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Optimized machine learning model for Alzheimer and epilepsy detection from EEG signals

P. Jasphin Jeni Sharmila and T. S. Shiny Angel

Department of Computational Intelligence, SRM IST, Kattankulathur, India

ABSTRACT

One of the common nervous system diseases in older adults is Alzheimer's and epilepsy, and the possibility of occurrence increases with age. The chances of seizure are high for patients with mild cognitive impairment and Alzheimer's disease. So, there is a bidirectional association between Alzheimer's and epilepsy, as both affect the neurodegenerative processes. Electroencephalogram (EEG) is a possible non-invasive measurement technique widely used to measure the variations in brain signals. EEG signal is analyzed to discriminate the Alzheimer and epilepsy. Numerous research works evaluated the clinical relevance of Alzheimer's and epilepsy. Specifically, machine learning-based evaluation models developed recently bring the facts by extracting features from the EEG signals. However, machine learning-based models lag in performance due to high dimensional EEG features. For initial feature selection particle swarm optimization is included in the proposed model and to reduce the computation complexity of the classifier, kernel PCA is incorporated for dimensionality reduction. Experimentations using benchmark Bon and Dementia datasets confirms the proposed model better performances in terms of precision, recall, f1-score and accuracy. The attained accuracy of 94% is much better than existing Gaussian Mixture Model (GMM), Relevance Vector Machine (RVM), Support Vector Machine (SVM), and Artificial Neural Network (ANN) methods.

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KEYWORDS
Alzheimer; epilepsy; machine learning; deep belief network; kernel PCA; tuna swarm optimization

1. Introduction

The specific reason for neurological disorders varies for each person. However, some common cause that leads to neurological disorders like Alzheimer's and epilepsy are genetic disorders, congenital abnormalities, lifestyle problems including malnutrition, etc., among the numerous neurological diseases, Alzheimer's and epilepsy have gained more attention in the research community. The most predominant neurodegenerative brain disease, Alzheimer's, affects older adults. Alzheimer's is an irreversible, neurological brain disorder, and it is a progressive disease that slowly reduces brain functions like thinking, memory skills, etc., by destroying the brain cells. Alzheimer's patients cannot perform simple tasks, and their daily activities become complex due to reduced brain functions. Alzheimer's is the primary reason for dementia. Alzheimer's progress is defined as customarily controlled in the initial stage, mild cognitive impairment (MCI) in the mid-stage, and finally, the Alzheimer's affected stage. World Alzheimer Report 2022 states that in 2019, the Alzheimer's rate was 55 million, increasing to 139 million in 2050 [1]. Figure 1 depicts a simple illustration that differentiates the brain of an average person, and Alzheimer affected person.

Another brain dysfunction neurological disease is epilepsy, where 50 million people around the globe suffer due to epilepsy. Epilepsy is a grave issue as the epileptic patient's premature death rate compared to average persons is three times higher. Epilepsy is declared when the patient faces more than two seizure attacks. Due to the discrepancy of inhibitory and excitatory synapses in the brain, an abnormal electrical action occurs during the epileptic seizure attack. The physicians diagnose both Alzheimer's and epilepsy through magnetic resonance imaging (MRI) images, computerized tomography (CT) scans, high-density electroencephalogram (EEG), and function MRI images. Among all, EEG is considered a simple and efficient medical test procedure widely used to detect Alzheimer's and epilepsy seizures. Alzheimer's and epilepsy are detected generally by physicians by visual examination of EEG recordings [3]. However, the visual examination is tiresome and imperfect in some cases. Examining EEG recording is complex, and even expert neurologists face challenges in finding the traces of disease activities.

Additionally, EEG analysis is not only used to detect Alzheimer's or epilepsy. It can be used for other neural-related medication procedures [4]. Due to this, an automated Alzheimer's and epilepsy detection procedure

CONTACT P. Jasphin Jeni Sharmila jasphinjenisharmilap.ci@outlook.com Department of Computational Intelligence, SRM IST, Kattankulathur, India

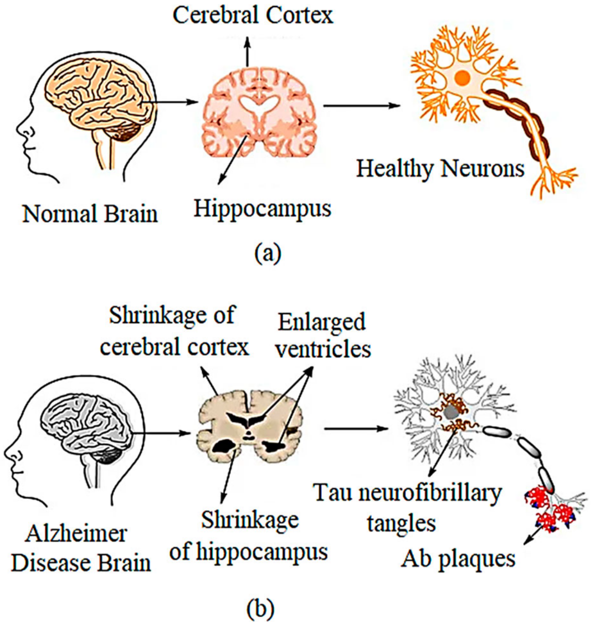

Figure 1. (a) Normal brain (b) Alzheimer's disease brain [2].

becomes essential to assist physicians in diagnosing the disease and reducing the time and cost. Researchers put forward numerous ideologies in the early diagnosis of this disease by studying the abnormalities.

Earlier Fourier transform-based approaches detect Alzheimer's and epilepsy from EEG signals. However, these methods must improve detection performance due to inefficient spectral estimation and noise sensitivity. Wavelet transform-based approaches in Alzheimer's and epilepsy detection lag in performance due to inappropriate selection of wavelet functions. Time and frequency distribution-based detection methods take more time for computation, and their extraction procedures are interdependent, making the detection process complex. Due to these limitations of traditional approaches, machine learning algorithms have been used to classify Alzheimer's and epilepsy seizures, which are more accurate than traditional methods and manual examination. Machine learning models consider the whole brain in a single modality or multi-modal dataset and learn the features to classify the abnormalities [5].

In Alzheimer's and epilepsy detection, feature classification is performed using machine learning algorithms like decision trees, naïve Bayes, k-nearest neighbor, and support vector machine algorithms [6,7]. Machine learning techniques perform better in detection performances; however, essential features must be selected to improve the classification and detection performances. Thus, in this research work, an optimized machine-learning model is presented for detecting Alzheimer's and epilepsy detection. The primary objective of this research work is to attain better detection performances. To attain this, in this research work, the optimal features are selected from the dataset using a particle swarm optimization algorithm and then classified using a deep belief network. The tuna swarm optimization algorithm optimizes the network parameters to improve the classification performance. The contributions of this research work are presented as follows.

- To classify Alzheimer's and epilepsy from EEG data using an optimized machine learning model. A deep belief network is used to classify the EEG data, and a novel tuna swarm optimization algorithm
- Optimizes the parameters.
- The particle swarm optimization (PSO) algorithm is used to select the optimal features from the dataset, which improves classification performance and reduces the classifier's computation complexity. The feature dimensions are also reduced using kernel principal component analysis (KPCA).
- Benchmark Bonn and Dementia datasets are used in the proposed model experimentation, and performances are verified regarding recall, precision, f1-score, and accuracy.

