An Advanced Deep Representation and Heuristic-based Model for Reliable Epileptic Seizure Detection from Electroencephalogram Signals

R. Selvam
Research Scholar,
Dept., of Computer Science, School of Computing Science,
Vels Institute of Science, Technology and Advanced Studies, Chennai-600117.
selvam78@gmail.com

Dr. R. Mahalakshmi
Associate Professor,
Department of Advanced Computing and Analytics,
School of Computing Sciences,
VISTAS, Chennai-600117.
rmahalakshmi.scs@vistas.ac.in

***Abstract*—An epileptic seizure is an unusual electrical flow in brain that causes a temporary disturbance in normal brain function and frequently results in convulsions or loss of consciousness. An electroencephalogram (EEG) is the most critical analytic device for epilepsy. Generally, the epileptic activity recognition that depends on finding particular patterns in the multi-modal EEG may be completed by a professional. The detection of seizures on EEG data is a challenging task that requires a relationship between clinical experts and machine learning (ML) specialists to ensure the consistency and precision of the detection approach for patients with epilepsy. Neural network (NN)-based deep learning (DL) models like recurrent NN (RNN) and convolutional NN (CNN) are applied on a labelled EEG dataset that comprises non-seizure and seizure parts. This paper proposes a complete and strong structure for epileptic seizure recognition (ESR) employing EEG signals by relating sophisticated DL techniques with a metaheuristic optimisation model. Primarily, the EEG signals undergo an efficient pre-processing phase for normalising and transforming the raw data into informative representations. Afterwards, a feature selection (FS) approach is used to improve discriminative ability by decreasing dimensionality. For seizure classification and recognition, effective DL structures are used. At last, metaheuristic-driven hyperparameter tuning is achieved to further enhance the classification precision and robustness of the system. Extensive experimental evaluation on benchmark EEG datasets proves that the proposed structures significantly outperform existing models.**

Keywords*— *Epileptic Seizure; Deep Learning; Electroencephalogram Signals; Metaheuristics Algorithm; Hyperparameter Tuning

I. INTRODUCTION

Epilepsy is a significant and prevalent brain disease that comprises recurrent brain seizures due to the uncontrolled electrical impulses [1]. These influences abandoned jerking, impulsive movements, and short-term consciousness loss. This disease is possibly harmful since it induces failure of the heart, brain, lungs, and even unexpected deaths due to accidents, so it is crucial. EEG signal is recorded electrical brain movement activity [2]. The electrodes are placed on various scalp parts during medical intervention and present multi-channel data [3]. Generally, medical professionals collect records by visually examining the long-range EEG. Therefore, it is highly suggested to utilise an automated ESR system [4]. Additionally, medical experts with different phases of diagnostic efficiency occasionally report inconsistent viewpoints under the diagnostic findings. Hence, the enhancement of an automatic and computer-aided diagnosis (CAD) for diagnosing epilepsy is instantly needed [5]. For the epileptic form EEG, several detection approaches are presented in previous research works. The existing technologies for seizure identification use hand-engineered methods for feature extraction with EEG data, such as non-linear signal examination through time-frequency, frequency, and time domains.

Visual analysis for seizure identification in EEG data takes a considerable period and results in a fault [6]. Then, an automatic framework for seizure identification with greater accuracy is essential. ML methods are utilised to predict epileptic seizures [7]. Alternatively, DL techniques are highly prevalent and valuable in various applications. The FS model includes the assessment of an optimal feature subset that indicates an expected set of data, and later, increases the performance of classification [8]. The FS method presents many desirable features. Also, by extracting the redundant and unrelated features, the refined feature subset, with reduced counts of features, will not directly diminish computational cost and time. The ultimate results of the FS model can require that features become essential in defining the comprehensive dataset [9]. It is perceptible that the FS methods produce input feature subsets, while the feature extraction approaches are utilised to create new features from the innovative datasets.

This study aims to develop an efficient ESR framework using EEG signals by addressing three primary objectives.

- To present an Epileptic Seizure Recognition using an Improved Chimp Optimisation Algorithm with Deep Learning (ESR-ICOADL) approach.
- To introduce a Robust Epileptic Seizure Recognition using Meta-heuristics-based Dimensionality Reduction with Deep Learning (RESR-MDRDL) method.
- To present a Lemurs Optimiser with Ensemble Deep Learning Epileptic Seizure Recognition (EOEDL-ESR) methodology using EEG signals.

