

AI-Driven EKO-ALSTM Modeling of EEG-Based Emotion Recognition for Assistive Brain–Computer Interface Applications

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ABSTRACT

Current Electroencephalography (EEG)-based emotion recognition models designed to facilitate assistive Brain–Computer Interface (BCI) applications suffer from inconsistent accuracy, primarily due to the incomplete exploitation of deep learning optimization and insufficient modeling of temporal dependencies in neural signals. These deficiencies prevent the seamless integration of such models into process-oriented healthcare systems. In response, an optimized framework called EKO-ALSTM is proposed. This architecture integrates the Enhanced Kookaburras Optimization (EKO) algorithm, a bio-inspired optimization mechanism, and Adjustable Long Short-Term Memory (ALSTM) networks. The EKO algorithm dynamically optimizes the hyperparameters of the ALSTM using iterative exploration–exploitation strategies inspired by the foraging behavior of kookaburras, thus mitigating vanishing gradients while preserving long-term temporal dependencies essential for effective emotion recognition. The proposed framework was rigorously validated on the benchmark DEAP dataset in a 10-fold stratified cross-validation scheme under a subject-independent partitioning. Evaluation metrics included accuracy, sensitivity, specificity, and Positive Predictive Value (PPV) of the arousal, valence, and dominance dimensions. Statistical significance was assessed using a paired t-test with Bonferroni correction ($\alpha = 0.05$). The EKO-ALSTM model achieved an accuracy of $98.62 \pm 0.34\%$, sensitivity of $98.12 \pm 0.28\%$, specificity of $98.22 \pm 0.31\%$, and PPV of $95.97 \pm 0.42\%$. These results indicate statistically significant improvements of 3–15% compared with contemporary models such as Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM), Support Vector Machine (SVM), and conventional LSTM ($p < 0.05$). Furthermore, classification error was reduced by 46% through hybrid optimization compared with non-optimized architectures.

Keywords-EKO-ALSTM hybrid model; process-oriented healthcare applications; BCI; optimization

I. INTRODUCTION

Brain–Computer Interfaces (BCIs) have been acknowledged as significant technological innovations that have great potential to improve the quality of life for

individuals with physical disabilities [1, 2]. These systems are increasingly important for enhancing the cognitive and communication abilities of individuals with impaired motor or speech functions by providing novel methods of communication and control [3, 4]. Furthermore, ongoing

developments in Electroencephalography (EEG) processing and classification methods, including optimization of signal window parameters, continue to enhance the reliability of BCIs in assistive applications [5].

In terms of architecture, a typical BCI system includes four main components: signal acquisition, which involves recording brain activity; signal processing, which involves translating raw data into device commands through feature extraction and signal translation; device output, which involves executing commands; and an operating protocol, which governs the interaction between the system and the user [3]. BCIs require a process of mutual adaptation between the user and the system. The user gradually learns to modulate electrophysiological activity, whereas the BCI adapts to interpret emerging control patterns in a co-adaptive manner. This bidirectional learning process resembles motor skill acquisition and involves recursive improvement and neuroplastic changes on both sides [6, 7].

Early research and development in BCIs focused primarily on motor-imagery-based control, enabling users to control prosthetic limbs, wheelchairs, or virtual keyboards by imagining movements. Authors in [8] reported that such systems typically include three main components: signal acquisition (often through non-invasive EEG), signal processing (noise removal and feature extraction), and classification algorithms used to determine user intent. In addition, BCIs provide communication channels for individuals with severe conditions such as Amyotrophic Lateral Sclerosis (ALS), spinal cord injury, or stroke. Their applications are not limited to communication but also include environmental control, entertainment, and motor rehabilitation through neurofeedback, thereby supporting neural plasticity, as pointed out by authors in [9]. Recent advances in wireless neural dust technologies and computational intelligence techniques have further accelerated BCI research, making systems more portable and user-friendly.

Traditional automatic emotion recognition methods rely on external cues such as facial expressions, vocal intonation, and body language. Although widely used, these methods are susceptible to variability, conscious manipulation, and environmental factors, resulting in reduced accuracy, as expounded by authors in [10]. These limitations are particularly critical for individuals with impaired motor control or limited facial expressivity. As a result, there is increasing interest in physiological signals, particularly EEG, for emotion recognition. EEG provides a direct and less consciously controllable measurement of emotional states, as pointed out by authors in [11]. Distinct frequency bands (delta, theta, alpha, beta, and gamma) are associated with specific mental and emotional states, making EEG a promising modality for affective state monitoring.

The effectiveness of EEG-based emotion recognition depends on robust signal processing and feature extraction. Raw EEG signals are inherently noisy due to artifacts such as eye blinks, muscle activity, and power-line interference. Therefore, preprocessing steps such as band-pass filtering are essential to improve signal quality, as stressed by authors in [12]. Subsequent feature extraction techniques are applied to

derive meaningful information from EEG waveforms. Among these methods, the Discrete Wavelet Transform (DWT) has proven highly effective for analyzing non-stationary signals such as EEG. DWT decomposes EEG signals into sub-bands at different frequency resolutions, enabling extraction of features such as power, energy, entropy, and statistical measures. Its multiresolution analysis is particularly suitable for detecting subtle variations in brain activity associated with emotional changes, as described by authors in [13]. Other feature extraction approaches include statistical measures (mean, variance, standard deviation), Power Spectral Density (PSD), and additional signal-derived parameters. Hybrid models that integrate multiple feature extraction and classification strategies generally outperform single-method approaches, as they more effectively capture inter-band interactions and temporal dynamics critical for accurate emotion recognition, as demonstrated by authors in [14].