The remaining discussions are arranged in the following order: Section 2 discuss the literature analysis of existing Alzheimer and epilepsy models. Section 3 describes the proposed detection model. Results and discussion are presented in section 4, and the conclusion is presented in the last section.

2. Related works

Similar methodologies in detecting Alzheimer's and epilepsy are studied and analyzed in detail in this section. The Alzheimer's disease (AD) early-stage detection model reported in [8] effectively differentiates health control subjects and mild cognitive impairment. The reliable piecewise aggregate approximation model compresses the high dimensional EEG data. Further, the compressed data is analyzed using permutation entropy and autoregressive model, which detects the changes. Finally, machine learning techniques like an Extreme learning machine, Support vector machine, and k-nearest Neighbor are used to classify the features. Experimental confirms that ELM attained better classification performance than other machine learning algorithms regarding execution time and accuracy. The Alzheimer detection model reported in [9] employed a surrogate decision tree classifier to differentiate patients with average and mild cognitive impairment. Features like maxima, minima, zero crossing, mean derivative value, relative power, and spectral ratios are selected for classification and attain better classification accuracy than conventional methods.

To overcome the manual limitations in analyzing EEG, a fusion method is presented in [10], including autoregression and variational mode decomposition

(VAD) algorithms for initial feature extraction and signal decomposition. In the signal decomposition, band-limited intrinsic mode functions using VAD are used, and a logarithmic operation was performed. The extracted features are finally classified using a random forest algorithm and attain better classification performances. The Alzheimer detection model reported in [11] presents a hybrid model that includes discrete wavelet transform multi-band decomposition method and cepstral distances. The cepstral distance is extracted to verify the lag between conventional band signals and cepstral. The hybrid model attained better classification performance, which effectively differentiates the various stages of Alzheimer's disease.

The epilepsy and Alzheimer detection model reported in [12] initially removes the noise artifacts in the preprocessing method. Through discrete wavelet transform, the signals are decomposed into several bands. The complexity and chaoticity are measured using the largest Lyapunov exponent and Shannon entropy methods. Finally, various machine learning algorithms are employed for classification, and the experimental analysis confirmed the k-nearest neighbor's better performance over other classification models. Support vector machine-based EEG analysis is widely used for Alzheimer's and epilepsy detection. EEG signal classification using the Universum SVM model is presented in [13], which generates data points by selecting universum from EEG data. In generating Universum data, outlier effects are removed, and the computation time and cost are reduced compared to conventional methods. A modified Universum model was presented in [14] for EEG classification as Universum twin SVM. The binary classification model is functional iterative model which considers the structural risk minimization theory. Then the regularization parameters are included to improve the stability in the classification process.

Feature extraction from EEG signals is essential for both Alzheimer's and epilepsy seizure detection. Spectrogram-based feature extraction presented in [15] initially employs Short Time Fourier Transform (STFT) for time–frequency representations. In order to obtain the spectrogram descriptors, spectral peaks are considered as reference points. Further, based on frequency and surface, the features are extracted. In another way, k-means is used to extract features, and finally, maximum peaks are detected using a local ternary pattern. All the extracted features are combined and classified using machine learning models like multilayer perceptron, support vector machine, and k-nearest neighbor models. Among all k-nearest neighbors, better performance is validated by the experimental analysis in detecting Alzheimer's and epilepsy diseases.

The seizure detection model presented in [16] includes transfer component analysis (TCA) for feature extraction. The Kernel Hilbert space approach is used in TCA for extracting the features. Further, the feature vectors are generated using the tocher technique and classified using a recurrent neural network. The presented network model attained better detection performances over conventional methods. The multi-task learning procedure presented in [17] for the Alzheimer detection model includes a discriminative convolutional high-order Boltzmann machine with hybrid feature maps. The presented model directly performs EEG spectral image classification using a deep Boltzmann machine. Elevated level of feature representation and enhanced classification accuracy are the observed merits of the presented model.

The epilepsy detection model presented in [18] compresses the EEG signals using compressive sensing and employs entropy models like sample entropy and permutation entropy models. The features are selected using ANOVA and classified using machine learning classifiers like discriminant analysis, Decision tree, k-nearest Neighbor, and support vector machine algorithms. Experimental results proved the better classification performance due to compressive sensing compared to traditional methods. An automated epilepsy detection model presented in [19] includes an analytic wavelet transform method for initial feature processing. Various entropies like log energy entropy, cross-correlation entropy, and Stein's unbiased risk estimate entropy are extracted and classified using machine learning models like least square support vector machine (LSSVM) and k-nearest neighbor classifiers. The LSSVM attained better accuracy compared to other methods.

The epilepsy detection model reported in [20] uses artificial neural networks, genetic algorithms, and gradient-boosting algorithms. The initial feature is extracted using discrete wavelet transform, and the feature dimensions are reduced using fuzzy logic. The artificial neural network is trained to detect epilepsy using gradient algorithms. A genetic algorithm defines the cross-validation, information, and stopping criteria. The presented detection model attained better reliability and complexity. The epilepsy detection model presented in [21] includes a penalized robust regression model for feature learning. The most prominent features are recognized and extracted using the regression model. Finally, the classification is performed using a random forest classifier and attained better seizure detection rates than traditional methods.

The seizure detection model reported in [22] includes generalized Stock well transform, random forest, and SVD methods. The local and global singular values are obtained using the single-value decomposition model. A random forest classifier is used to classify the global and local singular value vectors, defining the seizures' impacts. The presented detection model attained better detection accuracy than existing methods. The epileptic detection model reported in [23] includes performing feature extraction using the Mel frequency cepstral coefficient and classifying using the neural network model. Through frequency analysis considering filter bank, Mel frequency cepstral coefficients are measured. Experimental results confirmed that the regression neural network classification performance attained better sensitivity and specificity over existing methods.

The machine learning-based epilepsy detection model reported in [24] extracts the EEG dataset's power spectrum, bi-spectrogram, and correlogram features. Machine learning algorithms are used to classify the extracted features. Algorithms like decision trees, naïve Bayes, support vector machines, 1-nearest neighbors, and backpropagation-based multilayer perception algorithms are used in the analysis. Experimentation results confirm that support vector machines attained better classification performances over other machine learning algorithms. A time–frequency analysis model for epilepsy classification presented in [25] includes synchro extracting chirplet transform for classifying epilepsy classes. The signal energy concentrated time–frequency representation is obtained using the parameter chirp rate. Further instantaneous frequency trajectory is obtained using the time–frequency coefficients relevant to the synchro-extracting chirplet operator. Finally, the original signals are reconstructed using an instantaneous trajectory, and multiple classifications are performed using a support vector machine. The presented approach attained better classification performances and robustness against noise factors in the diagnosis of epilepsy disease.

