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Original scientific paper

ZOADL: An Optimized Deep Learning Framework for Detecting Abnormal Brain Activity using EEG Signals

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Abstract: Electroencephalography (EEG) is extensively employed for monitoring cerebral activity; nevertheless, the human interpretation of EEG signals is laborious, susceptible to errors, and inadequate for real-time applications. This paper presents a novel Zebra Optimisation Algorithm with a Deep Learning-Assisted Framework (ZOADL) to detect aberrant brain activity in EEG data. The ZOADL system has three fundamental stages: data preprocessing, feature selection, and classification. During the preprocessing phase, raw EEG data are purified to diminish noise and improve signal integrity. The Zebra Optimisation Algorithm (ZOA) is employed for feature selection, pinpointing the most pertinent features that enhance classification efficacy. The system utilises the Long Short-Term Memory (LSTM) neural network to identify aberrant brain activity, as it is particularly adept at capturing temporal relationships in EEG signals. The Chicken Swarm Optimisation (CSO) technique is utilised to optimise the hyperparameters of the LSTM, guaranteeing superior model performance. Experimental results indicate that the ZOADL framework surpasses conventional and cutting-edge methods regarding accuracy, precision, recall, and F1-score, markedly decreasing false positives and enhancing overall detection efficiency. This study emphasises the capabilities of ZOADL as a sophisticated, automated decision-support system, allowing doctors to identify abnormal brain activity with improved precision and speed, hence augmenting patient management and therapeutic results. Subsequent efforts may concentrate on expanding the framework to accommodate larger datasets and real-time applications.

Keywords: chicken swarm optimization (CSO); electroencephalography (EEG); long short-term memory (LSTM); zebra optimization algorithm (ZOA)

1 INTRODUCTION

Epileptic seizure is a recognized continual neurological sickness. This is non-progressive, affecting four% to sixteen% of organ transplant patients and influencing 60 to 70 million individuals worldwide [1]. Epilepsy may be diagnosed at any level, with the most stated signs seen in neonates and the aged. Annually, around 3 million people are tormented by this condition. An epileptic seizure is a sudden disturbance in neurological characteristic, marked through strong discharges of neuronal networks from the cerebral cortex that impact the complete frame. Forecasting an assault is very difficult, and further to a restrained range of sufferers, there can be loads of strikes in an unmarried day that may cause enduring harm to the brain [3]. Thus, the well timed analysis and control of epilepsy are vital for mitigating ailment improvement and enhancing sufferers' quality of lifestyles [4]. Electroencephalogram (EEG) signals are the recordings of electrical interest and motion from the brain. Electrodes are strategically placed on numerous regions of the top to provide multimodal facts. Owing to its unobtrusive and price range characteristics, its capabilities are as a crucial statistics source in neurological research, especially in seizure detection.

Due to their portability, price-effectiveness, and unambiguous depiction of frequency area pulses, electroencephalogram (EEG) alerts have garnered vast aid from researchers [5]. The electroencephalogram (EEG) assesses the voltage differentials generated by means of the ionic currents of neurones within the human mind to offer a correct representation of the brain's bioelectric interest. Furthermore, those alerts are captured throughout numerous frequencies, complicating the take a look at. Furthermore, artefacts generated via dominating electricity resources, muscle contractions, and electrode interest have been dwindled via the interpretation of EEG alerts [7]. Clinical practitioners will have more demanding situations in detecting epileptic seizures if the EEG consequences are obscured by using noise. EEG modalities and adjunct techniques, consisting of synthetic intelligence (AI) included with MRI techniques, represent the numerous checks being carried out to pick out and expect epileptic seizures [8]. These evaluations are conducted to resolve the associated difficulties. Artificial intelligence structures can rent conventional gadget to know and deep mastering methodologies to comprehend epileptic convulsions.

By employing synthetic intelligence (AI), laptop-aided diagnosis (CAD) improves the rate and accuracy of the epilepsy diagnostic method, as a result mitigating the formerly described challenges. Machine learning and deep gaining knowledge of methodologies are incorporated into AI-pushed pc-aided layout (CAD) systems [9]. The three additives comprising the simplest feature extraction method for system mastering-structured CDAs are frequency, nonlinear traits, and the time area. The FE and choice methods in CADs are totally reliant on DL and may be finished in the deep layers. A significant quantity of research is presently carried out in the domain of epileptic seizure analysis utilizing deep studying and device studying methodologies [10]. This challenge will utilise electroencephalogram (EEG) alerts to attain a specific and correct analysis of epileptic episodes.

