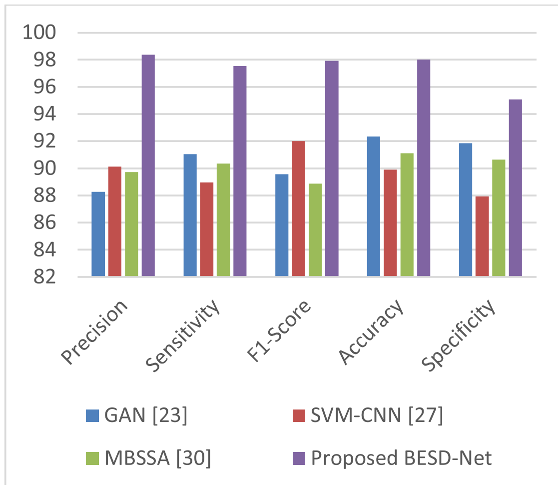

FIGURE 10. Performance comparison of proposed BESD-Net with existing methods.

of 3.86% in precision, 3.42% in sensitivity, 3.25% in F1-score, 1.61% in accuracy, and 1.02% in specificity compared to ResNet [17]. The proposed BESD-Net without ERF outperformed TQWT [19] with improvements of 6.81% in precision, 6.48% in sensitivity, 5.20% in F1-score, 5.58% in accuracy and 1.82% in specificity. The proposed BESD-Net without ERF achieved improvements of 4.53% in precision, 1.59% in sensitivity, 4.34% in F1-score, 2.89% in accuracy, and 1.03% in specificity compared to DCVAE [22].

Table 4 compares the performance of proposed BESD-Net with existing methods. Here, the conventional methods failed to analyze the brain seizure, where the proposed BESD-Net method accurately classifies as compared to existing GAN [23], SVM-CNN [27], and MBSSA [30]. Figure 10 shows the graphical representation of performance comparison of proposed BESD-Net with existing methods. The proposed BESD-Net achieved significant improvements