Machine learning based epilepsy detection model presented in [26] includes k-Nearest Neighbor to classify the optimal features extracted from the EEG signals. The presented model generates two feature vectors using hypercube-based feature extractor. For multilevel feature extraction, multilevel discrete wavelet transform is employed. Seven optimal features are extracted and classified to detect epilepsy. Experimental results confirms that the presented model attained 87.78% which is lesser than the recent detection models. The deep learning epilepsy detection model presented in [27] overcomes the limitations of machine learning algorithms. The presented approach samples the input and map the features into a matrix using Pearson correlation coefficient. This coefficient is used to define the statistical relationship between variables. Finally, the features are classified using the developed EpilepsyNet. Experimental section includes a tenfold cross validation to validate the generated results. However, the obtained accuracy of 85% is lesser than the current methods.

The epilepsy detection model presented in [28] includes the machine learning algorithm k-nearest neighbor for adequate classification. The presented model obtains two feature vectors using a hypercube-based feature extractor model. Further, multileveled feature extraction is performed using a multi-level discrete wavelet transform function. The extracted features are finally classified using k-nearest neighbor with high classification performance over other machine learning-based approaches. From the literature analysis, it can be summarized that the machine learning-based Alzheimer and epilepsy detection model outperforms traditional methods. Specifically, machine learning models like Naïve Bayes, decision tree, k-nearest neighbor, Random Forest, and Support Vector Machine algorithms are widely used for disease classification. Though the machine learning approaches perform better, the performance can be improved if optimization models are incorporated with machine learning algorithms for feature extraction. Thus, this research presents optimal feature extraction and an optimized machine-learning model for classifying Alzheimer's and epilepsy disease detection.

3. Materials and methods

The materials and methods used in the proposed Alzheimer's and epilepsy detection model are presented in this section. The discussion covers the dataset details, particle swarm optimization algorithm, deep belief network, and tuna search optimization algorithm. The complete process flow of the proposed model is depicted in Figure 2. The process starts with preprocessing input data, including categorical to numerical values. Then, null values in the dataset are replaced with zeros, and standard scaling is performed. The optimal features are selected from the preprocessed data using the particle swarm optimization algorithm.

A deep belief network is employed in the classification process, which classifies the optimal features obtained from the particle swarm optimization algorithm. A tuna search optimization algorithm is used in the proposed model to enhance the classification performance, by optimizing the network parameters. Thus, the classification model attained better classification performances in the detection of Alzheimer's and epilepsy detection process. The combined architecture is the major novelty of this research work. The presented model combines an efficient feature selection model and a better dimensionality reduction model. The optimized classifier enhances the classification accuracy which is unique from existing methods.

3.1. Dataset

The first dataset used in the experimentation is the Bonn dataset, a data collection recorded at the

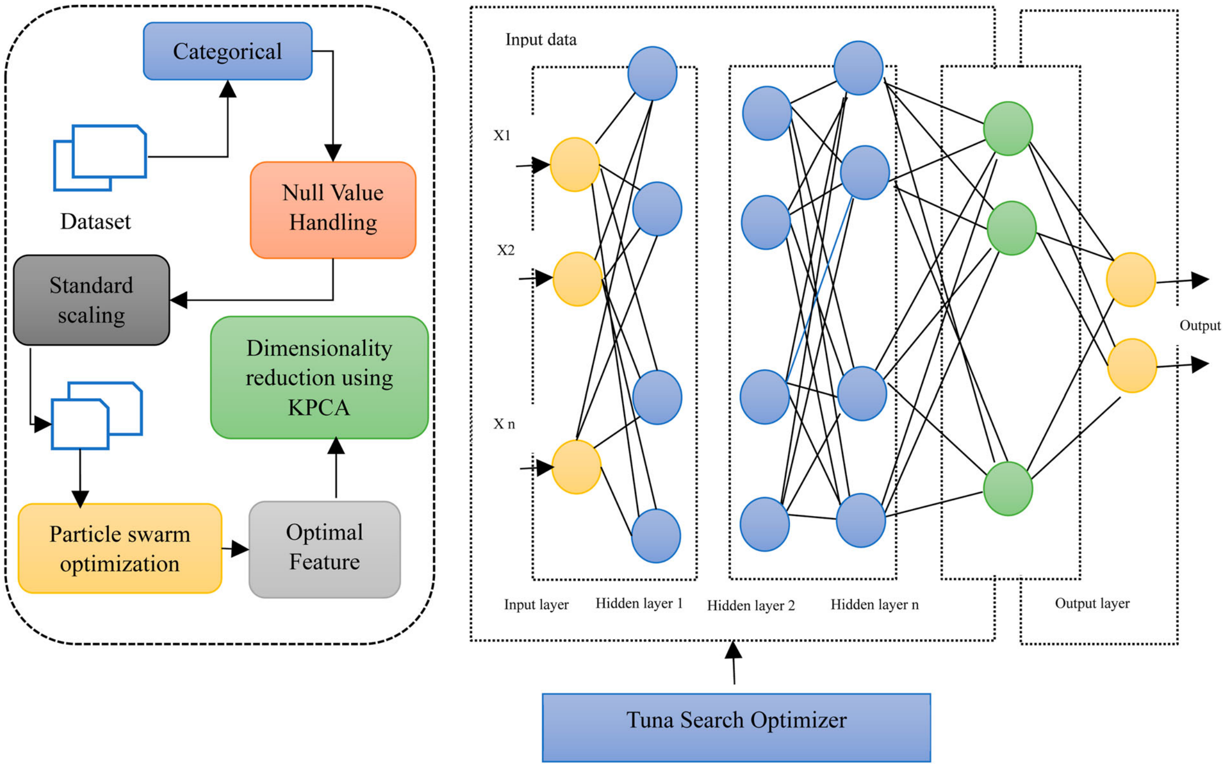

Figure 2. Proposed Alzheimer and epilepsy detection model.

University of Bonn. Epilepsy seizure analysis is widely performed using this dataset. The dataset has 500 EEG single-channel data sampled at 173.6 Hz for 23.6 s. The dataset has five classes of data: F, N, O, S, and Z. For each class, 100 channel recordings are present. Class O and Z are obtained from five healthy patients. The data S, F, and N classes are obtained from five patients who have epilepsy. The second dataset used in the experimentation is the Dementia Prediction Dataset, the publicly available dataset from the Kaggle repository. The dementia dataset has 150 subjects with longitudinal scan data. The age of the subjects is in the range 60–96. Out of 150, 72 subjects' data are characterized as non-demented, 64 subjects' data are characterized as demented, in that 51 subjects are characterized as mild to moderate Alzheimer's, and 14 subjects are characterized as non-demented in the subsequent visits.

3.2. Preprocessing

The proposed model's preprocessing step includes converting categorical values into numerical values, null value handling, and standard min–max normalization. In the initial conversion process, the categorical values in the dataset are converted into numerical values. After the conversion of numerical values, the null elements in the data are checked and converted into zero values. So that all the datasets' elements are occupied, avoid computation errors, and reduce the inaccuracy. Finally, for standard scaling, min–max normalization is employed, which normalizes the data in the dataset based on the minimum and maximum numerical values. Mathematically, the min–max normalization is formulated as

$$x = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_{max} indicates the maximum value and x_{min} indicates the minimum value. Further, the preprocessed is fed into an optimization model for selecting optimal features for the classification process.