II. RELATED WORKS

This section presents a literature review on ESR using EEG signals. Pouryosef et al. [10] introduced an innovative pipeline that is designed on the Bat algorithm (BA) and genetic algorithms (GA) for creating the features and reducing the size of EEG data. Later, the wavelet extraction and segmentation, the BA identifies a more significant feature. This technique utilises these features and a GA integrated with NN for automatically categorising the measures of the EEG signals. In [11], an ensemble method is proposed. Primarily, the Wavelet transform is utilised to extract features. While the sizes of features are greater, the features are diminished with the help of linear discriminant analysis (LDA). The meta-heuristic techniques are termed the Water cycling model and the Accelerative Particle Swarm Optimiser (APSO) approach. Divya and Devi [12] intended to completely automate a model that depends on a Hybrid Grey Wolf Optimiser-Improved Sine Cosine Algorithm enhanced SVM (HGWOISCA-SVM) for the classification of EEG signals. Generally, the entire EEG signal is denoised by implementing an extended function of wavelet threshold. Subsequently, three types of features, namely chaotic, time- and wavelet-based domain feature, are derived from the pre-processed EEG signal. At that time, the Enhanced Grasshopper Optimiser Algorithm (EGOA) is executed for selecting the optimal features with significant impact differences and minimising the dimension. Also, the chosen features are provided as input for differentiation of fine EEG signals.

Kumar et al. [13] presented a technique that is based on a BiLSTM architecture. Accordingly, Bi-LSTM protects the unstationary context of EEG data but minimises operation cost by utilising the local mean decomposition (LMD) model and statistical feature extractor methods. There are two different LSTM models with opposite transmission patterns incorporated into the deep model. The authors [14] introduced an Automated DL-based Brain Signal Classification for ESR (ADLBSC-ESD). Such an investigation comprises the architecture of the Improved TLBO (ITLBO) techniques with the purpose of selecting features. Furthermore, the DBN is employed for identification, and Swallow Swarm Optimising Algorithm (SSOA) is used for tuning. The authors [15] presented a hybrid DL model. A K-means SMOTE is utilised for balancing sample data. Next, a one-dimensional CNN (1D-CNN) is integrated with a BiLSTM model that depends on the Truncated BP through Time (TBPTT) technique. Ultimately, the above-mentioned technique employs softmax, and sigmoid classification methods are implemented for classification.

III. PROPOSED METHODOLOGY

This paper proposes a comprehensive ESR framework using EEG signals by addressing three distinct objectives through advanced DL and metaheuristic optimisation techniques. Fig. 1 represents the entire framework of three objectives.

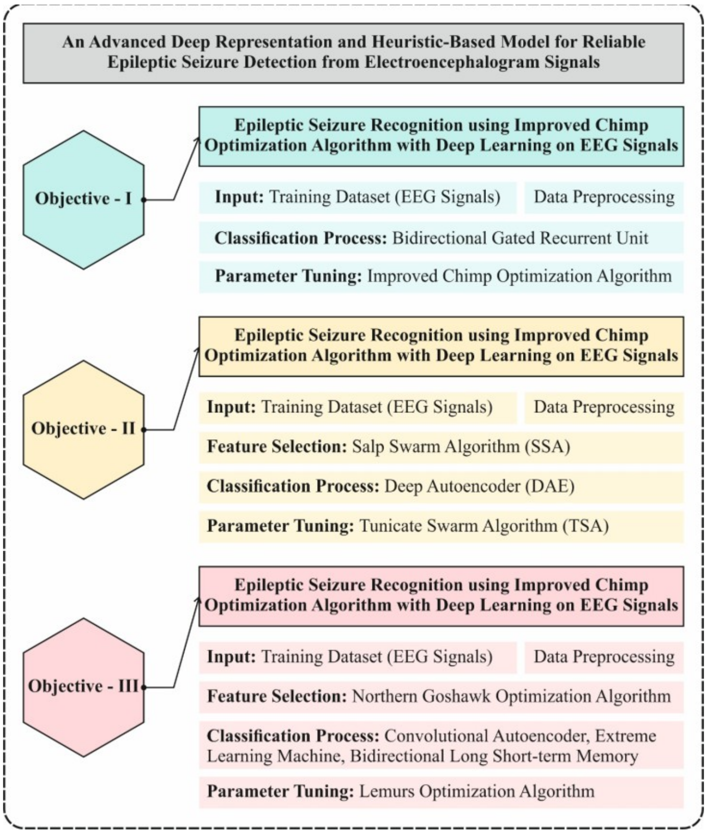

Fig. 1. Overall framework of three objectives

A. The Proposed Model of Objective I

This objective describes the ESR-ICOADL model. The aim is to inspect the EEG data for the classification and recognition of epileptic seizures. Initially, this is used to change the input data into proper setups. In addition, the bi-directional gated recurrent unit (BiGRU) model is employed for ESR. Finally, the parameter tuning of the Bi-GRU technique is improved by using ICOA, which helps to accomplish enhanced classification effectiveness.