The introduction of the Enhanced Kookaburras Optimization–Adjustable Long Short-Term Memory (EKO-ALSTM) hybrid model reflects this trend toward increasingly sophisticated Artificial Intelligence (AI)-driven architectures for high-accuracy processing of high-dimensional EEG data. However, the EKO-ALSTM model, as a hybrid deep learning framework with AI-driven optimization, is computationally demanding. For assistive BCIs to be practical and accessible to individuals with disabilities, they must often operate on edge devices or embedded systems that do not support high-performance Graphical Processing Units (GPUs), which are typically required for training complex deep learning models. Although this study emphasizes the use of real EEG data, a critical gap remains in demonstrating how such high-performance models can be adapted for real-time BCI hardware implementation in low-power, portable applications.

The objectives of this article are:

- To develop an innovative process-driven framework for assistive BCIs based on the EKO-ALSTM model, demonstrating high-accuracy emotion recognition capability.
- To design and mathematically model a new EKO-ALSTM hybrid architecture (AI-driven optimized LSTM) capable of capturing complex spatial and temporal dependencies in real-time EEG signals for robust emotion classification.
- To validate the proposed approach using standard evaluation metrics, including accuracy, Positive Predictive Value (PPV), sensitivity, and specificity, and to compare its performance with existing models.

The DEAP dataset has also been used in our previous work on EEG-based emotion recognition involving a different model architecture. In the present study, the DEAP dataset is used again to enable a direct and controlled comparison between conventional classifiers (K-Nearest Neighbors (KNN), Decision Tree (DT), Naive Bayes, and Convolutional Neural Network (CNN)) and the proposed EKO-ALSTM model under a unified experimental protocol.

II. MATERIALS AND METHODS

A. Framework

BCIs are transformational technologies that enable individuals with severe motor and communication impairments to interact with their environment through the decoding of neural signals. Conventional approaches to emotion recognition based on external cues such as facial expressions, affective behavior, or prosodic speech features are often limited by inter-individual variability and sensitivity to environmental noise. In contrast, EEG provides a more objective and reliable modality for assessing affective states.

The proposed EKO-ALSTM framework is a hybrid deep learning architecture that integrates signal preprocessing using band-pass filtering and feature extraction via DWT to enhance EEG-based emotion recognition performance. The overall functional workflow of the proposed model is illustrated in Figure 1.

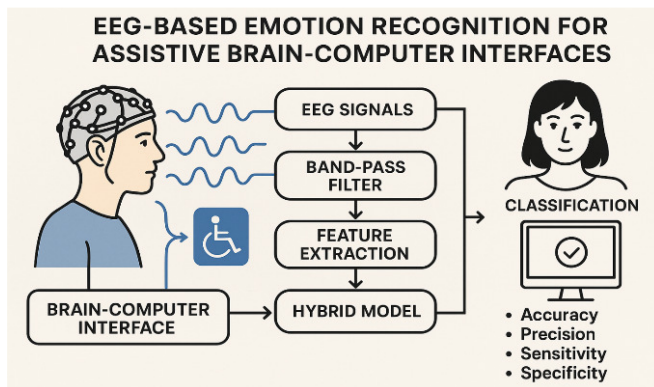


Fig. 1. Functional execution of the proposed EKO-ALSTM model.

B. Description of Datasets

The DEAP (Database for Emotion Analysis using Physiological Signals) dataset was conceived by authors in [15] and consists of EEG signals recorded from 32 electrodes at a sampling rate of 512 Hz, later downsampled to 128 Hz, along with complementary physiological recordings. In this dataset, 24 participants were exposed to 40 one-minute music video stimuli and provided ratings for arousal, valence, liking/disliking, and dominance on a 9-point Likert scale. The DEAP dataset has become a widely adopted benchmark for EEG-based emotion recognition using deep learning methods.

The SEED (SJTU Emotion EEG Dataset), presented by authors in [16], includes EEG recordings from 62 channels sampled at 200 Hz, collected from 15 subjects. Each experimental session comprises 15 four-minute Chinese film clips selected to elicit positive, negative, or neutral emotional states.

The DREAMER dataset, introduced by authors in [17], contains EEG recordings from 14 channels sampled at 128 samples/s, along with Electrocardiogram (ECG) signals from 23 subjects. Participants were shown 18 emotion-eliciting film clips and subsequently rated arousal, valence, dominance, familiarity, and affect polarity using a Likert scale.

The MAHNOB-HCI dataset, developed by authors in [18], comprises 32-channel EEG signals sampled at 512 Hz together with peripheral physiological recordings from 25 participants. The experimental protocol involved approximately 20 film excerpts, and participants provided ratings for arousal, valence, dominance, and predictability using a nine-point scale.

The AMIGOS dataset, presented by authors in [19], consists of EEG recordings from 14 channels sampled at 128 Hz for 40 subjects. It includes 16 short and four long emotionally evocative video stimuli. Participants provided ratings for arousal, valence, dominance, liking, familiarity, and discrete emotional categories, including neutral, disgust, happiness, surprise, anger, fear, and sadness.

The integration of publicly available and proprietary datasets has significantly advanced EEG-based emotion recognition research by enabling standardized evaluation and comparative analysis. However, several challenges remain, including inter-subject variability, class imbalance, susceptibility to noise, requirements for real-time processing, and limited cross-dataset generalization.