3.3. Particle swarm optimization (PSO)

PSO is a swarm-based optimization used for feature selection in the proposed work. PSO algorithm is formulated based on the particle's flying characteristics. Compared to other optimization algorithms, PSO is relatively simple to understand and converges quickly with better solutions. The parameter requirements of PSO is less and it can be used for wide range of optimization problems. The velocity and position play a crucial role in the optimization process. The fitness of each particle is defined based on these parameters. The selection of more optimal features from the dataset will reduce the computation complexity of the classifier and enhance the classification performance. Thus, PSO is used in the proposed model for optimal feature selection. The basic formulation of the PSO algorithm is based on different bird characteristics classes. The search abilities are defined in the algorithm. Initially, all the particles are assigned a random value, and the fitness is measured for each particle. Then, for the next position, the current fitness is defined, and if the present value is better than the previous best, then the current value is updated; otherwise, the old position is maintained as it is. This process is repeated in the PSO for all particles until the best solution for the given problem is obtained. The mathematical model which defines the PSO is defined as follows

$$v_i^d(t+1) = wv_i^d(t) + c_1r_1(pbest_i^d(t) - x_i^d(t)) + c_1r_1(pbest_i^d(t) - x_i^d(t)) \quad (2)$$

where velocity is indicated as v, inertia weight is indicated as w, d indicates the search space dimension, the number of iterations is indicated as t, the population is indicated as i, the acceleration factor is indicated as c_1 and c_2, two independent random numbers are indicated as r_1 and r_2. The personal best solution is indicated as *pbest*, and the global best solution is indicated as *gbest*. The velocity update in the optimization model is formulated as follows.

$$s(v_i^d(t+1)) = \frac{1}{1+e^{(-v_i^d(t+1))}} \quad (3)$$

The practical *pbest* and *gbest* are converted to the following equations

$$x_i^d(t+1) = \begin{cases} 1 & if\ rand < s(v_i^d(t+1)) \\ 0 & otherwise \end{cases} \quad (4)$$

where rand indicates the random number and its range is given as [0,1]. Based on the above terms, the *pbest* and *gbest* are converted as follows.

$$pbest_i(t+1) = \begin{cases} x_i(t+1) & if\ F(x_i(t+1)) < F(pbest_i(t)) \\ pbest_i(t) & otherwise \end{cases} \quad (5)$$

$$gbest_i(t+1) = \begin{cases} pbest_i(t+1) & if\ F(pbest_i(t+1)) < F(gbest_i(t)) \\ gbest_i(t) & otherwise \end{cases} \quad (6)$$

where the fitness function is indicated as F, inertia weight is formulated as

$$w = w_{max} - (w_{max} - w_{min})(t/T_{max}) \quad (7)$$

where maximum inertia weight is indicated as w_{max} and minimum inertia weight is indicated as w_{min}. The optimal features from the preprocessed data are selected based on the optimal particle swarm optimization algorithm optimal solution (Figure 3).

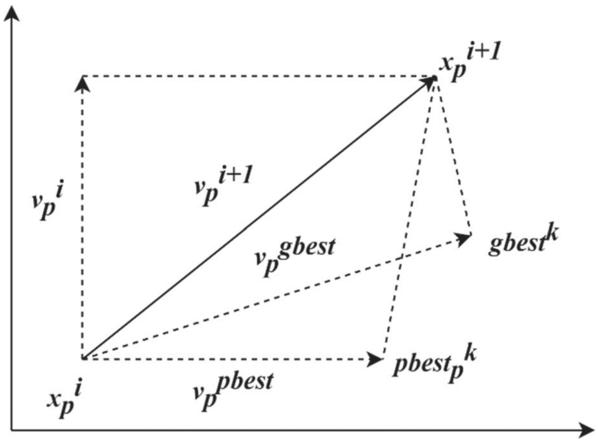

Figure 3. PSO search mechanism.

3.4. Kernel PCA

In the early stage of our research work [29], we have analyzed and identified that kernel PCA is more effective in reducing dimensions. Thus, in this research work dimensionality of features are reduced using the kernel principal component analysis. PCA is a statistical model that converts high-dimensional features into low-dimensional features, degrading the feature quality. For the given data $x \in R^m$, which has m samples, the following model is obtained to define PCA.

$$x = t_1p_1^T + t_1p_1^T + \ldots + t_mp_m^T \quad (8)$$

where the principal component vector is indicated as t_i, and the projection vector is indicated as p_i. The principal component is obtained as

$$t_i = xp_i \quad (9)$$

Further, using the value problem, the projection vector is obtained, which is given below.

$$\lambda_i p_i = \frac{1}{n-1}x^Txp_i \quad (10)$$

For nonlinear data decomposition, kernel PCA is used. In this process, using a nonlinear function ϕ, feature space is mapped into the nonlinear data. The decomposition is formulated as

$$\phi(x) = t_1p_1^T + t_1p_1^T + \ldots + t_fp_f^T \quad (11)$$

In the nonlinear case, the assumed function $\phi(.)$ is unknown, and pi is solved by substituting x with $\phi(x)$. Thus, in PCA, kernel trick is introduced, and the loading vector p_i is formulated in KPCA is given as

$$p_i = \phi^T(x)\alpha_i \quad (12)$$

where the linear transformation vector is indicated as α_i . Combining equations (10) and (12) to define the kernel matrix eigenvalue problem is given as

$$\lambda_i\alpha_i = \frac{1}{n-1}K\alpha_i \quad (13)$$

where the kernel matrix is indicated as K and formulated as $K = \phi(x)\phi^T(x)$. The high-dimensional features are reduced into low-dimensional ones using a kernel matrix. Features like MMSE, CDR, eTIV, and nWBV are selected from Dementia dataset for further classification.

3.5. Deep belief network (DBN)

The optimal features selected using particle swarm optimization are further classified using DBN. DBN is a simple and efficient machine learning model with a deep neural network and multiple stacked Restricted Boltzmann Machine (RBM). The RBM comprises a hidden layer and one visible layer. The neurons in the layers are interlinked. A complete architecture of a deep belief network is depicted in Figure 4.

The optimal features are classified using the optimized DBN. The RBM in the DBN is an energy-dependent model, and its energy function of the hidden and visible layers is formulated in a combined manner, as given below.

$$F(w,i|\theta) = -\sum_{j=1}^{o} w_1 b_j - \sum_{k=1}^{n} i_k c_k - \sum_{k=1}^{o}\sum_{k=1}^{n} w_j x_{jk} i_k \tag{14}$$

where b_j indicates the visible layer neuron bias factor, c_k indicates the hidden layer neuron bias factor, and x_{jk} indicates the visible and hidden layer link weight. The weight factor θ is formulated as $\theta = \{b_j, c_k, x_{jk}\}$. The visible and hidden layers connecting the neuron's likelihood function are formulated based on the following energy function.

$$P(w,i|\theta) = \frac{1}{a(\theta)} e^{-F(w,i|\theta)} \tag{15}$$

The hidden and visible layers are further considered to satisfy the condition of independence. Thus, the hidden layer k^{th} neuron state is activated and mathematically formulated as s probability function, expressed as follows.

$$p(i_k = 1|w) = g\left(\sum_j w_j x_{jk} + c_k\right) \tag{16}$$

The activation probability associated with the j^{th} visible layer neuron state provided the hidden layer neuron state function as follows.

$$p(w_j = 1|i) = g\left(\sum_j i_k x_{jk} + b_j\right) \tag{17}$$

A contrast divergence approach is used to reconstruct the input samples based on the data attributes in the RBM training process. Then, it is evaluated to obtain the original sample by adjusting the parameter θ. Generally, the θ is changed to obtain the maximum likelihood function; thus, the log-likelihood function is used to calculate the θ as follows.

$$M(\theta) = \sum_{o=1}^{O} p(w^o, i) \tag{18}$$

Further, the network parameters are optimized using the tuna swarm optimization algorithm to obtain better classification performances.