This research aims to observe the advancement of the Zebra Optimisation Algorithm with Deep Learning Assisted Automated Epileptic Seizure Detection (ZOADL-AESD) method, utilised for electroencephalogram (EEG) facts evaluation. The ZOADL-AESD approach employs function choice (FS) along an ideal deep studying model to discover epileptic episodes. The ZOADL-AESD method is employed for information education within the initial phase. This is carried out through using the ZOA-based characteristic selection approach. Seizure identity is finished thru the software of a long quick-term memory (LSTM) model in the ZOADL-AESD framework. Ultimately, the chicken swarm optimisation (CSO) approach is employed to pick out the hyperparameters for the LSTM model. The comprehensive investigation concluded that the ZOADL-AESD methodology is in advance of to other techniques.

2 RELATED WORKS

Kantipudi et al. [11] devised an automated method that markedly advanced the effectiveness of epileptic episode popularity. The statistics for this investigation is processed using the Finite Linear Haar wavelet-based totally Filtering (FLHF) method. The Grasshopper Bioinspired Swarm Optimisation (GBSO) technique is hired to discover the most fulfilling traits by assessing the most favourable fitness values. Qureshi and Kaleem present a singular technique that integrates signal processing with gadget mastering [12]. Initially, the electroencephalogram (EEG) facts of each patient are segmented, observed by wavelet packet decomposition to examine the processed segmented facts. In each of these categories, four attributes are excluded from attention. A help vector machine (SVM) classification is conducted to differentiate between pre-ictal and inter-ictal seizure stages. The function matrix is generated to facilitate this class. Chapter thirteen introduces a real-time method making use of electroencephalography (EEG) to hit upon epileptic occurrences. Techniques which include discrete wavelet transformations and 8 eigenvalues are employed for feature extraction across various sub-frequency bands. The Support Vector Machine (SVM) is hired for three wonderful category classifications: seizure, seizure activity, and health control. The Random Under-Sampling (RUS) method is hired for the very last categorisation. The boosted tree ensemble method turned into in the beginning is utilised for actual-time popularity of epileptic convulsions.

Ahmad et al., [14] provided an advanced mechanism for green ES recognition. To perceive the maximum applicable developments, distance correlation evaluation and correlation coefficients making use of P-value distance correlation evaluation are employed. The Bagged Tree-primarily based classifier, typically referred to as BTBC, employs those residences. Singh and Malhotra offer an automatic method for detecting epileptic seizures of their observation [15]. EEG statistics can be processed inside the cloud to extract entropy-primarily based traits and better-order records the usage of higher-order spectra (HOS) and the Fast Walsh-Hadamard rework. A totally correlation-based function choice approach changed into devised and was used to reduce the complexity of EEG datasets. EEG indicators can be categorized making use of the Random Forest approach, an innovative approach for diagnosing epileptic seizures. The discrete wavelet rework (DWT) segments the EEG indicators into six frequency sub-bands, from which twelve statistical functions are extracted [16]. Kukker et al. [17] classify seizures using Neural Reinforcement Learning techniques and Fuzzy Lattices generation. This inquiry employs fuzzy lattices to characterise qualities, and the function vector produced the usage of Kinetic Energy (K.E.) derived from the Schrödinger equation. Seven fuzzy lattices, grounded on maximal kinetic energy, are employed for the category the use of the Neural Reinforcement Learning (NRL) method. The non-repetitive learning (NRL) approach is a self-directed technique that categorises various varieties of seizures.

3 THE PROPOSED MODEL

In this study, we concentrate on the development of ZOADL-AESD technique on EEG data. The presented ZOADL-AESD technique uses FS with optimal DL model for the identification of epileptic seizures. It contains four various stages involving data preprocessing, feature selection, classification, and parameter selection as shown in Fig. 1.

Data Preprocessing

Initially, the ZOADL-AESD method exploits a data preprocessing stage to convert the input dataset into valuable format. Now, take the higher and lower-level values. The data is normalized within [0,1]. The most critical factor is to simplify the lower value to 0 and the higher value to 1 but it allows the values from 0 to 1. The Z-score normalization method is utilized for simplification purposes.