In this phase, lower and higher-level values were deliberated. Every data is arranged in the sequence of 0 to 1. The key factor is streamlining the minimal rate to zero along with the maximal rate to one, and it enables the value from [0-1]. For simplification objectives, the Z-score standardisation model is leveraged.

The LSTM module comprises numerous gates, like forget, input, output gates, and memory units, whereas an activation function, reset, and update gates form the GRU. The Bi-GRU comprises forward and backward layers that are processed in the same sequence. Both GRU states hold GRU components; every component contains dual gates, like resetting r and updating gate μ, with $Tanh$ and the activation function of sigmoid.

$$r_t = \sigma(w_r \cdot x_t + u_r \cdot h_{t-1}), \tag{1}$$

$$\mu_t = \sigma(w_\mu \cdot x_t + u_\mu \cdot h_{t-1}), \tag{2}$$

$$h_t = \tanh(w \cdot x_t + r_t \cdot u \cdot h_{t-1}), \tag{3}$$

$$h_t = (1 - \mu_t) \cdot h_{t-1} + \mu_t \cdot \tilde{h}_t, \tag{4}$$

$$y_t = \sigma(w_o \cdot h_t), \tag{5}$$

However, the resetting and updating gates are r_t and μ_t, respectively, in zero and one. The weighted parameters were w and u, and the input into the GRU layer is x_t, the weighted parameter amid the layer of inputs and outputs is w_0, and the outcome layer node at $t$ime t is y_t. The current candidate HL is depicted as $\tilde{h}_t$, the present and preceding HL is signified as h_t, h_{t-1}.

COA is a revolutionary optimiser whose central notion is based on the searching approach of chimps. Attackers, Drivers, Barriers, and Chasers are diverse groups of COAs. Usually, the searching procedure of chimpanzees is categorised into two stages. The former is driving, intercepting, and chasing prey, and the latter is attacking prey.

Surround Prey

The movement of chimpanzees encircles the prey in searching:

$$d = |c.xrey\ (t) - m.xhimp\ (t)| \tag{6}$$

$$x_{chimp}(t+1) = x_{prey}(t) - a \cdot d. \tag{7}$$

The distance between prey and chimp is specified in Eq. (6). The location upgrades calculation of chimpanzees is specified $in\ Eq.(7)$, t represents the counts of current iterations, x_{chimp} denotes the position vector for chimpanzees, and x_{prey} denotes the vector of prey position. The m and c were calculated utilising.

$$a = 2f \cdot r_1 - f. \tag{8}$$

$$c = 2r_2. \tag{9}$$

$$m = Chaotic\text{-}\ value, \tag{10}$$

Attack Prey

Usually, the f value lessens for pretending the approach of chimpanzees to the prey, and the fluctuation range of a diminishes. Every iteration, if the counts of f linearly fall from 2.5 to 0, subsequently the individual area of a differs among $[-f, f]$. If a exists in $[-f, f]$, then the chimp position is inside its existing and the prey position.

Search for Prey

According to the position of $x_{Attacker}$, $x_{Barrier}$, x_{chaser}, and x_{Driver}, chimpanzees search for prey. Chimpanzees distinctly move when discovering the prey, then round up to search once they spot prey. If $|a| > 1$, subsequently the chimpanzee divides by prey (local optimal solution), by searching for the finest prey (global optimal solution). The COA have c parameter by discovering novel outcomes.

B. The Proposed Model of Objective II

This objective presents the RESR-MDRDL model. The RESR-MDRDL focuses on the precise epileptic seizure's classification employing EEG data. In the initial phase, data pre-processing normalizes the input data. Also, the RESR-MDRDL method designs a salp swarm algorithm (SSA) that depends on an FS model for selecting an optimum feature set. For seizure detection, the deep auto-encoder (DAE) technique is used, and its efficacy may be boosted by the design of the tunicate swarm algorithm (TSA).