3.6. Tuna swarm optimization

Tuna swarm optimization is an intelligent swarm-based algorithm that is formulated based on food foraging behavior. TSO combines the local and global search capabilities and provides better balance between exploration and exploitation. Also compared to other swarm optimization algorithm the convergence efficiency of TSO is better. Due to this feature benefits, TSO is included in the proposed work for parameter optimization. Tuna fish is one of the marine predators which consumes midwater and surface fishes. They swim continuously in a unique manner where the long, thin tail swings, and the body stays rigid. Tuna fish travel as a group and find their prey based on intelligence. The optimization model is formulated based on spiral and parabolic foraging strategies. Spiral foraging is the first strategy where the fishes create a spiral arrangement to trap the prey in the shallow water. In the parabolic foraging, tunas enclose its prey. The optimization initially generates populations randomly in search space, which is formulated as

$$x_i^{\text{int}} = rand(u_b - l_b) + l_b \text{ for } i = 1, 2, \ldots, N_p \tag{19}$$

where the individual swarm is indicated as x_i^{int}, and the lower and upper boundaries are indicated as l_b and u_b, respectively. The total number of populations is Np, and the random vector, which is uniformly distributed from 0 to 1, is indicated as *rand*. When the tuna fishes encounter a group of fish, initially, they hunt the fish using a spiral foraging strategy. A tight spiral will be formed to catch the small fish groups. In the attack process, tunas exchange information to follow the prey fish groups. The spiral foraging behavior of tuna fishes are mathematically expressed as

$$x_i^{t+1} = \begin{cases} \alpha_1(x_{best}^t + \beta|x_{best}^t \\ -x_i^t|) + \alpha_2 x_i^t, & i = 1 \\ \alpha_1(x_{best}^t + \beta|x_{best}^t \\ -x_i^t|) + \alpha_2 x_{i-1}^t, & i = 2, 3, \ldots N_p \end{cases} \tag{20}$$

where

$$\alpha_1 = a + (1-a)\frac{t}{t_{max}} \tag{21}$$

$$\alpha_2 = (1-a) - (1-a)\frac{t}{t_{max}} \tag{22}$$

$$\beta = e^{bl} cos(2\pi b) \tag{23}$$

$$l = e^{3cos(((t_{max}+\frac{1}{t})-1)\pi)} \tag{24}$$

where the current optimal food source is x_{best}^t, weight coefficients are indicated as α_1 and α_2. The constant

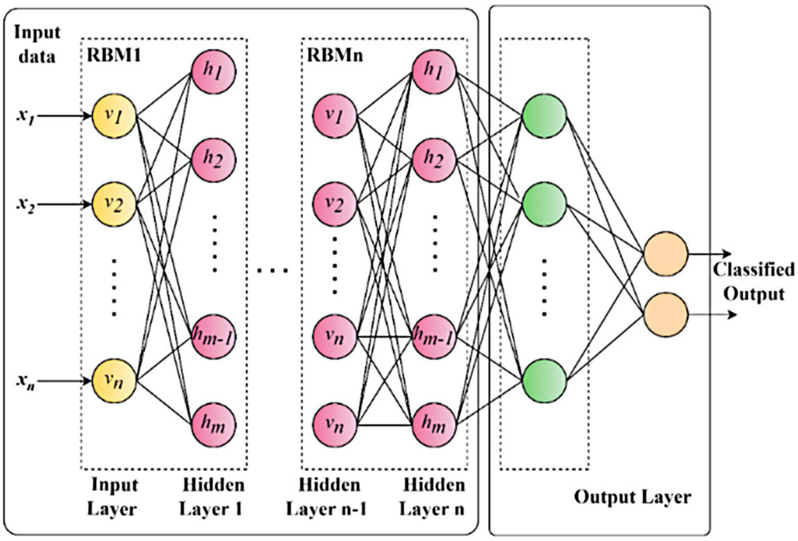

Figure 4. Deep belief network (DBN).

parameter, which defines which tune follows the optimal individual and previous individual, is indicated as a. Current iteration is indicated as t, and maximum iteration is indicated as t_{max}. b is a uniformly distributed random number in the range [0,1]. The exploration ability of tuna fish is better when they forage spirally. However, if the optimal individual does not identify the food, the fish follow the optimal individual, which is not performing group foraging. Thus, a random coordinate is generated in the search space, considering the spiral as the reference point. Thus, each individual searches a wider area, enhancing global exploration ability. Mathematically, this process is expressed as

$$x_i^{t+1} = \begin{cases} \alpha_1 (x_{rand}^t + \beta |x_{rand}^t \\ -x_i^t|) + \alpha_2 x_i^t, & i = 1 \\ \alpha_1 (x_{rand}^t + \beta |x_{rand}^t \\ -x_i^t|) + \alpha_2 x_{i-1}^t, & i = 2, 3, \ldots N_p \end{cases} \tag{25}$$

where search space randomly generated reference point is indicated as x_{rand}^t.

$$x_i^{t+1} = \begin{cases} \alpha_1 (x_{best}^t + \beta |x_{best}^t - x_i^t|) + \alpha_2 x_i^t, i = 1 & \\ \alpha_1 (x_{best}^t + \beta |x_{best}^t - x_i^t|) + \alpha_2 x_{i-1}^t, & i = 2, 3, \ldots N_p, if rand < \dfrac{t}{t_{max}} \\ \alpha_1 (x_{rand}^t + \beta |x_{rand}^t - x_i^t|) + \alpha_2 x_i^t, & i = 1 \\ \alpha_1 (x_{rand}^t + \beta |x_{rand}^t - x_i^t|) + \alpha_2 x_{i-1}^t, & i = 2, 3, \ldots N_p if\ rand \geq \dfrac{t}{t_{max}} \end{cases} \tag{26}$$

$$x_i^{t+1} = \begin{cases} x_{best}^t + rand(x_{best}^t - x_i^t) \\ +TFp^2 (x_{best}^t - x_i^t) & if\ rand < 0.5 \\ TFp^2 x_i^t & if\ rand \geq 0.5 \end{cases} \tag{27}$$

$$p = \left(1 - \frac{t}{t_{max}}\right)^{\left(\frac{t}{t_{max}}\right)} \tag{28}$$

The final mathematical expression that defines the spiral foraging is formulated in equation (26). In parabolic foraging, tunas form a parabolic structure, keeping the food as a reference point. Tunas hunt for food by searching around themselves. In finding an optimal solution, these two foraging processes are performed simultaneously, and the process is mathematically formulated in Equations 26 and 27. The random factor is indicated as TF, and its range is 1 or -1. In the hunting process, tuna use both strategies. For better optimization, a random initial population is considered for the given search space. Individuals will select any strategies for each iteration and regenerate search space positions as a probability factor z. In the complete process, continuous updating of positions is performed by all the individuals until the essential conditions are met.