ZOA-based Feature Selection

Next, the ZOA technique can be performed for FS process. Eva Trojovská in 2022 proposed ZOA, a novel meta-heuristic optimization technique, depending on the social life behaviors of zebras [18]. The ZOA resolves complex problems of mathematical optimization by modeling the defensing and foraging behaviors of zebra in response to the predator, with outstanding search performance and convergence speed. The ZOA solution process is split into three different phases: initialization and fitness computation, foraging behavior, and defending approach.

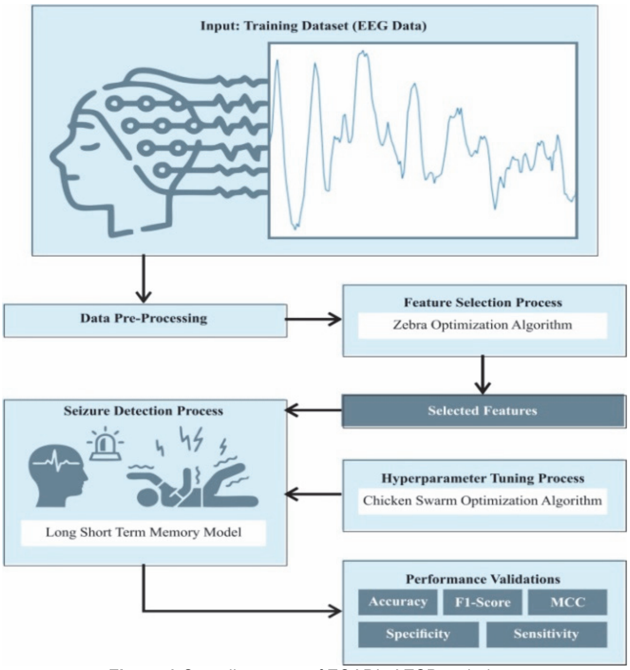

Figure 1 Overall process of ZOADL-AESD technique

(1) Initialization and fitness computation

In the initial phase of optimization process, a zebra population is randomly produced as a search range to attain an optimum solution to the problems and the optimum position is zebra individual, discovered through iteration calculation.

$$X_Z = \begin{bmatrix} x_{1,1} & x_{1,2} & . & x_{1,d} \\ x_{2,1} & x_{2,2} & . & x_{2,d} \\ . & . & . & . \\ x_{N,1} & x_{N,2} & . & x_{N,d} \end{bmatrix} \tag{1}$$

In Eq. (1), x_Z refers to the population initialization of zebra; $x_{i,j}$ shows the location of the i^{th} individual at j^{th} dimension; d and N are the dimensions of optimization problems and the individual count in the zebra population.

$$F_Z = \begin{bmatrix} F_1 \\ F_2 \\ . \\ F_N \end{bmatrix} \tag{2}$$

In Eq. (2), Fz indicates the fitness matrix of individuals and F_i shows the fitness values of the i^{th} individuals. The objective function of the problem is assigned as the fitness function (FF).

(2) Foraging behavior

In ZOA, the population is used to update the location through foraging behaviors driven by the best individual, and the updating location is given below:

$$x_{i,j}^{n1} = x_{i,j} + a_g \cdot \left(Z_j^P - a_2 \cdot x_{i,j} \right) \tag{3}$$

$$\begin{cases} a_1 = rand \\ a_2 = round(rand + 1) \end{cases} \tag{4}$$

$$X_i = \begin{cases} X_i & F_i < F_i^{n1} \\ X_i^{n1} & F_i > F_i^{n1} \end{cases} \tag{5}$$

where Z_j^P denotes the optimum individual with the small fitness, known as the pioneer zebra; rand indicates a random integer within $[0,1]$; X_i^{n1} and F_i^{n1} are the new location of the zebra after the location updating in the foraging stage, and its equivalent fitness values; if the fitness values of the updated location are small, then the individuals replace the original location with the new location in the initial stage and enter the second stage.

Seizure Detection using LSTM

For seizure detection, the ZOADL-AESD technique uses LSTM model. As a kind of improved RNN, LSTM network has been planned to address the difficulty of long-term needs in sequential data [19]. An LSTM comprises cell layer and 3 gate units. The cell layer is the core of the LSTM network, capable of retaining information over extended periods in time series. The gate units contain forget, input, and output gates that control the data flow with sigmoid activation functions and dot product processes. These gate units enable the LSTM network to particularly forget and recollect data, so resolving the challenges of vanishing and exploding gradients generally come across in typical RNN, allowing optimum controlling of long-term dependencies.