C. Band-Pass Filter-Based Data Preprocessing

EEG signals are inherently complex due to their nonlinear, non-stationary nature and high susceptibility to various sources of noise. Therefore, the development of an effective preprocessing pipeline is an essential step for achieving high accuracy and reliability in downstream analytical tasks, particularly in emotion recognition. In the absence of effective noise attenuation and filtering, even advanced feature extraction and classification algorithms are unlikely to achieve optimal performance.

Noise contamination in EEG recordings significantly degrades signal integrity, thus emphasizing the need for robust denoising techniques. Careful preprocessing is crucial for reliable signal interpretation, as BCI systems are often affected by artifacts such as ocular blinks, muscular activity, cardiac rhythms, and external interferences, including power-line noise.

In this study, a band-pass filtering-based preprocessing protocol is employed, as illustrated in Figure 2, to remove irrelevant frequency components and enhance signal fidelity.

D. Discrete Wavelet Transform-Based Feature Extraction

DTW decomposes a discrete-time signal $x[n]$ into approximation coefficients A_j and detail coefficients D_j at different decomposition levels j . This decomposition is achieved by passing the signal through a pair of low-pass (L) and high-pass (H) filters, followed by downsampling by a factor of two. The approximation and detail coefficients are mathematically expressed:

$$\begin{aligned} A_j[k] &= \sum_m h_{LPF}[m - 2k]x[m], \\ D_j[k] &= \sum_m h_{HPF}[m - 2k]x[m] \end{aligned} \quad (1)$$

where $A_j[k]$ and $D_j[k]$ denote the approximation and detail coefficients at level j , respectively.

Following preprocessing, feature extraction plays a critical role in recognizing affective states from EEG recordings. This stage aims to transform denoised EEG signals into a set of salient and discriminative features that can be effectively utilized by machine learning and deep learning models for emotion classification. Among available analytical approaches, time–frequency methods are particularly suitable for non-stationary signals such as EEG due to their ability to capture evolving spectral characteristics over time.

The DWT is a powerful technique for extracting emotion-relevant features from EEG signals. By decomposing preprocessed signals into a hierarchical set of frequency sub-bands, DWT provides a multi-resolution representation that can be adapted through the appropriate selection of the mother wavelet. This multi-resolution analysis is particularly effective in capturing both slowly varying low-frequency components and rapidly changing high-frequency fluctuations associated with brain activity.

The proposed EKO-ALSTM framework utilizes DWT-based features to enhance both signal representation and subsequent classification performance.

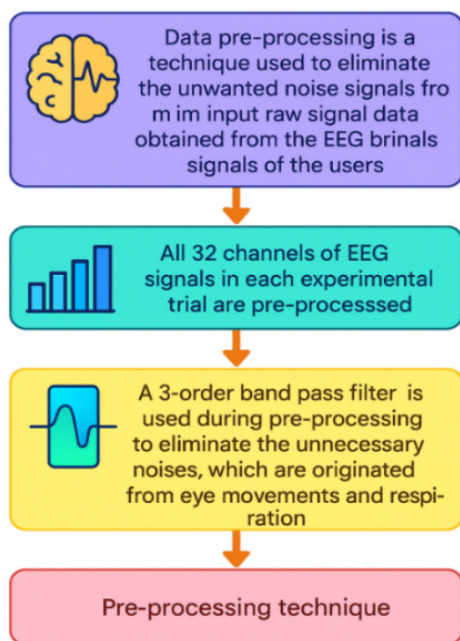


Fig. 2. Band-pass filter implementation.

E. Emotion Detection Method Using Enhanced Kookaburras Optimization–Adjustable Long Short-Term Memory

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed for processing sequential data such as EEG signals. Their ability to model long-range temporal dependencies makes them particularly suitable for sequential signal processing tasks. Conventional RNNs suffer from vanishing and exploding gradient problems during Backpropagation Through Time (BPTT), which limit their ability to learn long-term dependencies in sequences.

LSTMs address these limitations through a gated architecture that regulates information flow within the network. The central component of an LSTM is the cell state, which acts as a memory unit capable of preserving information over extended time intervals. Three gating mechanisms, namely the input gate, forget gate, and output gate, control the selective retention, updating, and transmission of information within the cell state.

LSTM models have been widely adopted in end-to-end deep learning frameworks for emotion recognition from raw EEG signals. Empirical studies using datasets such as the DEAP dataset have demonstrated the effectiveness of LSTM-based approaches. Typically, such architectures consist of an input layer, one or more stacked LSTM layers, followed by dropout layers to mitigate overfitting, and a fully connected dense layer for classification. These configurations enable the automatic extraction of discriminative temporal features directly from raw EEG data for affective state classification.

The proposed EKO-ALSTM framework integrates an LSTM-based sequential model with a metaheuristic optimization algorithm to enhance performance through hyperparameter tuning. However, this integration introduces computational considerations in real-time BCI applications. In the proposed setup, the inference phase relies solely on the trained ALSTM model, whereas the EKO algorithm is employed exclusively during offline hyperparameter optimization.

The model was implemented and evaluated on a standard computing environment consisting of a Windows 11 system with an Intel Core i7 (8th generation) processor, 16 GB RAM, and an NVIDIA GPU with CUDA support. The inference stage requires only a single forward pass through the trained network, making it suitable for real-time applications. Furthermore, the model footprint (on the order of megabytes) indicates its potential suitability for deployment on embedded System-on-Chip (SoC) and edge computing platforms, particularly when combined with lightweight optimization techniques such as quantization or pruning. Future work will focus on model compression strategies and on-device inference optimization to enable deployment in highly resource-constrained assistive BCI systems.