The summarized pseudocode for the tuna search optimization algorithm is given as follows.

4. Results and discussion

The proposed model performance analysis includes two different datasets in the experimentation. Benchmark Bonn and Dementia prediction dataset are used for the experimentation. Python tool is used for validating the proposed model performance, and two datasets are used to validate the proposed model performance. Python was installed in an Intel i5 processor with 8GB memory. The operating system is windows 11. Essential python packages like tensor flow $= =2.10.0$, keras, pandas, pretty table, pyqt5, matplotlib, ReliefF, phase pack, seaborn, tabulate, scikit-learn, Py_FS, and Numpy are included. The essential hyperparameters used for the proposed method are listed in Table 1.

The training time of proposed model is less than 30 min and for testing the computation time is approximately less than 2 min. The proposed model accuracy and loss curves for the Bonn dataset are depicted in Figure 5. The accuracy and loss are observed for 35

Pseudocode for Tuna swarm optimization algorithm

Input: Population size N_p*, maximum iteration* t_{max}
Output: Food location and fitness value
Initialize random population x_i^{int}, a, z
If $(t < t_{max})$
  Obtain the fitness value
    Update x_{best}^t
  For each tuna do
      Update α_1, α_2, p
        If $(rand < z)$ *then*
          Update the position x_i^{t+1}
          Else if $(rand \geq z)$ *then*
            If $(rand < 0.5)$ *then*
              If $\left(\frac{t}{t_{max}} < and\right)$ *then*
                Update the position x_i^{t+1}
              Else If $\left(\frac{t}{t_{max}} \geq and\right)$ *then*
            Update the position x_i^{t+1}
          Else If $(rand \geq 0.5)$ *then*
        Update the position x_i^{t+1}
      End for
    $T = t + 1$
    End while
  Return the best individual x_{best}^t *and the best fitness value* $F(x_{best})$
End

Table 1. Hyperparameter details.

S. No	Hyperparameter	Range/Value
1	Population size	50
2	Number of particles (population size)	50
3	Social factor c_2	2.5
4	Cognitive factor c_1	3
5	Maximum bound on inertia weight w_{max}	0.8
6	Maximum bound on inertia weight w_{min}	0.5
7	Maximum velocity	5
8	TSO Probability factor z	0.05
9	TSO Constant a	0.7
10	Number of epochs	35

epochs. From Figure 5, it can be observed that the proposed model attained better accuracy performance, and loss is minimal. The training and validation accuracy attained by the proposed model for Bonn dataset is 94.6% and 94%, respectively. Similarly, for the Dementia dataset, the proposed model attained better accuracy and loss values for 35 epochs, as depicted in Figure 6. The training and validation accuracy attained by the proposed model for Dementia dataset is 95.7% and 95%, respectively.

The confusion matrix obtained for the proposed ed model for the Bonn dataset and Dementia dataset is depicted in Figures 7 and 8, respectively. In the Bonn dataset, three classes of data are classified, which define the healthy, seizure, and seizure activity status. For the dementia dataset, the classification results are presented for demented and non-demented classes. The performance of the proposed model is validated using metrics like recall, precision, f1-score, and accuracy

Table 2. Overall performance analysis.

		Bonn		Dementia	
S. No	Metrics	Train	Test	Train	Test
1	Accuracy	0.946	0.940	0.957	0.950
2	Precision	0.955	0.938	0.960	0.949
3	Recall	0.944	0.935	0.955	0.945
4	F1-Score	0.949	0.934	0.957	0.947

for both datasets. The essential formulations for the performance metrics are given as follows.

$$Recall = \frac{TP}{TP + FN} \tag{29}$$

$$Precision = \frac{TP}{TP + FP} \tag{30}$$

$$F1\ score = \frac{(2 * Precision * Recall)}{Precision + Recall} \tag{31}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{32}$$

where the true positive values are indicated as TP, false positives are indicated as FP; true negatives are indicated as TN, and false negatives are indicated as FN.

The performance comparative analysis of the proposed model using the Bonn dataset is depicted in Figure 9(a) for metrics like accuracy, recall, precision, and f1-score. The results are presented for both training and testing processes. The proposed model attained 95.59% of precision, 94.45% of recall, 94.91% of f1-score, and 94.63% of accuracy in the training process. In the testing process, the proposed model attained 93.89% of precision, 93.59% of recall, 93.44% of f1-score, and 94% of accuracy. Due to optimal feature selection and optimized classifier parameters, the proposed model exhibited better accuracy for both datasets.

Figure 9(b) depicts the performance comparative analysis of the proposed model using the Dementia dataset for metrics like accuracy, recall, precision, and f1-score. The results are presented for both training and testing processes. The proposed model attained 96.01% of precision, 95.51% of recall, 95.70% of f1-score, and 95.74% of accuracy in the training process. In the testing process, the proposed model attained 94.99% of precision, 94.54% of recall, 94.76% of f1-score and 95.05% of accuracy. Table 2 depicts the overall performance analysis of the proposed model for both Bonn and dementia datasets. Training and testing process performance metrics are numerically presented in the tabulation. From the results, it can be observed that the proposed model performs better for both datasets and detects the impacts effectively.

Further, to compare the proposed model performance with existing algorithms, the results of Prasanna et al. [30] is used. Methods like the Gaussian Mixture Model (GMM), Relevance Vector Machine (RVM),

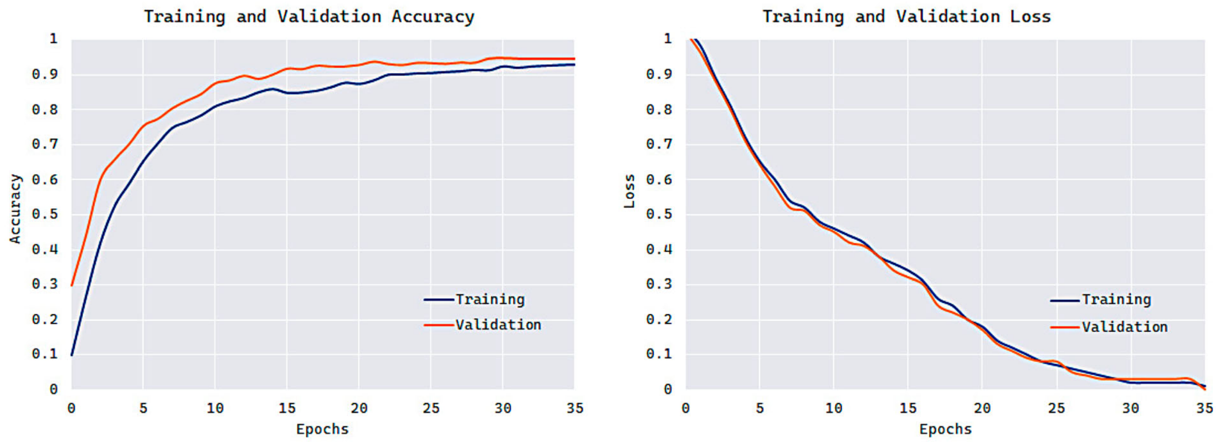

Figure 5. Accuracy and loss curves of the proposed model for the Bonn dataset.