Every data is normalised in the 0 to 1 order. The primary reason is to streamline lower values to 0 and greater values to one, but it enables the value from [0-1]. The Z-score standardisation model is employed for the objective of simplification.

SSA is a model that imitates the Salp swarm behaviours and like jellyfish, Salps form a swarm called a Salp chain.

Step1: Randomly generate an initial Salp in the searching area among the variable limits:

$$S(j, i) = rand(j, 1) * (UP\_i - LP\_i) + LP\_i \tag{11}$$

Now, i and j were the number of variables, respectively.

Step2: The position of Salp depicts the outcome that is calculated:

$$S = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1i} \\ S_{21} & S_{22} & \cdots & S_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ S_{m1} & S_{m2} & \cdots & S_{mi} \end{bmatrix} \tag{12}$$

Step3: To evaluate the fitness for each position of Salps:

$$OS = [OS_1 OS_2 OS_3 \cdots\cdots\cdots OS_m] \tag{13}$$

Step4: Sort the Salping position depending on fitness value:

$$L = \left\{ \begin{matrix} L_{11} & L_{12} & \cdots & L_{1d} \\ L_{21} & L_{22} & \cdots & L_{21} \\ \vdots & \vdots & \ddots & \vdots \\ L_{n1} & L_{n2} & \cdots & L_{nd} \end{matrix} \right\} \tag{14}$$

Step5: Arranging the target function of Salp position:

$$OL = [OL_1 OL_2 OL_3 \cdots\cdots\cdots OL_{\mathrm{m}}] \tag{15}$$

Step6: To upgrade the position of the leading Salp, depending on the targeted swarm:

$$S_{1,j\_new} = \begin{cases} F_j + c_1((Up_j - Lp_j)c_2 + Lp_j)\ c_3 \geq 0 \\ F_j - c_1((Up_j - Lp_j)c_2 + Lp_j)\ c_3 < 0 \end{cases} \tag{16}$$

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{17}$$

Here, m denotes the current iteration; c_2 and c_3 imply random values between 0 and [1]; M represents the maximal iteration value, and F_r implies the targeted swarm.

Step7: To upgrade the Salp position of the follower, depending on Eq. (18).

$$s_{i,j\_\mathrm{new}} = \frac{1}{2}\left(s_{i,j\_\mathrm{new}} + s_{i-1,j\_new}\right) \tag{18}$$

AE is a type of NN that encodes input data to rebuild succeeding data. To utilise this approach, the AE takes the significant input features. The sample of AE with input, output, and hidden layer (HL).

$$y(x) = f(W_1 x + b) \tag{19}$$

$$z(x) = g(W_2 x + c) \tag{20}$$

However, W_1 and W_2 signify the weight and succeeding decoder matrix layer, b and c depict encoded and decoded biased vector. The sigmoid function of logistic $1/(1 + \exp{(x)})$ is performed on $f(x)$ and $g(x)$.

Deep AE methodologies are among the most effective types of NN frameworks. The DAE model takes place from the pre-training layer of input, and then HL is the outcome of $the\ k^{th}$ HL, which is leveraged as input for the $(k + 1)^{th}$ HL. In this instance, the DAE model is carried out DAE model adequately by a calculation using a standard analysis at the determined model layer. It is performed by the DAE approach; the forecast is performed by the LR model. In this proposed methodology, the DAE is incorporated with a dropout process by handling several faults.

To project an innovative metaheuristic technique called the TSA that mimics the social searching behaviour of tunicates. Each tunicate is tubular and shows a jellylike tunic that aids in connecting tunicates. To transmit the calculation term of jet propulsion technique, it is vital to fulfil the following boundaries as (i) avoid crashes, (ii) move to the best searching individuals, and (iii) unite with the region closer to the best searching individuals. However, the swarm intellect gadget assists in upgrading the position of tunicates that rely on the optimal outcome.

C. The Proposed Model of Objective III

This objective provides the EOEDL-ESR model employing EEG signals. The EOEDL-ESR model intends to use an ensemble of three DL techniques for improving the seizure predictive process. The EOEDL-ESR model primarily undergoes data pre-processing and an FS process that depends on a northern goshawk optimiser (NGO). Moreover, an ensemble of three models, like bi-directional long short-term memory (BiLSTM), a convolutional autoencoder (CAE), and an extreme learning machine (ELM). For enhancing the detection outcomes, the hyperparameters associated with the DL model may be selected employing the LO model.