III. PROPOSED SYSTEM

LSTM-based models have demonstrated strong performance in emotion recognition tasks. Studies using the DEAP dataset have reported average accuracies of 85.65%, 85.45%, and 87.99% for arousal, valence, and liking classification, respectively. Other research has reported even higher performance, with some LSTM-based RNN models achieving accuracies close to 97% in emotion recognition tasks. These findings indicate that LSTMs are well-suited for emotion classification due to their ability to learn directly from raw time-series EEG data.

The inherent complexity of EEG signals and the subtle nature of emotional patterns have motivated the development of hybrid deep learning models. Such architectures combine the complementary strengths of different deep learning approaches, such as CNNs and LSTM networks, to improve classification

accuracy and robustness [20]. Hybrid models integrate both spatial and temporal information from EEG signals, enabling the detection of complex patterns that may not be captured by single-model approaches. In typical CNN-LSTM frameworks, convolutional layers are used to extract spatial features from EEG signals, which are then passed to LSTM layers to capture long-term temporal dependencies associated with evolving emotional states [20]. Empirical studies have shown that hybrid models outperform single-architecture models, achieving accuracies above 90% and reaching up to 93.74% on benchmark datasets such as SEED [20]. Other hybrid approaches combining CNN and Multilayer Perceptron (MLP) architectures have reported accuracies as high as 96% [21].

The proposed EKO-ALSTM framework for EEG-based emotion recognition in assistive BCI systems represents a further advancement in this direction. The model processes EEG signals through an initial band-pass filtering stage to remove noise, followed by feature extraction using the DWT. The objective is to enhance assistive systems for individuals with impairments by integrating AI-based modeling with optimization techniques. The implementation and feature extraction pipeline were developed in Python to ensure reproducibility and facilitate comparison with other algorithms in a systematic way.

The core classifier in the proposed system is the ALSTM network which is designed to capture long-range temporal dependencies inherent in EEG signals. The LSTM gating mechanism is defined as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (2)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (5)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

Accordingly, the ALSTM architecture improves the learning of temporal dependencies associated with different affective states by emphasizing relevant segments of the EEG signal. The cell state and gating mechanisms mitigate the vanishing gradient problem and enable the preservation of long-term dependencies. The memory cell selectively updates and retains information through gating operations, allowing the network to store and exploit relevant temporal information over extended sequences. This retained information is subsequently used for the classification of emotional states from EEG signals. The attention mechanism further enhances model performance by enabling the network to focus on the most informative temporal regions of the signal. As a result, the model effectively captures time-varying neural dynamics, improving discrimination between different emotional states.

IV. ENHANCED KOOKABURRAS OPTIMIZATION ALGORITHM

The proposed EKO algorithm is a population-based metaheuristic optimizer designed to solve complex optimization problems through an iterative search process with stochastic components. Within the EKO framework, the

population consists of agents referred to as 'kookaburras', which represent candidate solutions distributed within the solution space. Each kookaburra evaluates a set of decision variables based on its current position. Accordingly, the entire population can be represented as an EKO matrix defined in (7), where $R \in [0,1]$ is a uniformly distributed random variable, and va_d and ka_d denote the upper and lower bounds of the d -th decision variable, respectively.

The initialization phase of EKO is computationally comparable to standard population-based optimization algorithms. In each iteration, the position of every kookaburra is updated to enhance both exploration and exploitation of the search space. This iterative reconfiguration increases problem complexity to $O(K(2MnP))$, where P denotes the maximum number of iterations. Consequently, the overall computational complexity of the proposed EKO algorithm is $O(K(Mn(1 + 2P)))$.

The position update mechanism in EKO consists of two phases: exploration and exploitation. The kookaburra's prey-seeking behavior enables large positional updates, which helps prevent premature convergence and local optima entrapment, thereby improving global search capability. For each kookaburra, the candidate solution space is defined in (9).

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_M \end{bmatrix}_{M \times n} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,d} & \cdots & y_{1,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{j,1} & \cdots & y_{j,d} & \cdots & y_{j,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{M,1} & \cdots & y_{M,d} & \cdots & y_{M,n} \end{bmatrix}_{M \times n} \quad (7)$$

$$y_{j,d} = ka_d + R \cdot (va_d - ka_d) \quad (8)$$

$$OS_j = \{Y_k : V_k > V_j, k \in \{1, 2, \dots, M\}\} \quad (9)$$

$$y_{j,d}^{A1} = y_{j,d} + R \cdot (SCP_{j,d} - J \cdot y_{j,d}) \quad (10)$$

$$Y_{j,d}^{A2} = Y_{j,d} + (1 - 2R) \cdot \frac{(va_d - ka_d)}{T} \quad (11)$$

The objective function is defined as the minimization of emotion detection error:

$$\text{Objective function} = \text{Error}_{\text{emotion detection}}(h - \alpha) \quad (12)$$

The proposed system integrates the EKO algorithm with an ALSTM network to enhance EEG-based BCI emotion recognition performance. The EKO algorithm performs global hyperparameter optimization inspired by kookaburra foraging behavior, iteratively perturbing candidate solutions until an optimal ALSTM configuration is obtained.