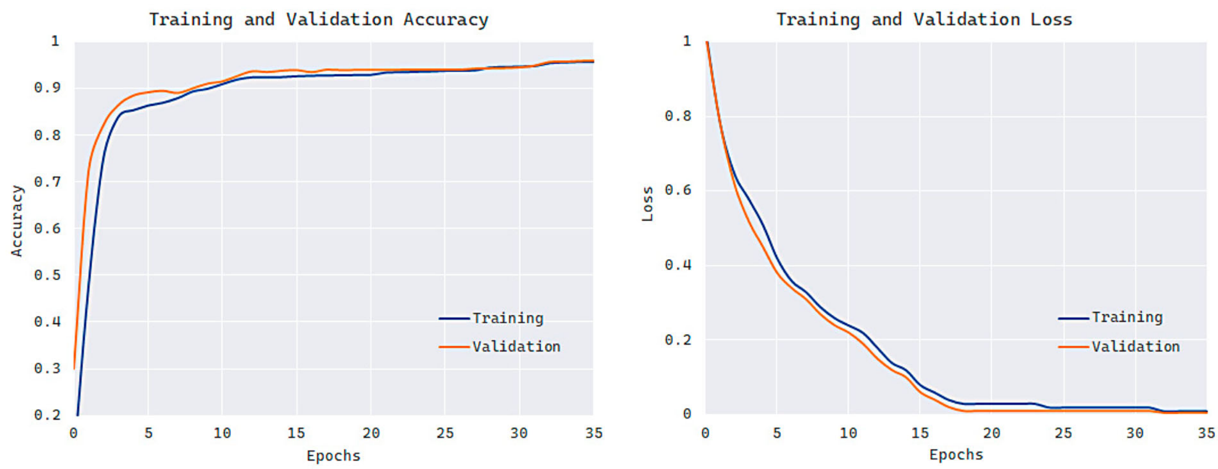

Figure 6. Accuracy and loss curves of the proposed model for the Dementia dataset.

Support vector machine (SVM), and Artificial Neural Network (ANN) models are used. The accuracy attained by the GMM is 56.50% which is 38% lesser than the proposed model. The accuracy attained by the RVM is 60% which is 34% lesser than the proposed model. The accuracy attained by the SVM is 88% which is 6% lesser than the proposed model. The accuracy attained by the ANN is 92.80% which is 1.2% lesser than the proposed model. Table 3 depicts the comparative analysis, and it can be observed from the results that the proposed model attained maximum classification accuracy over existing methods.

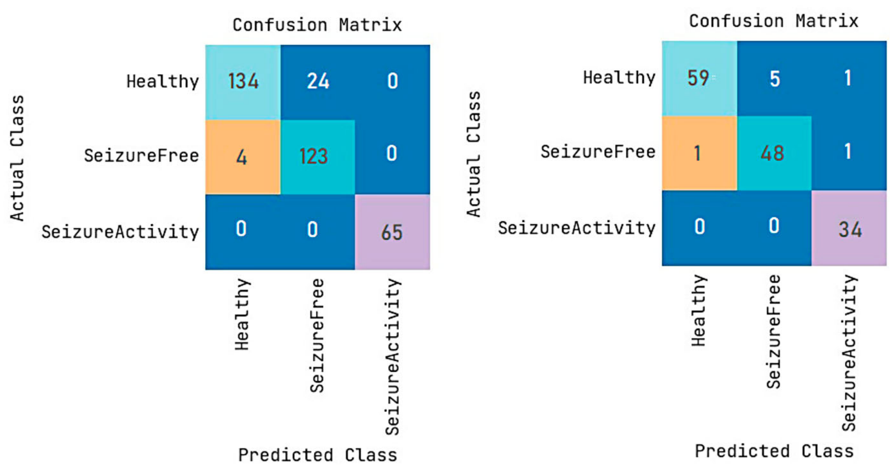

Figure 7. Confusion matrix of Bonn dataset (a) Training (b) Testing.

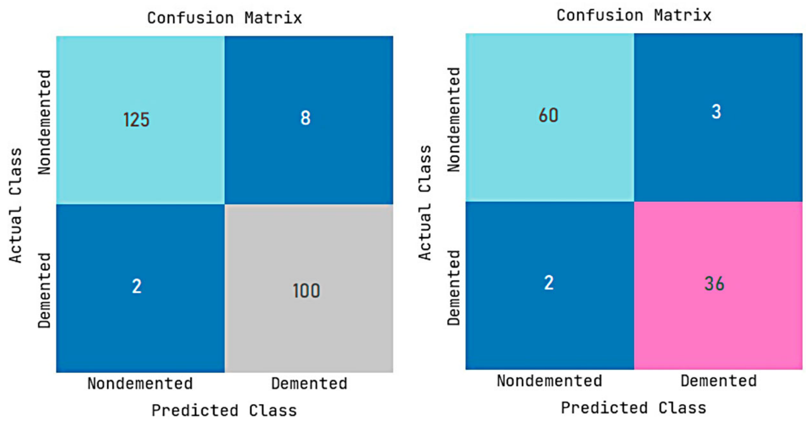

Figure 8. Confusion matrix of Dementia dataset (a) Training (b) Testing.

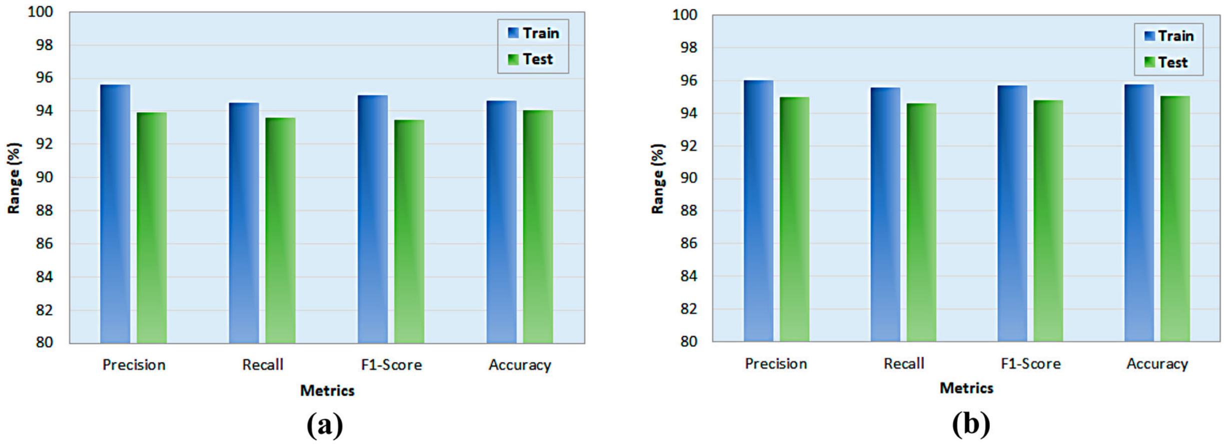

Figure 9. Performance metrics analysis (a) Bonn Dataset (b) Dementia Dataset.

Table 3. Performance comparative analysis with existing methods for the Bonn dataset.