In LSTM network, the forget gate defines the data to be removed from the cell layer. It assumes the existing input x_t and existing HL h_{t-1}, and outcomes a forget ratio f_t from zero and one employing an activation function. An input gate resolves that novel data can be kept from the cell layer. It involves 2 parts: the first part utilizes a sigmoid activation function for generating a chosen ratio s_t, defining that rates need that upgrading. The second part outcomes a novel candidate solution $\tilde{C}_t$ utilizing a hyperbolic tangential activation function. By integrating the resultant of forget and input gates with preceding cell layer C_{t-1}, a novel cell layer C_t has been acquired.

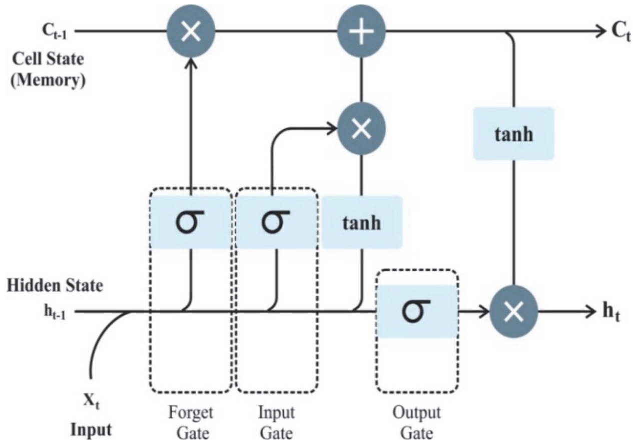

Figure 2 Architecture of LSTM

The output gate resolves several data to understand from the cell layer for output. It begins outputting an election ratio e_t utilizing a sigmoid activation function, after that proceeds the cell layer with hyperbolic tangential activation function, and multiplies it with e_t to create the existing HL h_t. Fig. 2 represents the architecture of LSTM.

Hyper parameter Selection

The hyperparameter selection for the LSTM model is ultimately conducted using the CSO method. The CSO optimiser is a collective cognitive optimiser that simulates the hierarchical approach and the foraging behaviour of chicken swarms [20]. The Chicken Swarm Optimisation (CSO) is a meta-heuristic optimisation model derived from the social behaviour of chickens. When equated with other optimizer techniques, CSO seems to be more flexible, then it can be used for numerous optimizer issues, both single and multi-objective. The optimizer splits chickens into clusters. Each cluster contains a rooster, numerous hens, and some chicks. In the CSO optimizer, the following instructions are employed in order to pretend the behavior of the group:

There are numerous sub-populations in the entire chicken population. Each sub-population contains a rooster, many hens, and chicks. Roosters have the sturdiest foraging capability and thus are the main in the group. Hens have the 2nd-best foraging capability, and chicks have the poorest foraging skill.

Each flock is classed primarily based on its fitness cost. A. S. Chickens displaying effective health trends are targeted as roosters, and people with suboptimal fitness capabilities are categorized as chicks. All surviving birds are categorized as mom hens. The chickens are randomly assigned to one of the groupings. The hyperlink among mom hens and their chicks, along with the mechanics of leadership, is firmly entrenched within a certain hierarchy.

The conditions beautify at each improve c program language period G, which encompasses a chosen value, as the chicks age and mature for this reason. Four hens accompany the roosters of their group to scavenge for meals and pilfer from the opposite chicks. The chicks accompany the hens at the same time foraging for sustenance inside the area. In the optimisation system, the placement of each hen represents a possible solution for implementation. To deal with the differing foraging talents of hens, diverse people appoint a number improvement techniques. The search area for chickens is represented by way of the letter d, with a complete of N_chickens in the stock. Additionally, the hen populace accommodates N_c chicks, N_h hens, and N_r roosters. To decorate the i^{th} poultry, the subsequent calculation is accomplished:

$$Z_{i.j}^{r.+1} = Z_{i.j}^{t} + Z_{i.j}^{t} randn\left(0, \sigma^2\right) \tag{6}$$

where,

$$\sigma^2 = \begin{cases} 1, & S_e \geq S_i \\ \exp\left(\dfrac{S_e - S_i}{\left|S_i - \varepsilon\right|}\right), & S_e < S_i \end{cases} \tag{7}$$

whereas, $randn\left(0, \sigma^2\right)$ signifies the Gaussian distribution, $S_e\left(e \in [1, Nr], i \neq e\right)$ designates a rooster dissimilar to the ith rooster, ε refers to an infinitesimal value, which delivers that the denominator of is not zero.