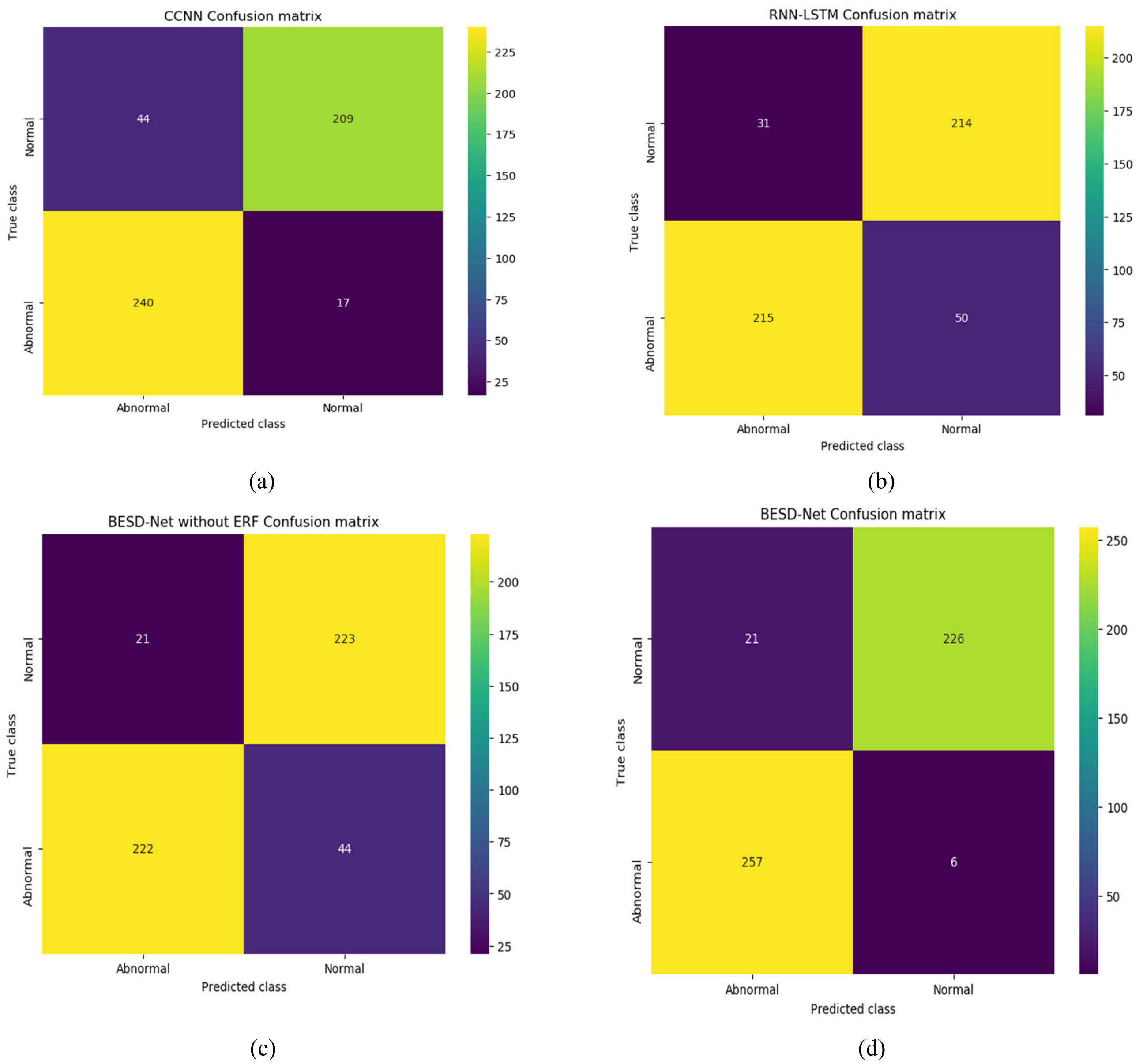

FIGURE 11. **Confusion matrix performance of ablation study. (a) CCNN, (b) RNN-LSTM, (c) BESD-Net without ERF, (d) BESD-Net.**

of 10.10% in precision, 2.09% in sensitivity, 8.35% in F1-score, 5.66% in accuracy, and 3.24% in specificity compared to GAN [23]. The proposed BESD-Net outperformed SVM-CNN [27] with improvements of 8.24% in precision, 0.16% in sensitivity, 9.90% in F1-score, 8.09% in accuracy and 7.16% in specificity. The proposed BESD-Net achieved impressive improvements of 8.63% in precision, 9.05% in F1-score, 6.88% in accuracy, and 4.43% in specificity compared to MBSSA [30].

D. CONFUSION MATRIX PERFORMANCE OF ABLATION STUDY

Figure 11 represents the confusion matrix performance of an ablation study conducted on different models. Table 5 shows the confusion matrix TP, TN, FP, and FN values of ablation study. The ablation study aims to evaluate the impact of removing specific components or functionalities from the models on their overall performance. A table that helps to visualize the performance of a classification model is called a confusion matrix. This table displays the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The examples that belong to a predicted class are represented across the rows of the matrix, whereas the instances that belong to an actual class are represented across the columns. The numbers of TP, TN, FP, and FN represent the number of cases for each class that were properly predicted as well as wrongly predicted.