The data is standardised in the range of 0 - 1. The central notion is to streamline the lesser outcome to $zero$ and the greater rate to one, but it permits the value from [0-1]. The Z-score standardisation approach is employed for the objective of simplification.

In this part, the manuscript projects an NGO model, and its mathematical model is discussed below. The northern goshawk proceeds to the group of Accipiter, chases smaller entities, namely mice, rabbits, squirrels, and even huge creatures like foxes and raccoons. Males are comparatively greater than females. The searching approach of northern goshawks is split into two segments: once the prey is identified, it travels at a higher speed towards them, and then chases the victim briefly in a tail-chase. An intellectual process of the Northern goshawk is acquiring and searching for prey.

Additionally, an ensemble of 3 classifiers, like ELM, CAE, and Bi-LSTM networks. The AE variance of CAE, here, a fully connected (FC) layer is replaced by the convolution (Conv) layer. CAEs acquire the advantages of both Conv layers and the unsupervised pre-training capability of AE. To compare with the standard AE model, the CAE covers the Conv layer from the encoder and the deconvolutional layers rather than the FC layer in the decoder. The current CAE comprises pooling, deconvolution, and convolutional layers.

The standard ELM approach comprises an input, output layer, and HL. Let a random training set $\aleph = \{(x_i, t_i) | x_j \in \mathbb{R}^n, t_i \in \mathbb{R}^m\}$, with $i = 1, \dots, N$, an activation function $g(x)$ $:\mathbb{R}^n \to \mathbb{R}^m$, and HL $L | L \leq N$, the training method of SLFN is specified:

$$\sum_{i=1}^{L} \beta_i\, g\left(w_i \cdot x_j + b_i\right) = t_j, j = 1, \dots, N, \tag{21}$$

Here, w_i and b_i signify the i^{th} weights and bias of HL, equivalent β_j denotes the i^{th} succeeding layer weight, and $w_i \cdot x_j$ signifies the inner product of w_i and x_j. Eq. (9) is specified in matrix notation as $H\beta = T$,

$$H = \begin{bmatrix} g(W_1 \mathrm{x}_1 + b_1) & \dots & g(W_L \mathrm{x}_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(w_1 x_N + b_1) & \dots & g(w_L x_N + b_L) \end{bmatrix}_{N\times L}, \beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_L \end{bmatrix}_{L\times m}, and\ T = \begin{bmatrix} t_1 \\ \vdots \\ t_N \end{bmatrix}. \tag{22}$$

However, H signifies the outcome matrix of HL. Consequently, the β_i weight of the outcome layer is calculated.

$$\beta = H^{\dagger} T, \tag{23}$$

Now, $H^{\dagger}$ implies the MPGI of matrix H.

The LSTM comprises a unique framework with three substantial gates, namely input, output, and forget. This framework permits the seizure of long-term dependence, greater than the capability of ordinary RNNs. The Bi-LSTM covers LSTM by managing order in both directions, forward and reverse. The final forecast incorporates HL from both directions:

$$h_t = \vec{h}_t \oplus \overleftarrow{h}_t, \tag{24}$$

Now, h_t takes the direction of forward $\vec{h}_t$ and reverse $\overleftarrow{h}_t$ and $\oplus$ depicts the procedure of concatenation. The solution h_t succeeds in integrating the backward and reverse HL at time t.

The LO method depicts a sophisticated, nature-inspired meta-heuristic crafted to tackle global optimisers. Depending on the intricate social activity of prosimian chimpanzees' built-in closer islands, the LO methodology imitates the unique locomotive designs of these organisms. To manage social groups named troops, lemurs exhibit 2 locomotor actions, namely dance-hopping and leaping. In contrast, dance-hopping connects with an organised, general movement carried by lemurs in their herds. LO merges these natural lemur activities into its optimiser, but the agent represents each probable outcome known as "lemur". The location of the lemur is connected with the candidate outcome in the specified hunting region. The LO technique initiates an FF to accomplish the improved outcomes of the classifier. It describes a positive numeral to recommend the improved concert of candidate outcomes. The classifier rate of error reduction is viewed as FF, which is set at Eq. (25).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{No.of\ misclassified\ samples}{Overall\ samples} \times 100 \quad (25)$$

IV. EXPERIMENTAL VALIDATION

The simulation validation is conducted utilising the ESR dataset from the UCI ML repository [16]. The dataset encompasses 11500 samples categorised into five classes as detailed in Table 1. The dataset comprises single-channel EEG recordings from 500 subjects, each recorded for 23.6 seconds at 173.61 Hz (4097 data points). Each sample is initially represented by 178 features, from which an optimal subset of 86 features is selected through the proposed FS process to improve classification performance.