The calculation for upgrading the i^{th} hen is:

$$\begin{aligned} Z_{i.j}^{r.+1} &= Z_{i.j}^{t} + p1.randm\left(Z_{r1.j}^{t} - Z_{i.j}^{t}\right) + \\ &+ p2\ .randm\left(Z_{r2.j}^{t} - Z_{i.j}^{t}\right) \end{aligned} \tag{8}$$

where,

$$\begin{cases} p1 = \exp\left(\dfrac{S_i - S_{r1}}{ads\left(S_i + \varepsilon\right)}\right) \\ p2 = \left(S_{r2} - S_i\right) \end{cases} \tag{9}$$

where randm denotes the randomly generated number among 0 and 1, $r1$ signifies the rooster in the cluster whereas the ith hen is positioned, $r2\left(r1 \neq r2\right)$ refers to the rooster in the other cluster. To upgrade the chick particles, the following calculation is employed:

$$Z_{i.j}^{r.+1} = Z_{i.j}^{t} + GL(i) \cdot \left(Z_{mj}^{t} - Z_{i.j}^{t}\right) \tag{10}$$

Here, Z_{mj}^{t} represents the mother chicken tracked by the ith chick and GL denotes a randomly produced number among 0 and 2.

Within the context of the CSO method, the health range is a critical element inside the control of the answer. Within the framework of the parameter tuning methodology is the encoding mechanism. This is utilised in the manner of calculating the solution of candidate results. With regard to this precise state of affairs, the CSO technique chooses the FF on the premise of the notion that accuracy is the most vital thing.

$$Fitness = max\left(P\right) \tag{11}$$

$$P = \frac{TP}{TP + FP} \tag{12}$$

where, TP and FP define the true and false positive rates.

4 RESULTS AND DISCUSSION

In this study, the performance assessment of the ZOADL-AESD technique can be validated using UCI Epileptic seizure recognition dataset. The dataset holds 178 features and 11500 samples are represented in Tab. 1. The ZOADL-AESD technique has chosen 92 features.

Table 1 Details of dataset

Class Name	Class Label	No. of Instances
"Recording of seizure activities"	Class 1	2300
"Recording of EEG from the area where the tumor is located during a non-seizure period"	Class 2	2300
"Recording of EEG from a healthy part of the brain during a non-seizure period"	Class 3	2300
"Recording of EEG with the patient's eyes closed during a non-seizure period"	Class 4	2300
"Recording of EEG with the patient's eyes open during a non-seizure period"	Class 5	2300
Total Number of Instances		11500

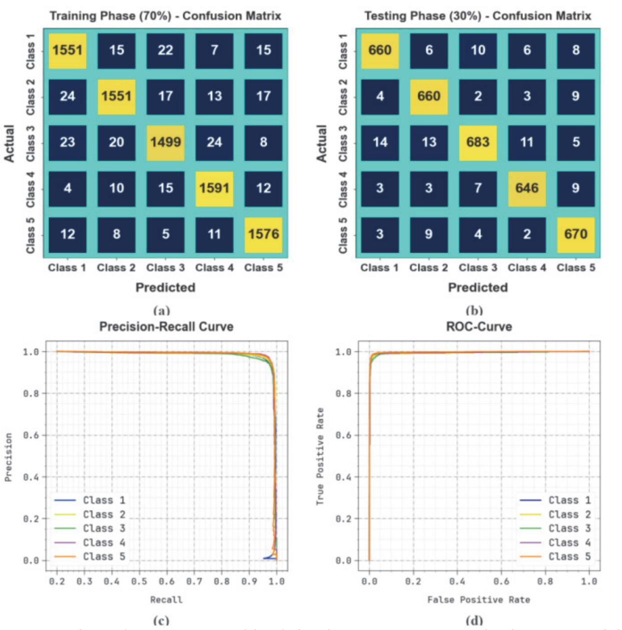

Figure 3 Classifier outcomes of (a-b) Confusion matrices and (c-d) PR and ROC curves