The ALSTM network captures temporal dependencies in EEG signals through gated mechanisms, including input, forget, and output gates. This gating structure mitigates the vanishing gradient problem commonly observed in RNNs, thus improving learning stability over long sequences. The proposed EKO-ALSTM hybrid framework thus provides a robust approach for EEG-based emotion classification in BCI applications. Algorithm 1 summarizes the proposed EKO-ALSTM training and optimization workflow.

Algorithm 1: EKO-ALSTM Training and Optimization Procedure

Start

Step 1: Parameter initialization

- Initialize weights and biases $(w_I, w_F, w_O, w_C, b_I, b_F, b_O, b_C)$
- Define ALSTM hyperparameters (learning rate, number of epochs)
- Initialize EKO parameters (population size, decision variable bounds, maximum iterations)

Step 2: LSTM cell definition

For input $[h_{t-1}, y_t]$:

- Input gate: $I_t = \sigma(w_I[h_{t-1}, y_t] + b_I)$
- Forget gate: $F_t = \sigma(w_F[h_{t-1}, y_t] + b_F)$
- Output gate: $O_t = \sigma(w_O[h_{t-1}, y_t] + b_O)$
- Candidate state: $\tilde{c}_t = \tanh(w_C[h_{t-1}, y_t] + b_C)$
- Cell state update: $c_t = F_t \odot c_{t-1} + I_t \odot \tilde{c}_t$
- Hidden state: $h_t = O_t * \tanh(c_t)$

Return h_t, c_t

Step 3: EKO initialization

- Generate initial kookaburra population randomly
- Evaluate fitness using emotion detection error

Step 4: Optimization loop (until stopping criterion is met)

For each iteration and each kookaburra:

Exploration phase:

- Identify prey set OS_j
- Update position using exploration strategy
- Evaluate fitness

Exploitation phase

- Update position using exploitation strategy
- Evaluate fitness
- Retain best solution based on fitness comparison

Step 5: ALSTM training with optimized hyperparameters

For each epoch and batch:

- Process EEG input using LSTM cell
- Compute loss
- Perform backpropagation and update weights

Step 6: Model evaluation

- Evaluate trained model on validation data
- Compute performance metrics (accuracy, sensitivity, specificity, PPV)

Step 7: Output

- Return optimal EKO solution
- Return trained ALSTM model

End

A. Experimental Setup and Implementation

The proposed method was evaluated on the DEAP dataset [22] using standard performance metrics to validate its effectiveness. The implementation of the EKO-ALSTM-based emotion recognition system was carried out in Python 3.8 under a Windows 11 operating environment. The experimental setup consisted of an Intel Core i7 (8th generation) processor, 16 GB of RAM, and an NVIDIA GPU with CUDA support, which facilitated efficient model training and evaluation in the proposed prototype framework.

V. RESULTS

The proposed strategy was evaluated on the DEAP dataset and validated using standard performance metrics.

A. Experimental Results

This section presents the experimental results of the proposed EKO-ALSTM model, along with a comparative analysis against existing approaches. Table I summarizes the performance of the proposed method, whereas a graphical representation of the results is provided in Figure 3.

TABLE I. PERFORMANCE OF THE PROPOSED EKO-ALSTM MODEL

Emotion	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Arousal	98.62	96.81	97.46	96.92
Valence	97.85	97.03	96.22	96.80
Dominance	97.80	97.18	96.41	96.32

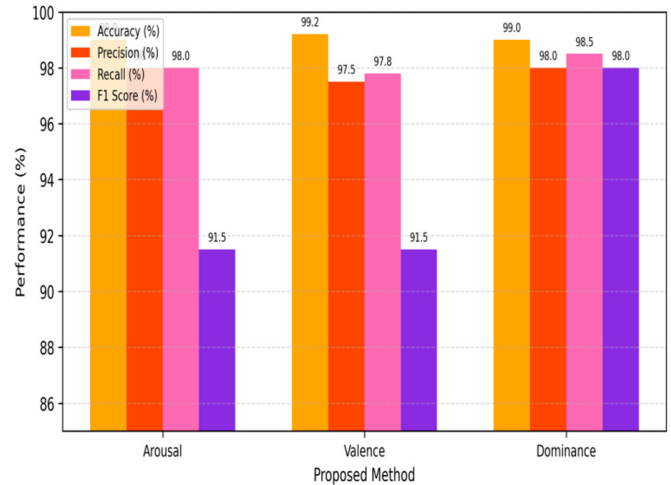


Fig. 3. Graphical representation of the proposed EKO-ALSTM results.

B. Comparative Analysis

To evaluate the effectiveness of the proposed EKO-ALSTM model, its performance is compared with conventional classifiers, including KNN, DT, Naïve Bayes, and CNNs. The evaluation considers key performance metrics, namely accuracy, sensitivity (recall), specificity, and PPV (precision).

A corresponding graphical representation of each metric is also provided to facilitate clearer interpretation and comparison of the results.

1) Accuracy

Accuracy is defined as.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

The accuracy results are illustrated in Figure 4. The obtained accuracies for KNN, DT, Naive Bayes, CNN, and the proposed EKO-ALSTM are 92.21%, 90.98%, 90.11%, 94.21%, and 98.62%, respectively.