The seizure detection results of the three objective techniques are clearly demonstrated in Table 2 and Fig. 2. The values indicate the effective ability of the objective methods in the detection process. With objective 1, the model achieves an average $accur_y$ of 90.64%, $sensi_y$ of 82.18%, $speci_y$ of 82.18%, F_{score} of 83.93%, and MCC of 68.16%. Moreover, with objective 2, the model accomplishes an average $accur_y$ of 94.14%, $sensi_y$ of 85.34%, $speci_y$ of 96.34%, F_{score} of 85.36%, and MCC of 81.75%. Finally, with objective 3, the model realises an average $accur_y$ of 98.04%, $sensi_y$ of 95.10%, $speci_y$ of 98.78%, F_{score} of 95.09%, and MCC of 93.88%.

TABLE I

DETAILS ON DATASET

Classes	Class Label	Instance No.
"Recording of seizure activities"	Class1	2300
"Recording of EEG from the area where the tumour is located during a non-seizure period"	Class2	2300
"Recording of EEG from a healthy part of the brain during a non-seizure period"	Class3	2300
"Recording of EEG with the patient's eyes closed during a non-seizure period"	Class4	2300
"Recording of EEG with the patient's eyes open during a non-seizure period"	Class5	2300
Overall Instances		**11500**

TABLE II

AVERAGE OUTCOME OF THREE OBJECTIVES WITH DIFFERENT MEASURES

Class	Accuracy	Sensitivity	Specificity	F-Score	MCC
Objective 1	90.64	82.18	82.18	83.93	68.16
Objective 2	94.14	85.34	96.34	85.36	81.75
Objective 3	98.04	95.10	98.78	95.09	93.88

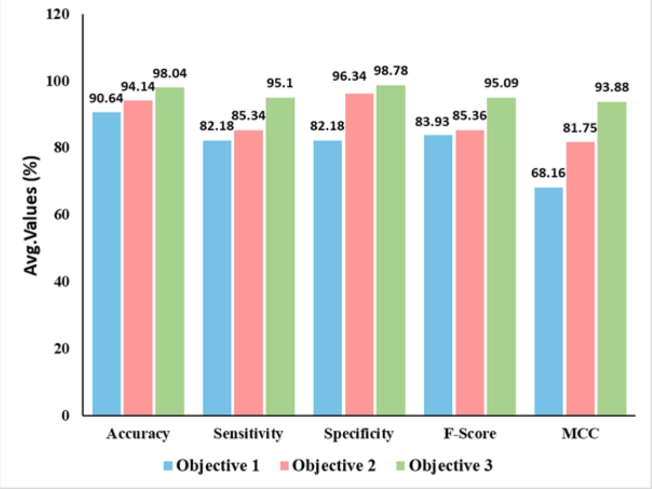

Fig. 2. Average outcome of three objectives

Fig. 3 represents the training (TRAG) and validation (VALN) $accur_y$ of 70% and 30% over 25 epochs. Both TRAG and VALN curves steadily increase and slowly converge, which indicates the model is learning efficiently. The VALN $accur_y$ reliably stays somewhat superior to the TRAG $accur_y$, signifying that the model could not overfit and is simplifying well to unnoticed data. The variations in $accur_y$ are predictable because of the task difficulty, then the completely increasing trend determines a robust result and consistency of the model.