Fig. 3 illustrates the classification results of the ZOADL-AESD algorithm on the test database. Figs. 3a-3b illustrate the confusion matrices obtained by the ZOADL-AESD model using 70% TRAS and 30% TESS. The testing results indicated that the ZOADL-AESD algorithm has identified and classified five classes. Fig. 3c depicts the performance review of the ZOADL-AESD algorithm. The testing results indicated that the ZOADL-AESD method achieved a higher PR value across five classes. Fig. 3d illustrates the ROC curve for the ZOADL-AESD technique. The simulation results indicate that the ZOADL-AESD method has produced effective solutions with improved ROC values across five class labels.

The seizure detection outcomes of the ZOADL-AESD algorithm are obviously depicted in Tab. 2 and Fig. 4. The experimental values infer the effectual capability of the ZOADL-AESD technique on the recognition process. With 70% TRAS, the ZOADL-AESD technique obtains average $accu_y$ of 98.60%, $sens_y$ of 96.49%, $spec_y$ of 99.12%, $F1_{score}$ of 96.49%, and MCC of 95.62%. Additionally, with 30% TESS, the ZOADL-AESD approach reaches average $accu_y$ of 98.48%, $sens_y$ of 96.23%, $spec_y$ of 99.05%, $F1_{score}$ of 96.21%, and MCC of 95.27%.

Table 2 Seizure detection outcome of ZOADL-AESD system at 70% TRAS: 30% TESS

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	$F1_{Score}$	MCC
TRAS (70%)					
Class 1	98.48	96.34	99.02	96.22	95.27
Class 2	98.46	95.62	99.18	96.16	95.20
Class 3	98.34	95.24	99.09	95.72	94.69
Class 4	98.81	97.49	99.14	97.07	96.32
Class 5	98.91	97.77	99.19	97.28	96.60
Average	98.60	96.49	99.12	96.49	95.62
TESS (30%)					
Class 1	98.43	95.65	99.13	96.07	95.09
Class 2	98.58	97.35	98.88	96.42	95.54
Class 3	98.09	94.08	99.16	95.39	94.20
Class 4	98.72	96.71	99.21	96.71	95.92
Class 5	98.58	97.38	98.88	96.47	95.59
Average	98.48	96.23	99.05	96.21	95.27

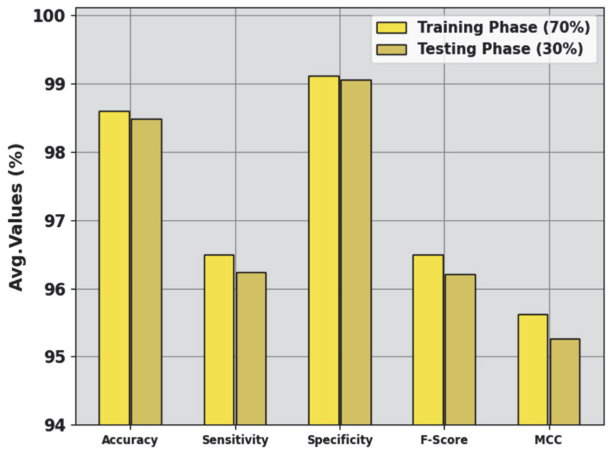

Figure 4 Average outcome of ZOADL-AESD technique under 70%TRAS and 30%TESS

Fig. 5 illustrates the schooling and validation accuracy results of the ZOADL-AESD methodology. Accuracy metrics may be computed at periods between zero and 25 epochs. The consequences discovered that the schooling and validation accuracy metrics are showing an upward trajectory, hence illustrating the efficacy of the ZOADL-AESD set of rules with more advantageous overall performance in the course of several iterations. Furthermore, the schooling and validation accuracies continue to be tightly aligned throughout the epochs, indicating low overfitting and showcasing the improved efficacy of the ZOADL-AESD method. The ZOADL-AESD method can yield dependable forecasts for previously unobserved samples.