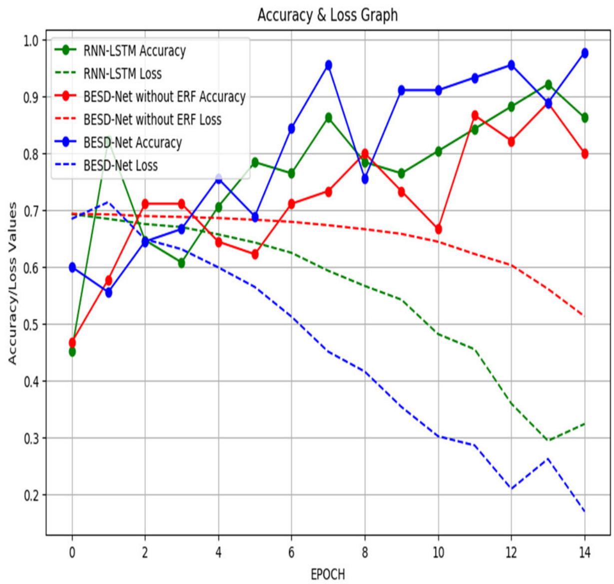

FIGURE 12. **Accuracy and loss graph of ablation study.**

TABLE 5. **Confusion matrix values of ablation study.**

Method	TP	FP	FN	TN
CCNN	44	209	240	17
RNN-LSTM	31	214	215	50
BESD-Net without ERF	21	223	222	44
BESD-Net	21	226	257	6

Figure 12 represents the accuracy and loss graph for an ablation study conducted over 14 epochs. The graph illustrates the changes in accuracy and loss values over the course of training or evaluation. A performance indicator known as accuracy counts how many occurrences have been appropriately labeled as their respective categories. Typically, it is expressed as a percentage of the total. The accuracy values are shown on the y-axis of the graph, while the number of epochs is represented along the x-axis of the graph. The inaccuracy or mismatch that occurs between the expected outputs of the model and the actual labels is denoted by the term "loss." A loss function, such as mean squared error (MSE) or cross-entropy loss, is often used in order to do the calculation. When the loss value is smaller, the predictions made by the model are more in line with the actual labels. On the graph, the loss values are depicted along the y-axis, while the number of epochs is represented along the x-axis.

One whole iteration of training the model by applying it to the entirety of the training dataset is referred to as an epoch. During each epoch, the model makes predictions, calculates the loss, and adjusts its parameters through the optimization algorithm (e.g., gradient descent) to improve its performance. The x-axis in the graph represents the number of epochs, indicating the progression of training or evaluation over time. Here, the proposed BESD-Net has improved accuracy and reduced loss over other methods.

V. CONCLUSION

This paper proposes a hybrid method utilizing the signal processing methodologies and a fusion of deep learning techniques. A CCNN based on deep learning was employed to extract disease-specific features from the preprocessed EEG dataset. Then, an ERF feature selection technique, based on machine learning, was applied to identify optimal features highly correlated with disease-dependent properties from the CCNN features. Finally, a RNN utilizing BLSTM was utilized for enhanced classification of brain seizures based on the selected ERF features. The conclusions drawn from the simulation showed that the suggested BESD-Net achieved improved performance compared to existing methods. It has achieved a superior classification accuracy of 95%. The BESD-Net architecture will be further refined in the future as part of the project's scope. This will include the incorporation of advanced deep learning methods and the investigation of the possibilities of transfer learning to improve the generalization capabilities of the model. In addition, increasing the dataset to include a greater variety of patient profiles and taking into consideration the possibility of real-time implementation are two ways in which the suggested method's practicability and usefulness in clinical settings may be improved.

REFERENCES

[1] M. A. Alsuwaiket, "Feature extraction of EEG signals for seizure detection using machine learning algorthims," *Eng. Technol. Appl. Sci. Res.*, vol. 12, no. 5, pp. 9247–9251, Oct. 2022.

[2] P. Dhar, V. K. Garg, and M. A. Rahman, "Enhanced feature extraction-based CNN approach for epileptic seizure detection from EEG signals," *J. Healthcare Eng.*, vol. 2022, Mar. 2022, Art. no. 3491828.

[3] S. Pattnaik, N. Rout, and S. Sabut, "Machine learning approach for epileptic seizure detection using the tunable-Q wavelet transform based time–frequency features," *Int. J. Inf. Technol.*, vol. 14, no. 7, pp. 3495–3505, Dec. 2022.