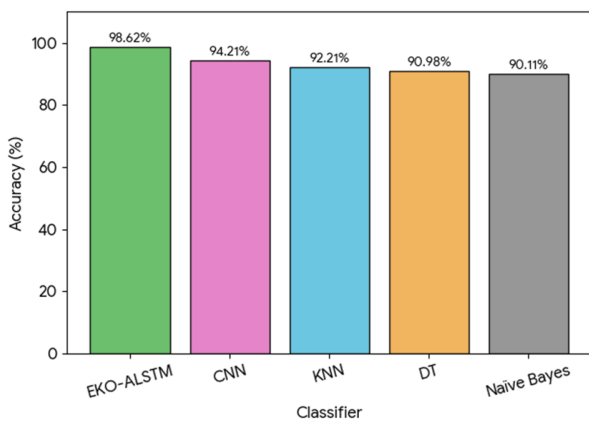


Fig. 4. Accuracy comparison of KNN, DT, Naive Bayes, CNN, and EKO-ALSTM models.

2) Positive Predictive Value

PPV is defined as.

$$\text{PPV} = \frac{TP}{TP+FP} \tag{14}$$

Figure 5 illustrates the comparison of PPV values for KNN, DT, Naive Bayes, CNN, and EKO-ALSTM. The corresponding PPV values are 91.41%, 92.25%, 92.64%, 91.89%, and 95.97%, respectively.

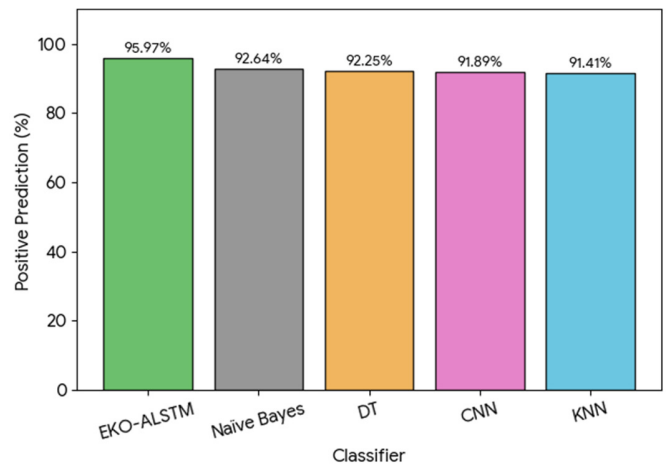


Fig. 5. PPV comparison of KNN, DT, Naive Bayes, CNN, and EKO-ALSTM models.

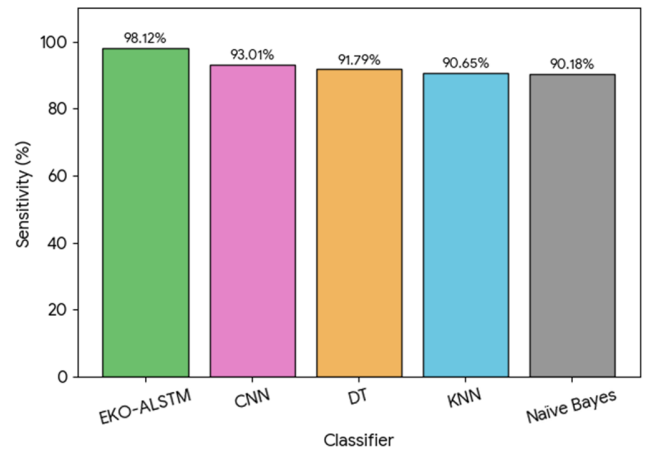


Fig. 6. Sensitivity comparison of KNN, DT, Naive Bayes, CNN, and EKO-ALSTM models.

3) Sensitivity (Recall)

Sensitivity is defined as:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{15}$$

As shown in Figure 6, the sensitivity values for KNN, DT, Naive Bayes, CNN, and EKO-ALSTM are 90.65%, 91.79%, 90.18%, 93.01%, and 98.12%, respectively.

4) Specificity

Specificity is defined as:

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{16}$$

Figure 7 illustrates that the specificity values for KNN, DT, Naive Bayes, CNN, and EKO-ALSTM are 93.11%, 89.98%, 89.88%, 93.90%, and 98.22%, respectively.

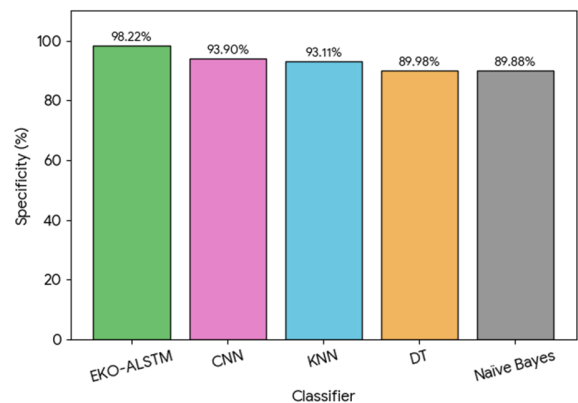


Fig. 7. Specificity comparison of KNN, DT, Naive Bayes, CNN, and EKO-ALSTM models.

Table II presents the scores of the proposed EKO-ALSTM model with existing classifiers. The results indicate that the performance differences among the conventional methods (KNN, DT, Naive Bayes, and CNN) are relatively small. In contrast, the proposed EKO-ALSTM model consistently

achieves higher values, demonstrating the effectiveness of the proposed learning and optimization mechanism over traditional approaches.