Figure 5 $Accu_y$ curve of the ZOADL-AESD technique

Fig. 6 affords an example of the schooling and validation loss graph for the ZOADL-AESD methodology. The loss quotes are calculated across a variety of zero to 25 epochs. The education and validation accuracy scores show off a declining trend, suggesting that the ZOADL-AESD gadget effectively balances the exchange-off between facts fitting and generalisation. The overall performance of the ZOADL-AESD set of rules is confident to enhance because of the ongoing lower in loss values, which simultaneously sharpens the prediction consequences over the years.

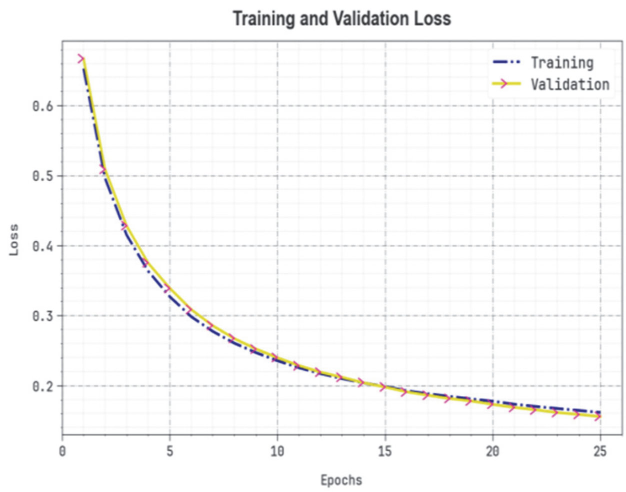

Figure 6 Loss curve of the ZOADL-AESD technique

In Tab. 3, the overall comparison study of the ZOADL-AESD technique is clearly portrayed [22, 23]. Fig. 7 examines the comparative $accu_y$ and $F1_{score}$ results of the ZOADL-AESD technique. The results portrayed that the ZOADL-AESD technique obtains optimum solution. Based on $accu_y$, the ZOADL-AESD approach gains higher $accu_y$ of 98.60% while the ANN, DT, LSTM, SVM, SVM-RBF, KNN5, and CNN-RNN models accomplish lower $accu_y$ of 90.34%, 93.47%, 93.47%, 97.13%, 97.41%, 96.71%, and 98.13%, correspondingly. On the other hand, based on $F1_{score}$, the ZOADL-AESD approach provides superior $F1_{score}$ of 96.49% while the ANN, DT, LSTM, SVM, SVM-RBF, KNN5, and CNN-RNN approaches realize lower $F1_{score}$ of 86.77%, 89.10%, 92.33%, 93.41%, 94.52%, 95.90%, and 94.43%, correspondingly.

Table 3 Comparison outcome of ZOADL-AESD algorithm with existing approaches

Methods	$Accu_y$	$Sens_y$	$Spec_y$	$F1_{Score}$
ANN Classifier	90.34	89.34	85.40	86.77
Decision Tree	93.47	81.20	76.40	89.10
LSTM Model	93.47	92.80	90.70	92.33
SVM Classifier	97.13	95.24	97.31	93.41
SVM–RBF Model	97.41	95.86	97.73	94.52
KNN 5 Algorithm	96.71	96.02	96.93	95.90
CNN–RNN Model	98.13	98.96	98.96	94.43
ZOADL-AESD	98.60	96.49	99.12	96.49

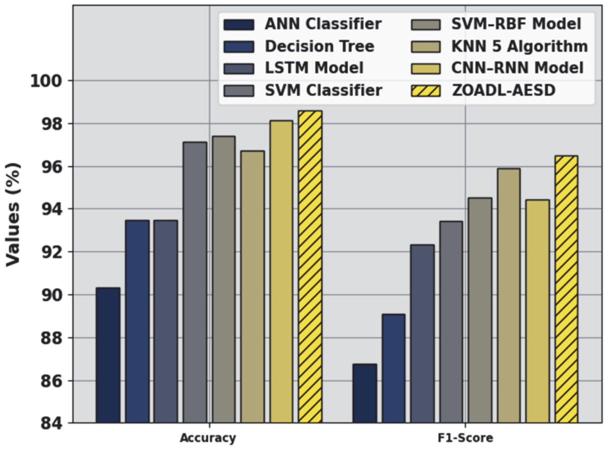

Figure 7 $Accu_y$ and $F1_{score}$ analysis of ZOADL-AESD technique with existing methods