[4] R. K. Joshi, V. M. Kumar, M. Agrawal, A. Rao, L. Mohan, M. Jayachandra, and H. J. Pandya, "Spatiotemporal analysis of interictal EEG for automated seizure detection and classification," *Biomed. Signal Process. Control*, vol. 79, Jan. 2023, Art. no. 104086.

[5] C. O. Adetunji, O. T. Olaniyan, O. Adeyomoye, A. Dare, M. J. Adeniyi, and A. Enoch, "An intelligent diagnostic approach for epileptic seizure detection and classification using machine learning," in *Artificial Intelligence for Neurological Disorders*. New York, NY, USA: Academic Press, 2023, pp. 225–243.

[6] M. S. Nafea and Z. H. Ismail, "Supervised machine learning and deep learning techniques for epileptic seizure recognition using EEG signals—A systematic literature review," *Bioengineering*, vol. 9, no. 12, p. 781, 2022.

[7] N. A. Samee, N. F. Mahmoud, E. A. Aldhahri, A. Rafiq, M. S. A. Muthanna, and I. Ahmad, "RNN and BLSTM fusion for accurate automatic epileptic seizure diagnosis using EEG signals," *Life*, vol. 12, no. 12, p. 1946, 2022.

[8] A. K. Idrees, S. K. Idrees, R. Couturier, and T. Ali-Yahiya, "An edge-fog computing-enabled lossless EEG data compression with epileptic seizure detection in IoMT networks," *IEEE Internet Things J.*, vol. 9, no. 15, pp. 13327–13337, Aug. 2022.

[9] R. U. N. Neelappa and H. M. Harish, "Automatic diseases detection and classification of EEG signal with pervasive computing using machine learning," *Int. J. Pervasive Comput. Commun.*, vol. 19, no. 3, pp. 432–450, May 2023.

[10] S. Poorani and P. Balasubramanie, "Deep learning based epileptic seizure detection with EEG data," *Int. J. Syst. Assurance Eng. Manage.*, vol. 2023, pp. 1–10, Jan. 2023.

[11] A. M. Hilal, A. A. Albraikan, S. Dhahbi, M. K. Nour, A. Mohamed, A. Motwakel, A. S. Zamani, and M. Rizwanullah, "Intelligent epileptic seizure detection and classification model using optimal deep canonical sparse autoencoder," *Biology*, vol. 11, no. 8, p. 1220, 2022.

[12] X. Liu, J. Wang, J. Shang, J. Liu, L. Dai, and S. Yuan, "Epileptic seizure detection based on variational mode decomposition and deep forest using EEG signals," *Brain Sci.*, vol. 12, no. 10, p. 1275, 2022.

[13] J. Escorcia-Gutierrez, K. Beleño, J. Jimenez-Cabas, M. Elhoseny, M. D. Alshehri, and M. M. Selim, "An automated deep learning enabled brain signal classification for epileptic seizure detection on complex measurement systems," *Measurement*, vol. 196, Jun. 2022, Art. no. 111226.

[14] S. Zhang, G. Liu, R. Xiao, W. Cui, J. Cai, X. Hu, Y. Sun, J. Qiu, and Y. Qi, "A combination of statistical parameters for epileptic seizure detection and classification using VMD and NLTWSVM," *Biocybern. Biomed. Eng.*, vol. 42, no. 1, pp. 258–272, 2022.

[15] C. Daftari, S. Jainish, and S. Manan, "Detection of epileptic seizure disorder using EEG signals," in *Artificial Intelligence-Based Brain-Computer Interface*. New York, NY, USA: Academic Press, 2022, pp. 163–188.

[16] A. Anuragi, D. S. Sisodia, and R. B. Pachori, "Epileptic-seizure classification using phase-space representation of FBSE-EWT based EEG sub-band signals and ensemble learners," *Biomed. Signal Process. Control*, vol. 71, Jan. 2022, Art. no. 103138.