S. No	Methods	Accuracy (%)
1	Gaussian Mixture Model (GMM) [30]	56.50
2	Relevance Vector Machine (RVM) [30]	60.00
3	Support Vector Machine (SVM) [30]	88.00
4	Artificial Neural Network (ANN) [30]	92.80
5	Proposed model	94.00

5. Conclusion

An optimized machine learning-based Alzheimer and epilepsy detection model is presented in this research work. The proposed detection model includes particle swarm optimization for optimal feature extraction, kernel principal component analysis for feature dimensionality reduction, and an optimized deep belief network for feature classification. The network parameters of the deep belief network are optimized using the tuna swarm optimization algorithm. Experimentation using the benchmark Bonn and Dementia dataset validated the proposed model's better precision, recall, f1-score, and accuracy performances. The proposed model attained a better classification accuracy of 94% for the Bonn dataset and 95.05% for the dementia dataset. The proposed model performance is compared with existing methods like support vector machine, artificial neural network, and Gaussian mixture model and validated the superior performance in terms of accuracy. Though the proposed model attained better classification accuracy than existing methods, however it can be improved if the classifier includes recent deep learning algorithms. The depth features can provide more accuracy in the classification process.

Thus, in further, the research work can be extended using deep learning algorithms to improve the classification performances. Specifically, time series deep learning models like recurrent neural network, long short-term memory can be included to attain better performances.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

[1] Alberdi A, Aztiria A, Basarab A. On the early diagnosis of Alzheimer's disease from multi-modal signals: a survey. Artif Intell Med. 2016;71:1–29.
[2] Ayodele KP, Ikezogwo WO, Ogunbona P. Supervised domain generalization for integrating disparate scalp EEG datasets for automatic epileptic seizure detection. Comput Biol Med. 2020;120:1–8.
[3] Gupta D, Gupta U, Sarma HJ. Functional iterative approach for universum-based primal twin bounded

support vector machine to EEG classification (FUPTB-SVM). Multimed Tools Appl. 2023;328:1–48. doi: 10.1007/s11042-023-16412-8.
[4] Yavuz E, Cem Kasapbaşı M, Yazici R. An epileptic seizure detection system based on cepstral analysis and generalized regression neural network. Biocybernet Biomed Eng. 2018;38(2):201–216.
[5] Ferreri F, Miraglia F, Rossini PM. Electroencephalographic hallmarks of Alzheimer's disease. Int J Psychophysiol. 2022;181:85–94.
[6] Biagetti G, Crippa P, Turchetti C. Classification of Alzheimer's disease from EEG signal using robust-PCA feature extraction. Procedia Comput Sci. 2021;192: 3114–3122.
[7] Tasci I, Tasci B, Rajendra Acharya U. Epilepsy detection in 121 patient populations using hypercube pattern from EEG signals. Inf Fusion. 2023;96:252–268.
[8] Tasci I, Tasci B, Barua PD, et al. Epilepsy detection in 121 patient populations using hypercube pattern from EEG signals. Inf Fusion. 2023;96:252–268.
[9] Jasphin Jeni Sharmila P, Shiny Angel TS. A survey on linear and non-linear dimensionality reduction techniques. Des Eng. 2021;7:8765–8785.
[10] Tales Oliva J, Luís Garcia Rosa J. Classification for EEG report generation and epilepsy detection. Neurocomputing. 2019;335:81–95.
[11] Khan KA, Shanir PP, Farooq O. A hybrid local binary pattern and wavelets-based approach for EEG classification for diagnosing epilepsy. Expert Syst Appl. 2020;140:1–9.
[12] Zeng K, Yan J, Wang Y, et al. Automatic detection of absence seizures with compressive sensing EEG. Neurocomputing. 2016;171:497–502.
[13] Bachmann M, Lass J, Hinrikus H. Single channel EEG analysis for detection of depression. Biomed Signal Process Control. 2017;31:391–397.
[14] Neale N, Padilla C, Zaman S. Neuroimaging and other modalities to assess Alzheimer's disease in down syndrome. NeuroImage: Clinical. 2018;17:263–271.
[15] Lih OS, Jahmunah V, Palmer EE, et al. Epilepsynet: novel automated detection of epilepsy using transformer model with EEG signals from 121 patient population. Comput Biol Med. 2023;164:107312.
[16] Kocadagli O, Langari R. Classification of EEG signals for epileptic seizures using hybrid artificial neural networks-based wavelet transforms and fuzzy relations. Expert Syst Appl. 2017;88:419–434.
[17] Prasanna J, Subathra MSP, Mohammed MA, et al. Detection of focal and non-focal electroencephalogram signals using fast walsh-hadamard transform and artificial neural network. Sensors. 2020;20(17):1–20. doi:10.3390/s20174952.
[18] Rodrigues PM, Teixeira JP, Garrett C, et al. Alzheimer's early prediction with electroencephalogram. Procedia Comput Sci. 2016;100:865–871.
[19] Rodrigues PM, Freitas D, Garrett C. Electroencephalogram hybrid method for Alzheimer early detection. Procedia Comput Sci. 2018;138:209–214.
[20] Richhariya B, Tanveer M. EEG signal classification using universum support vector machine. Expert Syst Appl. 2018;106:169–182.
[21] Ramos-Aguilar R, Arturo Olvera-López J, Sánchez-Urrieta S. Feature extraction from EEG spectrograms for epileptic seizure detection. Pattern Recognit Lett. 2020;133:202–209.
[22] Hussein R, Elgendi M, Ward RK. Robust detection of epileptic seizures based on L1-penalized robust regression of EEG signal. Expert Syst Appl. 2018;104:153–167.
[23] Ibrahim S, Djemal R, Alsuwailem A. Electroencephalography (EEG) signal processing for epilepsy and autism spectrum disorder diagnosis. Biocybernet Biomed Eng. 2018;38(1):16–26.
[24] Siuly ÖFA, Kabir E, Şengür A, et al. A new framework for automatic detection of patients with mild cognitive impairment using resting-state EEG signals. IEEE Trans Neural Syst Rehabil Eng. 2020;28(9):1966–1976. doi:10.1109/TNSRE.2020.3013429
[25] Zhang T, Chen W, Li M. AR-based quadratic feature extraction in the VMD domain for the automated seizure detection of EEG using random forest classifier. Biomed Signal Process Control. 2017;31:550–559.
[26] Zhang T, Chen W, Li M. Generalized Stockwell transform and SVD-based epileptic seizure detection in EEG using random forest. Biocybernet Biomed Eng. 2018;38(3):519–534.
[27] Gupta V, Priya T, Yadav AK, et al. Automated detection of focal EEG signals using features extracted from flexible analytic wavelet transform. Pattern Recognit Lett. 2017;94:180–188.
[28] Bi X, Wang H. Early Alzheimer's disease diagnosis based on EEG spectral images using deep learning. Neural Netw. 2019;114:119–135.
[29] Jiang Y, Chen W, You Y. Synchro extracting chirplet transform-based epileptic seizures detection using EEG. Biomed Signal Process Control. 2021;68:1–11.
[30] Breijyeh Z, Karaman R. Comprehensive review on Alzheimer's disease: causes and treatment. Molecules. 2020;25(24):1–28. doi:10.3390/molecules25245789.