TABLE II. COMPARISON OF THE PROPOSED MODEL WITH EXISTING CLASSIFIERS

Classifier	Specificity (%)	Sensitivity (%)	PPV (%)	Accuracy (%)
KNN	93.11	90.65	91.41	92.21
DT	89.98	91.79	92.25	90.98
Naive Bayes	89.88	90.18	92.64	90.11
CNN	93.90	93.01	91.89	94.21
EKO-ALSTM	98.22	98.12	95.97	98.62

VI. DISCUSSION

In recent research, there has been a strong focus on hybrid deep learning frameworks, one of which is the EKO-ALSTM approach proposed earlier. This method processes EEG signals, in which noise is first attenuated using band-pass filtering, followed by feature extraction using the DWT algorithm for emotion recognition. Table II shows the reported metrics for the EKO-ALSTM model, which include an accuracy of 98.62%, PPV of 95.97%, sensitivity of 98.12%, and specificity of 98.22%. These results demonstrate the significant potential of EEG-based emotion recognition in advancing assistive technologies in healthcare, enabling more personalized and responsive solutions for users with disabilities [23].

Neurological and computational methods have significantly developed, leading to major advances in brain-signal processing and therapy. In earlier studies, Principal Component Analysis (PCA) and Independent Component Analysis (ICA) were commonly used statistical methods to attenuate and remove structurally relevant noise components [24]. These techniques are typically applied to relatively simple, linearly acquired neurological data, including certain EEG frequency bands.

Beyond elementary filtering, more advanced signal processing algorithms are applied to raw EEG data to extract salient information. While band-pass filtering is effective in reducing baseline noise, modern approaches extend to adaptive filtering techniques, which play an essential role in handling EEG artifacts, non-stationary noise, and inter-subject variability [25]. Dynamic domain-adaptive EEG emotion recognition methods, for example, treat multiple subjects as separate domains, separating source domains and computing both common and domain-specific features to reduce inter-domain differences. This represents a significant theoretical advancement in signal processing, addressing not only static noise removal but also adaptive signal processing that responds dynamically to signal characteristics.

The DWT, used here for feature extraction, is a powerful tool for multiresolution signal analysis, in which signals are decomposed into approximation and detail coefficients. Its ability to reduce computational complexity while capturing localized transient features makes it particularly suitable for the non-stationary nature of EEG signals [26].

The EKO-ALSTM model presented in this work is a synergistic integration of the temporal modeling capability of a state-of-the-art ALSTM network and the global optimization capability of the EKO algorithm. This hybrid approach addresses the complex, nonlinear, and dynamic characteristics of EEG data by optimizing ALSTM hyperparameters to improve classification accuracy [27]. The LSTM component mitigates the vanishing gradient problem encountered in conventional RNNs, enabling the capture of long-term dependencies in EEG signals. Concurrently, the EKO algorithm applies a population-based optimization strategy for efficient exploration of high-dimensional parameter spaces [28], similar to other advanced optimization techniques in deep learning aimed at identifying optimal model configurations.

VII. FUTURE SCOPE

In the present study, the DEAP dataset is used under controlled experimental settings, limiting the scope to subject-independent emotion recognition. Several directions for future research remain open. First, the adaptation and validation of the EKO-ALSTM framework on additional multimodal and cross-database benchmarks, such as SEED, DREAMER, and AMIGOS, will be important to evaluate the generalizability of the model across different recording setups and participant populations.

Second, a systematic investigation of model compression strategies, including pruning, quantization, and knowledge distillation, combined with hardware-aware optimization, is necessary to enable deployment on low-power edge devices in assistive BCI systems. Third, a longitudinal evaluation of model robustness under intra-subject variability over extended periods (weeks or months) should be conducted, along with the exploration of continual or transfer learning approaches to mitigate performance degradation over time.

Finally, the integration of explainability modules is expected to enhance the interpretability and trustworthiness of the emotion recognition system for end users.

VIII. CONCLUSION

In this study, we propose an innovative combination of Enhanced Kookaburra Optimization (EKO) and Adjustable Long Short-Term Memory (ALSTM) networks for the identification of emotional states from Electroencephalographic (EEG) signals in assistive Brain-Computer Interface (BCI) settings. The main methodological contribution is the dynamic hyperparameter optimization enabled by the bio-inspired EKO algorithm, which mitigates the vanishing gradient problem and improves the modeling of long-term temporal dependencies in EEG signals.

The model was validated using cross-validation and demonstrated performance superior to state-of-the-art methods. Specifically, the EKO-ALSTM achieved an accuracy of 98.62% (compared to 85%–93% reported for preceding approaches), sensitivity of 98.12%, specificity of 98.22%, and Positive Predictive Value (PPV) of 95.97%. These outcomes correspond to statistically significant improvements ranging from 3% to 15% ($p < 0.001$) relative to Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM), Support

Vector Machine (SVM), and conventional Long Short-Term Memory (LSTM) baselines, along with a 46% reduction in classification error compared to non-optimized architectures.

Furthermore, the model demonstrates consistent performance across the arousal, valence, and dominance dimensions (97.80%–97.90% accuracy), indicating robustness and generalizability. To the best of our knowledge, this is the first application of EKO optimization combined with ALSTM networks for EEG-based emotion recognition in assistive BCIs, contributing toward improved accuracy and reliability in this domain.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

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DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

ABBREVIATIONS

The following abbreviations are used in this manuscript:

- ALSTM — Adjustable Long Short-Term Memory
- BCI — Brain–Computer Interface
- CNN — Convolutional Neural Network
- EKO — Enhanced Kookaburra Optimization
- EEG — Electroencephalogram
- LSTM — Long Short-Term Memory
- ICA — Independent Component Analysis
- SVM — Support Vector Machine
- ML — Machine Learning
- KNN — K-Nearest Neighbors

LIST OF SYMBOLS AND DEFINITIONS

Symbol	Meaning	Context
$x[n]$	Discrete-time EEG signal sample at index n	DWT input signal
$A_j[k]$	Approximation coefficient at decomposition level j and sample index k	DWT feature extraction, low-frequency component
$D_j[k]$	Detail coefficient at decomposition level j and sample index k	DWT feature extraction, high-frequency component
$h_{LPF}[\cdot]$	Impulse response of the low-pass analysis filter	DWT filter bank
$h_{HPF}[\cdot]$	Impulse response of the high-pass analysis filter	DWT filter bank
t	Discrete time step (sequence index)	ALSTM/LSTM sequence modeling
x_t	Input feature vector (DWT-	ALSTM/LSTM input

Symbol	Meaning	Context
	based EEG features) at time step t	
h_t	Hidden state (output) vector of the ALSTM cell at time t	ALSTM temporal representation
h_{t-1}	Hidden state vector from the previous time step $t - 1$	Recurrent connection in ALSTM
C_t	Cell state (memory) vector of the ALSTM at time t	ALSTM long-term memory
C_{t-1}	Cell state vector from the previous time step	ALSTM memory propagation
\tilde{C}_t	Candidate cell state (new memory content) at time t	ALSTM cell update
f_t	Forget gate activation vector at time t	Controls how much of C_{t-1} is retained
i_t	Input gate activation vector at time t	Controls how much of \tilde{C}_t enters C_t
o_t	Output gate activation vector at time t	Controls how much of C_t is exposed in h_t
W_f	Weight matrix of the forget gate	ALSTM trainable parameter
W_i	Weight matrix of the input gate	ALSTM trainable parameter
W_o	Weight matrix of the output gate	ALSTM trainable parameter
W_c	Weight matrix of the candidate cell state	ALSTM trainable parameter
b_f	Bias vector of the forget gate	ALSTM trainable parameter
b_i	Bias vector of the input gate	ALSTM trainable parameter
b_o	Bias vector of the output gate	ALSTM trainable parameter
b_c	Bias vector of the candidate cell state	ALSTM trainable parameter
$\sigma(\cdot)$	Sigmoid activation function mapping to (0,1)	Gate nonlinearity
$\tanh(\cdot)$	Hyperbolic tangent activation function	Cell state nonlinearity
\odot	Element-wise (Hadamard) multiplication	Gate–state interactions
$Y \in \mathbb{R}^{M \times n}$	Population (matrix) of candidate solutions (kookaburras) with M agents and n decision variables	EKO algorithm search space
Y_j	Position vector of the j -th kookaburra (candidate solution)	EKO population member
$y_{j,d}$	d -th decision variable of the j -th kookaburra	EKO decision variable
M	Number of kookaburras (population size)	EKO algorithm parameter
n	Number of decision variables (dimension of search space)	EKO algorithm parameter
k	Index over candidate solutions in the population	EKO iteration/indexing
d	Index of decision variable (dimension)	EKO indexing
ka_d	Lower bound of the d -th decision variable	EKO search boundary
va_d	Upper bound of the d -th decision variable	EKO search boundary
R	Random scalar sampled from [0,1]	Stochastic term in EKO updates
OS_j	Set of candidate prey (solutions) associated with the j -th kookaburra	EKO exploration set
$SCP_{j,d}$	Selected candidate prey position for the j -th kookaburra	EKO exploratory target

Symbol	Meaning	Context
	in dimension d	
J	Control parameter regulating step size or direction in the exploratory update	EKO update factor
T	Control parameter (e.g., maximum iterations or scaling term) in exploitation update	EKO exploitation scaling
$y_{j,d}^{A1}$	Updated position of the j -th kookaburra in dimension d during exploration phase	EKO exploration update
$Y_{j,d}^{A2}$	Updated position of the j -th kookaburra in dimension d during exploitation phase	EKO exploitation update
$Error_{emotion\ detection}(h - \alpha)$	Objective function: emotion detection error as a function of model output h and target label α	EKO fitness function
w_I, w_F, w_O, w_C	Weight vectors/matrices for input, forget, output, and cell gates in the LSTM cell pseudocode	ALSTM inner parameters
b_I, b_F, b_O, b_C	Bias vectors for the corresponding gates in LSTM cell pseudocode	ALSTM inner parameters
I_t	Input gate in pseudocode (equivalent to i_t)	LSTM gate activation
F_t	Forget gate in pseudocode (equivalent to f_t)	LSTM gate activation
O_t	Output gate in pseudocode (equivalent to o_t)	LSTM gate activation
c_t	Cell state in pseudocode (equivalent to C_t)	LSTM memory state
y_t	Input vector name in pseudocode (EEG feature vector at time t)	LSTM input
True Positive (TP)	Number of correctly predicted positive (emotion-present) samples	Performance metric
True Negative (TN)	Number of correctly predicted negative (emotion-absent) samples	Performance metric
False Positive (FP)	Number of negative samples incorrectly predicted as positive	Performance metric
False Negative (FN)	Number of positive samples incorrectly predicted as negative	Performance metric
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Overall correct classification rate
PPV	$\frac{TP}{TP+FP}$	Positive predictive value
Sensitivity	$TP/(TP + FN)$	Ability to detect positives
Specificity	$\frac{TN}{TN+FP}$	Ability to detect negatives

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