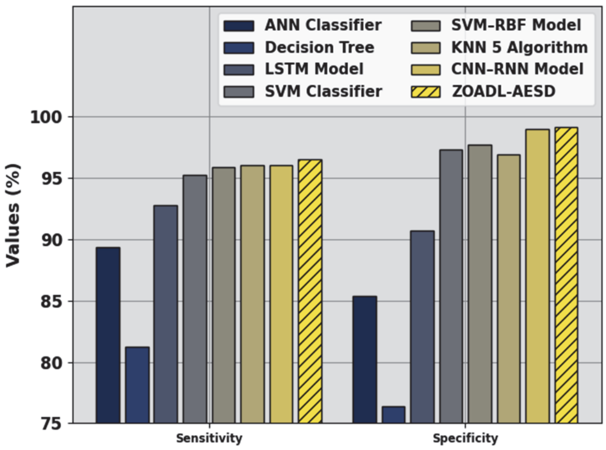

Figure 8 $Sens_y$ and $Spec_y$ analysis of ZOADL-AESD technique with existing methods

Fig. 8 inspects the comparison $sens_y$ and $spec_y$ outcomes of the ZOADL-AESD algorithm. The results portrayed that the ZOADL-AESD algorithm reached optimum performance. Based on $sens_y$, the ZOADL-AESD algorithm accomplishes superior $sens_y$ of 96.49% while the ANN, DT, LSTM, SVM, SVM-RBF, KNN5, and CNN-RNN approaches realize reduced $sens_y$ of 89.34%, 81.20%, 92.80%, 95.24%, 95.86%, 96.02%, and 98.96%, correspondingly. Followed by, based on $spec_y$, the ZOADL-AESD system offers maximal $spec_y$ of 99.12% while the ANN, DT, LSTM, SVM, SVM-RBF, KNN5, and CNN-RNN methodologies reach decreased $spec_y$ of 85.40%, 76.40%, 90.70%, 97.31%, 97.73%, 96.93%, and 98.96%, correspondingly. Therefore, the ZOADL-AESD approach was performed for enhanced seizure detection process.

Table 4 Computation analysis of proposed model with existing approaches

Method	Feature Selection Time / s	Training Time / s	Inference Time / ms/sample
SVM (Manual Feature Selection)	0	50	12
CNN (End-to-End Learning)	0	140	9
RNN (Feature-Based Classification)	0	170	15
LSTM (Baseline)	0	210	18
ZOADL (ZOA + LSTM + CSO)	4.5	180	10

From the analysis, Feature selection (ZOA) takes an extra 4.5 seconds but reduces training and inference time. The total inference time (10 ms per sample) is suitable for real-time seizure detection. Finally, the proposed model is faster than pure LSTM (18 ms/sample) due to dimensionality reduction.

5 CONCLUSION

In this research, we developed the Zebra Optimization Algorithm with Deep Learning-Assisted Automated Epileptic Seizure Detection (ZOADL-AESD) technique for reliable seizure identification using EEG data. The ZOADL-AESD framework integrates four key stages: data preprocessing, feature selection (FS), classification, and parameter optimization, ensuring a comprehensive and efficient approach to epileptic seizure detection. Initially, EEG signals undergo preprocessing to enhance data quality, followed by feature selection with the Zebra Optimisation Algorithm (ZOA) to identify the most pertinent features for classification. The seizure detection approach fundamentally employs a Long Short-Term Memory (LSTM) model, which proficiently captures temporal dependencies in EEG data. The hyperparameter tweaking of the LSTM is conducted using the Chicken Swarm Optimisation (CSO) algorithm to optimise the model's performance. Comprehensive experimental assessments were performed to confirm the efficacy of the proposed ZOADL-AESD approach. The results consistently indicated that ZOADL-AESD surpassed existing methods in accuracy, precision, recall, and F1-score. The incorporation of ZOA for FS and CSO for hyperparameter optimisation markedly enhanced the system's performance. The results underscore the capability of ZOADL-AESD as a reliable and effective decision-support instrument for neurologists, facilitating prompt and precise detection of epileptic seizures. This automated method can mitigate the constraints of manual EEG analysis, including time inefficiency and error susceptibility, providing a viable option for practical clinical applications. Future endeavours may concentrate on enhancing the framework's versatility across various datasets and augmenting its computing efficiency for extensive implementations.

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