[17] S. Saminu, G. Xu, S. Zhang, I. A. El Kader, H. A. Aliyu, A. H. Jabire, Y. K. Ahmed, and M. J. Adamu, "Applications of artificial intelligence in automatic detection of epileptic seizures using EEG signals: A review," *Artif. Intell. Appl.*, vol. 1, no. 1, pp. 11–25, 2023.

[18] X. Qiu, F. Yan, and H. Liu, "A difference attention ResNet-LSTM network for epileptic seizure detection using EEG signal," *Biomed. Signal Process. Control*, vol. 83, May 2023, Art. no. 104652.

[19] G. Kaushik, P. Gaur, R. R. Sharma, and R. B. Pachori, "EEG signal based seizure detection focused on Hjorth parameters from tunable-Q wavelet sub-bands," *Biomed. Signal Process. Control*, vol. 76, Jul. 2022, Art. no. 103645.

[20] N. Jiwani, K. Gupta, M. H. U. Sharif, N. Adhikari, and N. Afreen, "A LSTM-CNN Model for epileptic seizures detection using EEG signal," in *Proc. 2nd Int. Conf. Emerg. Smart Technol. Appl. (eSmarTA)*, Oct. 2022, pp. 1–5.

[21] M. R. Yousefi, S. Golnejad, M. M. Hosseini, and A. Dehghani, "Comparison of EEG based epilepsy diagnosis using neural networks and wavelet transform," 2022, *arXiv:2204.04488*.

[22] S. Sivasaravanababu, V. Prabhu, V. Parthasarathy, and R. K. Mahendran, "An efficient epileptic seizure detection based on tunable Q-wavelet transform and DCVAE-stacked bi-LSTM model using electroencephalogram," *Eur. Phys. J. Special Topics*, vol. 231, nos. 11–12, pp. 2425–2437, Aug. 2022.

[23] B. Gao, J. Zhou, Y. Yang, J. Chi, and Q. Yuan, "Generative adversarial network and convolutional neural network-based EEG imbalanced classification model for seizure detection," *Biocybern. Biomed. Eng.*, vol. 42, no. 1, pp. 1–15, 2022.

[24] K. V. N. Kavitha, S. Ashok, A. L. Imoize, S. Ojo, K. S. Selvan, T. A. Ahanger, and M. Alhassan, "On the use of wavelet domain and machine learning for the analysis of epileptic seizure detection from EEG signals," *J. Healthcare Eng.*, vol. 2022, Feb. 2022, Art. no. 8928021.

[25] G. Kumar, S. Chander, and A. Almadhor, "An intelligent epilepsy seizure detection system using adaptive mode decomposition of EEG signals," *Phys. Eng. Sci. Med.*, vol. 45, no. 1, pp. 261–272, 2022.

[26] I. M. Khan, M. M. Khan, and O. Farooq, "Epileptic seizure detection using EEG signals," in *Proc. 5th Int. Conf. Comput. Informat. (ICCI)*, Mar. 2022, pp. 111–117.

[27] F. Mohammad and S. Al-Ahmadi, "Epileptic seizures diagnosis using amalgamated extremely focused EEG signals and brain MRI," *Comput. Mater. Continua*, vol. 74, no. 1, pp. 623–639, 2023.

[28] M. Varlı and H. Yılmaz, "Multiple classification of EEG signals and epileptic seizure diagnosis with combined deep learning," *J. Comput. Sci.*, vol. 67, Mar. 2023, Art. no. 101943.

[29] Z. Brari and S. Belghith, "A new algorithm for Largest Lyapunov Exponent determination for noisy chaotic signal studies with application to Electroencephalographic signals analysis for epilepsy and epileptic seizures detection," *Chaos, Solitons Fractals*, vol. 165, Dec. 2022, Art. no. 112757.

[30] S. M. Ghazali, M. Alizadeh, J. Mazloum, and Y. Baleghi, "Modified binary salp swarm algorithm in EEG signal classification for epilepsy seizure detection," *Biomed. Signal Process. Control*, vol. 78, Sep. 2022, Art. no. 103858.

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