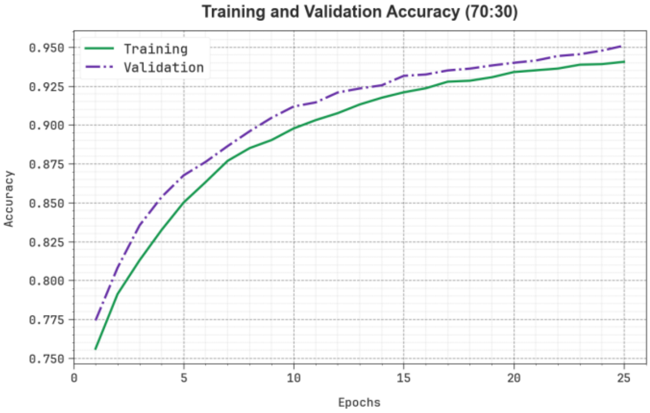

Fig. 3. $Accur_y$ curve of 70:30

Fig. 4 demonstrates the TRAG loss and VALN loss of 70% and 30% over 25 epochs. Both TRAG loss and VALN loss curves display a dependable descending trend, indicating that the model is efficiently minimising error through learning. The VALN loss remains smaller than the TRAG loss at most epochs, indicating enhanced simplification and no indication of overfitting. Even though some variations are detected, it is suitable, gradually stable, and reliable.

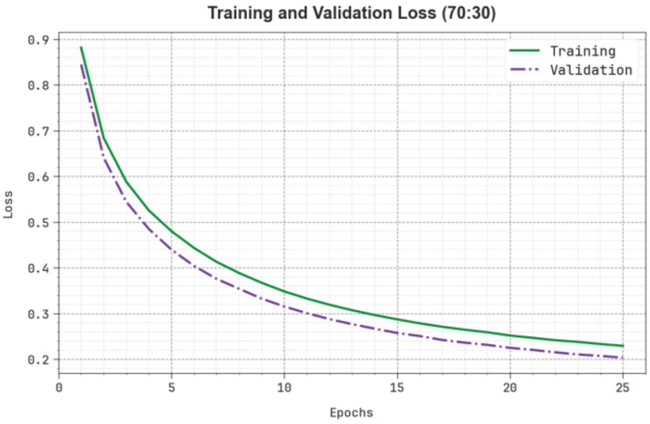

Fig. 4. Loss curve of 70:30

In Table 3 and Fig. 5, a detailed comparison $accur_y$ study of the three objectives with existing techniques is clearly reported. The outcomes inferred that the KNN approach has shown ineffectual detection outcomes with the least $accur_y$ of 76.00%. Likewise, the linear SVM technique has exhibited higher performances with $accur_y$ of 76.70%. In the meantime, the MLP approach has shown considerable results with $accur_y$ of 78%. Furthermore, the KELM, M-Gaussian-SVM, and SA-KELM methodologies have accomplished reasonable outcomes with $accur_y$ of 80.53%, 81.40%, and 82.49%. Finally, the three objectives, such as ESR-ICOADL, RESR-MDRDL, and EOEDL-ESR methodologies, demonstrate superior performance with increased $accur_y$ of 90.64%, 94.14%, and 98.04%. These outcomes indicate that all three objectives are effective and are successfully applied to improve the ESR and classification process.

TABLE III

COMPARATIVE OUTCOME OF THREE OBJECTIVES WITH EXISTING METHODS

Models	Accuracy (%)
KELM Algorithm	80.53
SA-KELM	82.49
M-Gaussian-SVM	81.40
Linear SVM	76.70
KNN Model	76.00
MLP Algorithm	78.00
ESR-ICOADL (Objective 1)	90.64
RESR-MDRDL (Objective 2)	94.14
EOEDL-ESR (Objective 3)	98.04

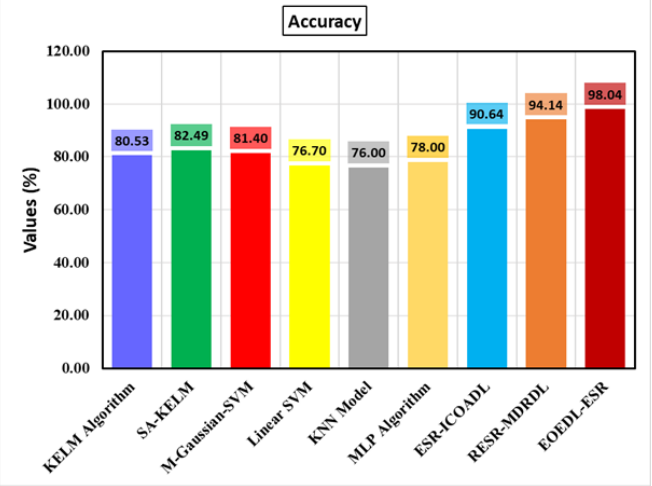

Fig. 5. Comparative outcome of three objectives with existing methods

V. CONCLUSION

This study presents a comprehensive and robust structure for ESR using EEG signals by integrating advanced DL approaches with heuristic optimisation algorithms. Primarily, the EEG signals undergo an effective pre-processing stage to normalise and transform the raw data into informative representations. Afterwards, an FS strategy is employed to improve discriminative capability while reducing dimensionality. For seizure recognition and classification, robust DL architectures are utilised. Finally, metaheuristic-based parameter tuning was executed to further increase the classification accuracy and robustness of the model. Extensive experimental validation on benchmark EEG datasets demonstrates that the proposed framework significantly outperforms existing approaches.

REFERENCES

[1] Poorani, S. and Balasubramanie, P., 2023. Deep learning based epileptic seizure detection with EEG data. *International Journal of System Assurance Engineering and Management*, pp.1-10.

[2] Gramacki, A. and Gramacki, J., 2022. A deep learning framework for epileptic seizure detection based on neonatal EEG signals. *Scientific Reports*, *12*(1), p.13010.

[3] Malekzadeh, A., Zare, A., Yaghoobi, M., Kobravi, H.R. and Alizadehsani, R., 2021. Epileptic seizures detection in EEG signals using fusion handcrafted and deep learning features. *Sensors*, *21*(22), p.7710.

[4] Zaid, Y., Sah, M. and Direkoglu, C., 2023. Pre-processed and combined EEG data for epileptic seizure classification using deep learning. *Biomedical Signal Processing and Control*, *84*, p.104738.

[5] Ibrahim, F.E., Emara, H.M., El-Shafai, W., Elwekeil, M., Rihan, M., Eldokany, I.M., Taha, T.E., El-Fishawy, A.S., El-Rabaie, E.S.M., Abdellatef, E. and Abd El-Samie, F.E., 2022. Deep-learning-based seizure detection and prediction from electroencephalography signals. *International Journal for Numerical Methods in Biomedical Engineering*, *38*(6), p.e3573.

[6] Varlı, M. and Yılmaz, H., 2023. Multiple classification of EEG signals and epileptic seizure diagnosis with combined deep learning. *Journal of Computational Science*, *67*, p.101943.

[7] Sadam, S.S.P. and Nalini, N.J., 2024. Epileptic seizure detection using scalogram-based hybrid CNN model on EEG signals. *Signal, Image and Video Processing*, *18*(2), pp.1577-1588.

[8] Singh, K. and Malhotra, J., 2022. Smart neurocare approach for detection of epileptic seizures using deep learning based temporal analysis of EEG patterns. *Multimedia Tools and Applications*, *81*(20), pp.29555-29586.

[9] Hilal, A.M.; Albraikan, A.A.; Dhahbi, S.; Nour, M.K.; Mohamed, A.; Motwakel, A.; Zamani, A.S.; Rizwanullah, M. Intelligent Epileptic Seizure Detection and Classification Model Using Optimal Deep Canonical Sparse Autoencoder. Biology 2022, 11, 1220.

[10] Pouryosef, M., Abedini-Nassab, R. and Akrami, S.M.R., 2024. A Novel Framework for Epileptic Seizure Detection Using Electroencephalogram Signals Based on the Bat Feature Selection Algorithm. *Neuroscience*, *541*, pp.35-49.

[11] Panda, S., Mishra, S., Mohanty, M.N. and Satapathy, S., 2023. Seizure detection using integrated metaheuristic algorithm based ensemble extreme learning machine. *Measurement: Sensors*, *25*, p.100617.

[12] Divya, P. and Devi, B.A., 2022. Hybrid metaheuristic algorithm enhanced support vector machine for epileptic seizure detection. *Biomedical Signal Processing and Control*, *78*, p.103841.

[13] Kumar, P.R., Shilpa, B., Jha, R.K. and Mohanty, S.N., 2023. A novel end-to-end approach for epileptic seizure classification from scalp EEG data using deep learning technique. *International Journal of Information Technology*, pp.1-9.

[14] Escorcia-Gutierrez, J., Beleno, K., Jimenez-Cabas, J., Elhoseny, M., Alshehri, M.D. and Selim, M.M., 2022. An automated deep learning enabled brain signal classification for epileptic seizure detection on complex measurement systems. *Measurement*, *196*, p.111226.

[15] Ahmad, I., Wang, X., Javeed, D., Kumar, P., Samuel, O.W. and Chen, S., 2023. A Hybrid Deep Learning Approach for Epileptic Seizure Detection in EEG signals. *IEEE Journal of Biomedical and Health Informatics*.

[16] https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition