International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 20s, 2025
https://www.theaspd.com/ijes.php

Enhancing GAIT Analysis: Integrating Trickster Coyote Optimization With FL-BiLSTM Classifier For Exclusion Of Carried Objects

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Abstract: *In this research paper, an innovative approach for emotion classification is presented using a hybrid model called Augmented Trickster Coyote-based Federated Learning Bidirectional Long Short-Term Memory (FL-BiLSTM) classifier. The hyper parameters of the FL-BiLSTM classifier are optimized using the Trickster Coyote Optimization (TCO) algorithm, resulting in improved classification accuracy. The effectiveness is demonstrated by extensive experiments and comparisons with existing methods.*

Introduction: *Emotion recognition plays a crucial role in various applications, including human-computer interaction and affective computing. Federated Learning (FL) provides a privacy-friendly approach for training deep learning models on distributed datasets. However, the performance of FL models can be affected by a suboptimal choice of hyper parameters.*

Objectives: *- Create a unique way to emotion recognition utilizing a hybrid model, and improve the performance of Federated Learning-based emotion categorization by optimizing the hyper parameters. Extensive trials and comparisons with existing approaches will be used to demonstrate the optimized model's efficiency.*

Methods: *- We suggest the Federated Learning Bidirectional Long Short-Term Memory (FL-BiLSTM) classifier for emotion classification. Apply the Trickster Coyote Optimization (TCO) method to optimize the FL-BiLSTM classifier's hyper parameters. Employ Federated Learning to train an emotion classification model on distributed data while maintaining anonymity.- Conduct studies that contrast the efficacy of the suggested model with other methods that are currently in use.*

Results: *The suggested Augmented Trickster Coyote-based FL-BiLSTM model outperforms previous techniques in terms of classification accuracy. The TCO method successfully improves the FL-BiLSTM's hyperparameters that resulting in higher scores on recognizing emotions tests. The sensitivity of the trickster coyote-based FL-BiLSTM obtains a noteworthy 98.800% when the training rate is set to 80% after 100 epochs. The trickster coyote-based FL-BiLSTM has a specificity of 89.198% & a training percentage of 70% after 100 epochs.*

Conclusions: *The hybrid model, which combines Federated Learning, BiLSTM, and TCO, provides a promising method to identify emotions with higher accuracy & privacy-preserving features. The TCO method optimizes hyperparameters, improving the performance of the FL-BiLSTM classifier, making it a useful tool for distributed emotion classification applications. The proposed approach surpasses existing models, indicating that it has potential applications in human-computer interaction or social computer systems.*

Keywords: *Emotion Recognition, Feature Selection, GAIT, Optimization, Trickster Coyote.*

1. INTRODUCTION

Emotions are fundamental to human communication and behaviour. Recognizing emotions through various cues (such as facial expression, vocal tone, and physiological signals) enables machines to understand them and respond appropriately. Emotion recognition has become an important field of research due to its extensive applications in human-computer interaction (HCI), affective computing, and sentiment analysis. It enables computers to understand and respond to human emotions, leading to more natural and engaging interactions [1]. Deep learning models are incredibly powerful tools, but their training often requires huge amounts of data. Conventional approaches to emotion recognition often rely on centralized data collection, which raises privacy concerns [2]. Federated Learning (FL) addresses privacy concerns by training models on decentralized data sources (e.g., on users' devices) without sharing the raw data. This eliminates the need for centralized data storage and protects user privacy [3]. One challenge with FL is the efficient optimization of hyper parameters across distributed nodes. Choosing the optimal hyper parameters (e.g., learning rate, batch size) for FL models is a challenge due to this heterogeneity [4]. This paper presents a novel hybrid approach that combines Trickster Coyote Optimization (TCO) with Federated Learning and Bidirectional Long Short-Term Memory (BiLSTM) networks for emotion classification. The proposed hybrid model combines Federated Learning (FL) and Bidirectional Long Short-Term Memory (BiLSTM). BiLSTM processes sequences bidirectional and effectively captures context for emotion classification. The Trickster Coyote Optimization (TCO) algorithm optimizes the hyper parameters of the FL-BiLSTM classifier. TCO adapts to the FL context and thus improves the performance of the model [5-7].

1.1. FL-BiLSTM Classifier

Federated learning (FL) is a decentralized approach to machine learning in which multiple devices or nodes train a shared model together while keeping their data local. This technique addresses privacy concerns by keeping data on users' devices and minimizing data transmission to a central server [8]. FL is particularly useful in scenarios where data privacy is critical, such as healthcare, finance, and personal devices. With FL, the central server coordinates model training by sending model parameters to the nodes. The nodes train the model locally using their data and then send updated parameters back to the central server. This iterative process continues until the model converges or achieves the desired performance.

Bidirectional Long Short-Term Memory (BiLSTM) networks are a recurrent neural network (RNN) architecture used to detect sequential patterns in data [9]. Unlike typical RNNs, which only process data in one way (forward or backward), BiLSTMs handle data in both directions at once. This bidirectional processing enables the model to incorporate both past and future context information, making it extremely useful for sequence modelling problems [10-11]. BiLSTMs are made up of forward and backward LSTM layers, each of which processes input sequences in its own direction. The outputs from both directions are usually concatenated or merged to form a complete representation of the input sequence.

The FL-BiLSTM classifier uses the strengths of both FL and BiLSTMs to classify emotions while respecting anonymity. FL guarantees that sensitive user data is kept on individual devices, which addresses privacy issues connected with centralized data collecting. Each node in the FL arrangement trains the BiLSTM model with its own data, limiting raw data exchange while yet contributing to the model's learning process [12-13]. This distributed learning strategy protects data privacy while maintaining model performance.

BiLSTM networks excel in recognizing sequential dependencies and context in textual material. BiLSTMs can capture nuanced patterns and semantic information required for accurate emotion classification by utilizing bidirectional processing. The model learns to extract relevant elements and representations from text sequences, allowing it to accurately differentiate between different emotional expressions.

The FL-BiLSTM classifier takes advantage of the collaborative nature of federated learning, which aggregates knowledge from multiple data sources without centralizing data storage [14]. This collaborative learning methodology encourages model generalization across diverse user demographics, languages, and situations, resulting in higher classification accuracy and robustness.

Optimizing hyper parameters is critical for reaching peak model performance. Hyper parameter adjustment becomes more difficult in FL environments because nodes have different data distributions and computational resources [15] Advanced approaches like Trickster Coyote Optimization (TCO) can be used in the FL framework to effectively search for optimal hyper parameter configurations, improving model convergence and accuracy.

1.2. Utilization of Trickster Coyote Optimization (TCO) Algorithm for Hyper Parameter Optimization

The efficacy of any deep learning model, including the FL-BiLSTM classifier, is strongly dependent on its hyper parameters. These are parameters that influence the model's learning process, such as the learning rate, the number of hidden layers in the BiLSTM network, and the dropout rate. Choosing the best hyper parameters can have a substantial impact on the model's capacity to learn and generalize effectively. However, manually adjusting hyper parameters can be arduous and time-consuming. This section will look at how TCO is used for hyper parameter optimization in the FL-BiLSTM classifier.

Because of limited data availability and connection cost, federated learning complicates hyper parameter adjustment as compared to typical centralized learning methods. In FL, each device trains the model on its own local data. In comparison to a centralized dataset, this data may be smaller and less diverse. This can make it difficult for typical optimization techniques to identify optimal hyper parameters that work effectively across all devices. FL algorithms use communication between devices and a central server to share model updates. Frequent hyper parameter changes might increase communication overhead, affecting training efficiency.

Trickster Coyote Optimization (TCO) is a relatively recent metaheuristic algorithm inspired by coyotes' intelligence and adaptability in the wild. The TCO algorithm employs a combination of exploration and exploitation tactics to efficiently find optimal solutions to complicated optimization problems. In recent years, TCO has received attention in the field of machine learning for its usefulness in increasing classifier performance, particularly in difficult tasks such as sentiment analysis, picture identification, and disease prediction.

TCO directs the FL-BiLSTM classifier to optimal settings that maximize predicted accuracy while minimizing overfitting via repeated optimization cycles. The repetitive nature of TCO allows the algorithm to fine-tune the classifier's parameters and weights, resulting in improved model resilience and generalization to previously unseen data. TCO can overcome the issues of optimizing complicated deep learning models with high-dimensional parameter spaces and non-convex optimization landscapes by tapping into the collective intellect of a population of trickster coyotes.

The rest of the paper is organized as follows: Section 2 presents a comprehensive assessment of the existing work on emotion identification using gait photos. Section 3 describes the system model, including both the architecture and the innovative optimization technique. Section 4 thoroughly analyses the performance of the system and breaks down the results obtained. Finally, Section 5 concludes the paper by summarizing key findings and outlining potential future directions.

II. LITERATURE REVIEW

Significant progress has been made in artificial intelligence and machine learning in the past few years, especially in the area of NLP. Using deep learning models and metaheuristic techniques together to maximize effectiveness and efficacy is one such creative strategy. The Trickster Coyote Optimization method has garnered interest in this particular context due to its efficacy in searching intricate solution spaces and optimizing function assessment. The purpose of this article is to investigate how TCO can be used to improve the FL-BiLSTM classifier, which is a version of the Bidirectional Long Short-Term Memory model designed for text classification and sentiment analysis applications. This work intends to advance the state-of-the-art in NLP techniques by increasing the FL-BiLSTM model's classification precision as well as the rate of convergence by utilizing the special search features of the TCO algorithm.

Harisu Abdullahi Shehu et al. [16] provided a time-based PSO variation by adding a time constant to the PSO method's velocity update mechanism to prevent premature convergence, especially while working with a dataset of emotional video frames. The JAFFE (77.15% vs. 75.61%) and NIMH-ChEFS (71.57% vs. 70.53%) datasets show that the time-based PSO variant (both the binary and the continuous PSO) performs non-significantly better than the standard PSO techniques; however, the CK+ dataset shows a significantly higher performance (96.19% vs. 94.06%). Nakisa et al. [17] present an original structure that makes use of evolutionary computation (EC) techniques to automatically find the best subset of EEG features. Two publicly available datasets (MAHNOB, DEAP), as well as a newly created dataset obtained with a mobile EEG sensor, have been used to thoroughly assess the suggested framework. The outcomes validate that feature selection for the purpose of determining the optimal EEG features & channels to optimize performance on a four-quadrant emotion classification task may be efficiently supported by EC algorithms. Pratibha Sonawane et al. [18] investigated the effects of feature selection for Electroencephalograph (EEG) signals. Principal component analysis (PCA) and Walsh Hadamard Transform (WHT) feature extraction and selection are areas of ongoing study. For feature selection, the Cat Coyote Optimization Algorithm (CCOA) is recommended. The characteristics are categorized using decision tree classifiers and bagging techniques. Gaganjot Kaur et al. [19] intended to provide the most recent thorough analysis of emotion detection methods employing Electroencephalography (EEG) signals, feature extraction, feature selection, and classification. It also highlights current issues in the field and prospective areas for future research. Qingke Zhang et al. [20] suggested the Optimization State-based Coyote Optimization Algorithm (OSCOA), a variation of the COA. A Population Optimization State Estimation Mechanism is used in the OSCOA method to estimate the current population optimization state. The OSCOA method, along with seven effective optimizers, is put through extensive testing and analysis on 71 benchmark functions taken from the CEC2014, CEC2017, and CEC2022 benchmark suites in order to verify the efficacy of the suggested algorithm. These thorough experiments' findings show OSCOA's competitive performance. Additionally, in order to evaluate the OSCOA algorithm's practicality in solving real-world issues, two applications are taken into consideration: the deployment of wireless sensor networks and picture segmentation. Luefeng Chen et al. [21] For dynamic emotion detection in human-robot interaction, AdaBoost-KNN with adaptive feature selection and direct optimization is suggested. This allows real-time dynamic emotion recognition based on facial expressions. The suggested method outperforms AdaBoost-KNN, adaptive feature selection-based AdaBoost-KNN, and AdaBoost-KNN with direct optimization in terms of recognition rate, according to the results. Additionally, it outperforms the rates attained by AdaBoost, KNN, and SVM, three other well-known recognition techniques. Rajawat et al. [22] provided a brand-new, effective face recognition technique that is unaffected by minute changes in background, lighting, and stance. The suggested method extracts textural features and visual information, respectively, using the gray-level co-occurrence matrix (GLCM) and discrete cosine transform (DCT). In addition to significantly cutting down on recognition time, the suggested technique performs better when it comes to background and position variation. The effectiveness and performance of the current method are enhanced by this one. Jun Liu et al. [23] To increase the accuracy of facial expression classification, a unique deep model is suggested. Lastly, we run a number of tests on four benchmark datasets—the CK+, the JAFFE, the Oulu-CASIA, and the AR—in order to assess the suggested model. The outcomes demonstrate that the suggested model attains state-of-the-art recognition rates, which are, in order, 98.9%, 96.8%, 94.5%, and 98.7%. Devi et al. [24] Four main steps are involved in the development of a novel facial emotion recognition system (FER): (a) face detection; (b) feature extraction; (c) optimal feature selection; and (d) classification. Mean Fitness Oriented JA+FF position update (MF-JFF) is a revolutionary hybrid technique that performs the best feature selection and weight optimization of NN. Subsequently, the performance of the model is validated using an algorithmic examination. The investigation revealed that the accuracy gained for γ at 0.6 was 2.2% higher than the values attained for γ = 0.2, 0.4, 0.8, and 1 in that order. Christina Brester et al. [25] Using a collection of speech-based emotion detection tasks in the English and German languages, the effectiveness of feature selection methods based on the evolutionary multi-objective optimization algorithm is examined. The advantages of the established algorithmic techniques are illustrated by contrasting them, for the datasets involved, with PCA. Approaches that are presented enable a classifier to perform better while using fewer features overall. The findings indicate that applying the suggested strategies could reduce the number of characteristics for some of the corpora from 384 to 64.8 and increase the accuracy of emotion recognition by up to 29.37% relative improvement.

3. METHODOLOGY

3.1 Augmented trickster coyote-based federated learning deep BiLSTM classifier for emotion classification

The FL-BiLSTM based emotion classification, which offers deeper contextual features in feature vectors mixed with context, is proposed for obtaining superior detection accuracy while preventing users' privacy. The weighted average parameters of the FL-BiLSTM training result model, which has strong detection performance and complies with user privacy standards, can be used to learn the various features of the dataset. The augmented trickster coyote optimization technique effectively tunes the FL-BiLSTM classifier weight parameters and chooses the best solution. First, while distributed learning strives to speed up training, federated learning's primary goal is to safeguard users' private information. Second, no client device's data distribution can be determined through federated learning. Distributed learning, on the other hand, enables the arbitrary allocation of portions of the entire learning data. The proposed federated learning uses a cutting-edge federated learning framework to jointly train the used BiLSTM classifier.

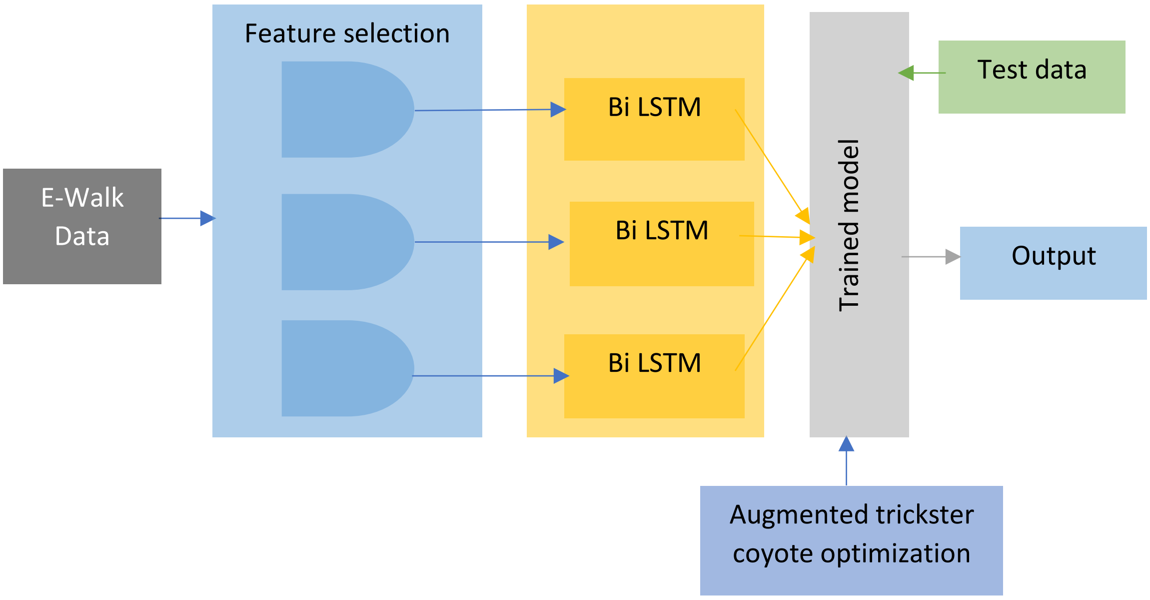


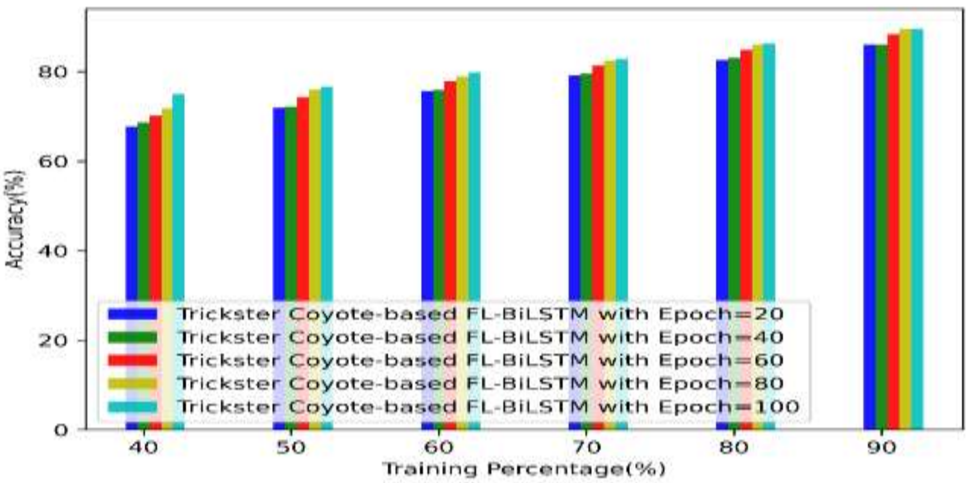
Fig 1. Federated learning-based BiLSTM

4. Results and Discussion

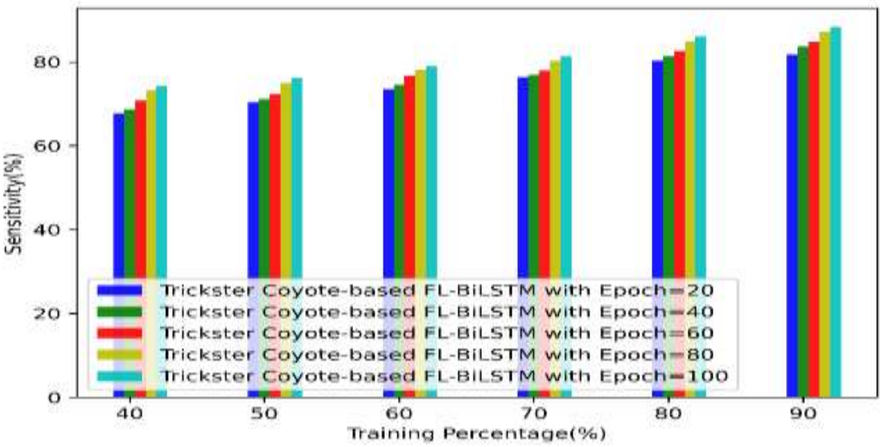
The proposed trickster coyote-based FL-BiLSTM classifier efficiency is revealed in this section with the various performance measures as accuracy, sensitivity, and specificity, for both the k-fold as well as the training percentage.

4.1 Performance analysis based on training percentage

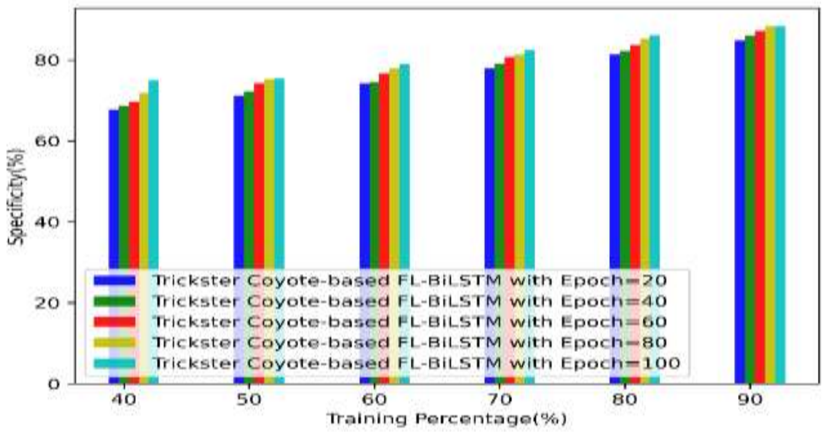
Fig 2 provides an insight into the performance of the trickster coyote-based FL-BiLSTM concerning accuracy, sensitivity, and specificity across various training percentage settings. Specifically, as depicted in Figure 2a), the accuracy of the trickster coyote-based FL-BiLSTM reaches 93.809% when the training percentage is set at 90%, after 100 epochs. Moving on to Figure 2b), we can observe that the sensitivity of the trickster coyote-based FL-BiLSTM achieves a notable 98.800% when the training percentage is set to 80%, following 100 epochs. Lastly, Figure 2c) illustrates that the specificity of the trickster coyote-based FL-BiLSTM stands at 89.198% with a training percentage of 70%, also after 100 epochs.



(a)



(b)



(c)

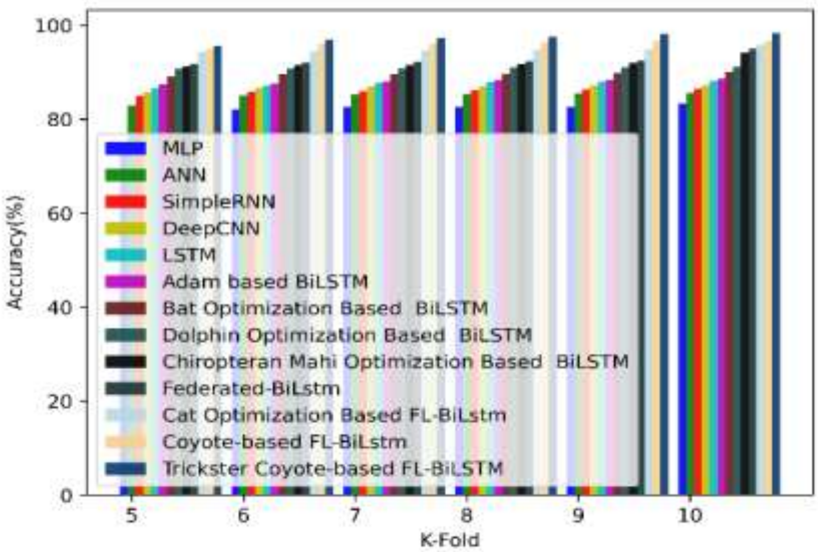
Fig 2. Performance based on training percentage: a) accuracy, b) sensitivity, c) specificity

4.2 Comparative methods

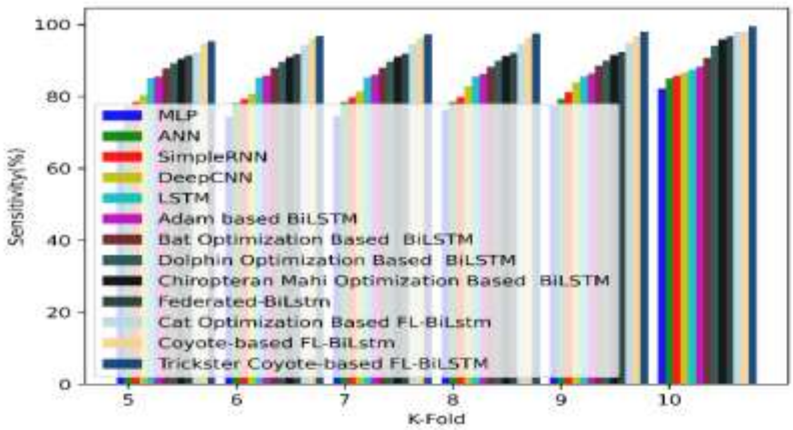
Multilayer perceptron (MLP) [20], Artificial Neural Network (ANN) [21], Simple Recurrent Neural Network (RNN) [22], Deep convolutional neural network(CNN) [23], Long short-term memory (LSTM) [24], Adam-based BiLSTM [25], Bat optimization-based BiLSTM [26], Dolphin optimization-based BiLSTM [27], Chiropteran Mahi optimization-based BiLSTM, Federated-BiLSTM, Cat optimization-based FL-BiLSTM, Coyote-based FL-BiLSTM.

4.1.1 Comparison based on k-fold

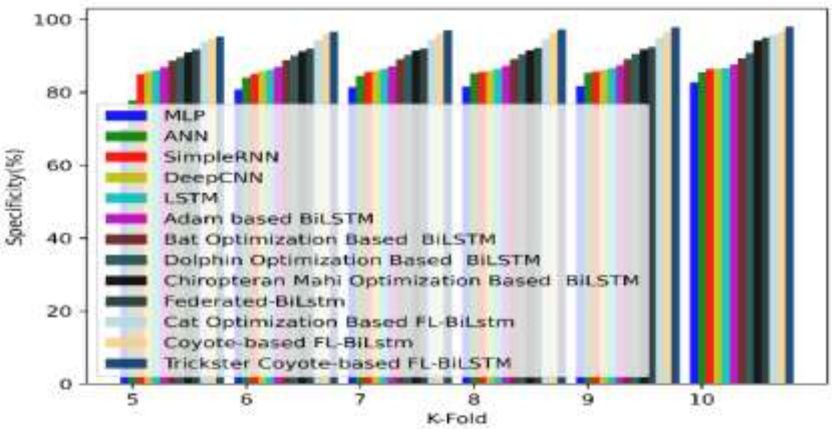
Fig 3, which includes three subplots a), b), c), offers a comparative assessment of the performance of various models or methods across different levels of a parameter, specifically focusing on accuracy, sensitivity, and specificity, for the k-fold 5, 6, 7, 8, 9, 10. In particular, when evaluating accuracy, the "Proposed trickster coyote-based FL-BiLSTM" model stands out with an impressive accuracy rate of 98.41% for k=10. This high level of accuracy suggests that this method demonstrates remarkable efficiency and effectiveness in the task being evaluated. Moreover, this model not only excels in accuracy but also exhibits outstanding sensitivity, achieving a rate of 99.60 %. Additionally, the model showcases a commendable level of specificity, with a rate of 99.60 %.



(a)



(b)

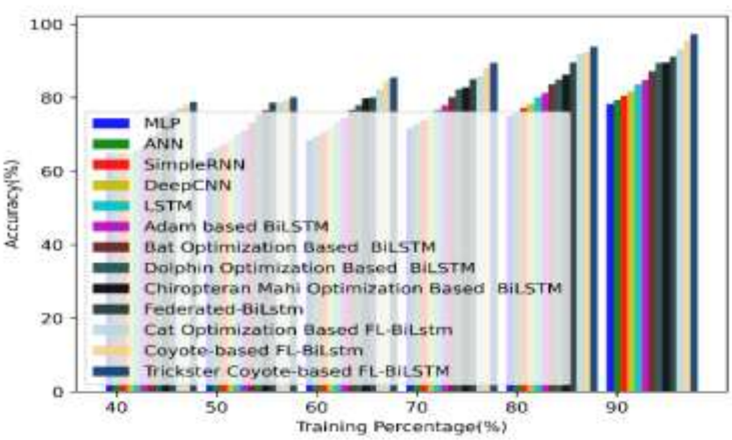


(c)

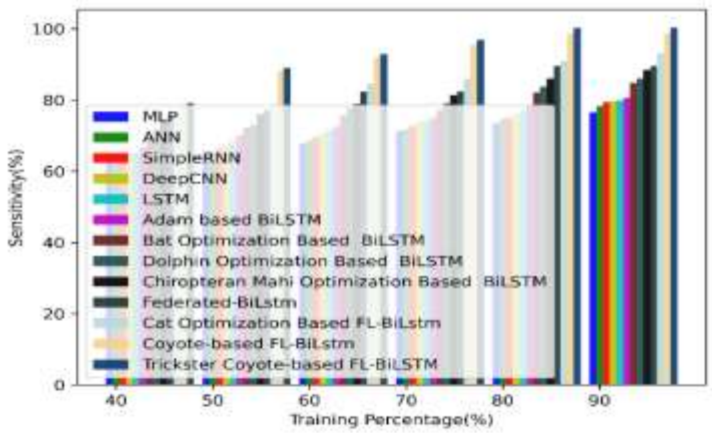
Fig 3. Comparison based on k-fold: a) accuracy, b) sensitivity, c) specificity

4.1.2 Comparison based on training percentage

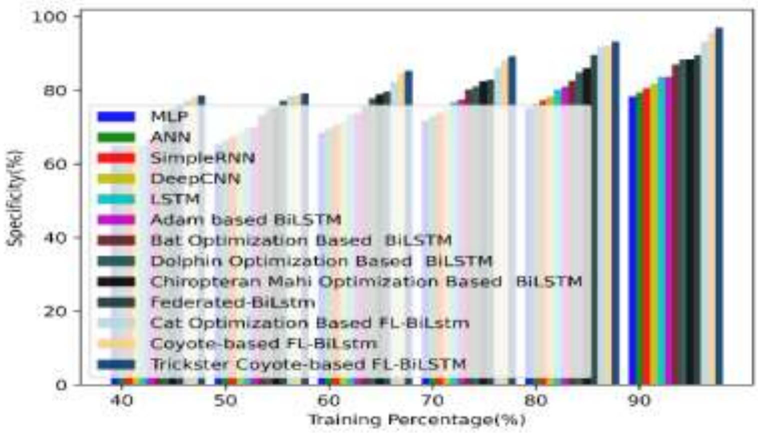
Fig 4, which includes three subplots a), b), c), offers a comparative assessment of the performance of various models or methods across different levels of a parameter, specifically focusing on accuracy, sensitivity, and specificity, while maintaining a training percentage of 40%, 50%, 60%, 70%, and 80%. In particular, when evaluating accuracy, the "Proposed trickster coyote-based FL-BiLSTM" model stands out with an impressive accuracy rate of 97.39% for the 80% training data scenario. This high level of accuracy suggests that this method demonstrates remarkable efficiency and effectiveness in the task being evaluated. Moreover, this model not only excels in accuracy but also exhibits outstanding sensitivity, achieving a rate of 99.2%. Additionally, the model showcases a commendable level of specificity, with a rate of 97.09%.



(a)



(b)



(c)

Fig 4. Comparison based on training percentage: a) accuracy, b) sensitivity, c) specificity

4.3 Comparative Discussion

In summary, table 1 summarises the performance of various models on the Ewalk Dataset, highlighting their accuracy, sensitivity, and specificity under two different experimental settings. The results suggest that the proposed trickster coyote-based FL-BiLSTM model consistently performs exceptionally well across all evaluated metrics and conditions.

Table I. Comparative performance of the existing and trickster coyote-based FL-BiLSTM method.

	Ewalk Dataset					
	K-fold 10			Training percentage 90		
Methods	Accu-racy %	Sensi-tivity %	Speci-ficity %	Accu-racy %	Sensi-tivity %	Spec-ificity %
MLP	83.29	82.22	82.75	78.28	76.54	78.28
ANN	85.63	84.94	85.49	79.41	78.28	79.41
Simple RNN	86.47	85.78	86.33	80.56	79.41	80.56
Deep CNN	87.32	86.62	86.44	81.71	79.63	81.71
LSTM	88.16	87.46	86.76	83.65	79.82	83.65
Adam Based BiLSTM	88.66	88.30	87.60	84.82	80.56	83.66
Bat Optimization-Based BiLSTM	90.12	90.82	89.28	87.18	84.78	87.04
Dolphin Optimization-Based BiLSTM	91.16	94.18	90.82	89.51	86.00	88.37
Chiropteran Mahi Optimization-Based BiLSTM	94.18	95.86	94.18	89.59	88.38	88.39
Federated-BiLSTM	95.02	96.71	95.02	91.22	89.58	89.58

Cat optimization-based FL-BiLSTM	95.86	98.00	95.86	93.22	93.22	93.22
Coyote-based FL-BiLSTM	96.71	98.00	96.71	95.68	98.80	95.68
Proposed trickster coyote-based FL-BiLSTM	98.41	99.60	98.11	97.38	98.23	97.08

The method employs an adaptive thresholding-based technique to extract a region of interest from the video frames. This technique enhances performance by focusing on relevant visual information, reducing noise, and irrelevant details. The augmented trickster coyote optimization method is a significant advantage. This approach aids in selecting the most relevant and informative features, effectively reducing the dimensionality of the data while retaining its discriminative power. Feature selection is crucial for model efficiency and interpretability. This approach has the potential to outperform traditional methods by capturing nuanced emotional cues in video data while offering the benefits of federated learning for privacy-preserving applications.

5. CONCLUSION

This paper presents an emotion recognition model based on the movement recognition technique is presented, in which the augmented trickster coyote-based FL-BiLSTM is utilized for both feature selection and classifier training. The obtained features are used to train and test the FL-BiLSTM classifier, and the performance is improved by augmented trickster coyote optimization through efficient parameter adjustment. Additionally, the residual connections are integrated to provide the required features, thus improving the classifier's performance in recognizing emotions. The performance of the augmented trickster coyote-based FL-BiLSTM classifier is more efficient than other existing methods, with the accuracy of 97.385%, sensitivity of 99.285 %, and specificity of 97.085 % respectively. In the future, the performance of emotion recognition from the walking videos is enhanced by extracting more relevant features from the skeletonised image sequences.

REFERENCES

[1] Kranti Kamble & Joydeep Sengupta. (2023). A comprehensive survey on emotion recognition based on electroencephalograph (EEG) signals. Multimedia Tools and Applications, Volume 82, pages 27269–27304, (2023)
[2] Bajaj V, Taran S, Sengur A (2018) Emotion classification using flexible analytic wavelet transform for electroencephalogram signals. Health Inf Sci Syst 6:12
[3] Garg A, Chaturvedi V, Kaur AB, Varshney V, Parashar A (2022) Machine learning model for mapping of music mood and human emotion based on physiological signals. Multimed Tools Appl:1–41
[4] Lin Shu,Jinyan Xie,Mingyue Yang,Ziyi Li,Zhenqi Li,Dan Liao,Xiangmin Xu * andXinyi Yang.(2018). A Review of Emotion Recognition Using Physiological Signals. Sensors, 18(7).
[5] Li, Z.; Tian, X. Shu, L., Xu, X., Hu, B. (2017). Emotion Recognition from EEG Using RASM and LSTM. In Proceedings of the International Conference on Internet Multimedia Computing and Service, Tsingtao, China, pp. 310–318.
[6] Zheng, W.L., Dong, B.N., Lu, B.L. (2014). Multimodal emotion recognition using EEG and eye tracking data. In Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 5040–5043.
[7] Duan, R. (2014). Video Evoked Emotion Recognition Based on Brain Electrical Signals. Master's Thesis, Shanghai Jiaotong University.
[8] S. Sai Satyanarayana Reddy,Ashwani Kumar,Kayhan Zrar Ghafoor,Ved Prakash Bhardwaj, S. Manoharan.(2022). CoySvM-(GeD): Coyote Optimization-Based Support Vector Machine Classifier for Cancer Classification Using Gene Expression Data.
[9] Agrafioti, F.; Hatzinakos, D.; Anderson, A.K. (2012). ECG Pattern Analysis for Emotion Detection. IEEE Trans. Affect. Comput. 3, 102–115.
[10] Lisetti, C.L., Nasoz, F. (2004). Using Noninvasive Wearable Computers to Recognize Human Emotions from Physiological Signals. EURASIP J. Appl. Signal Process. 1672–1687.
[11] Costa, J., Adams, A.T., Jung, M.F., Guimbretière, F., Choudhury, T. (2017). EmotionCheck: A Wearable Device to Regulate Anxiety through False Heart Rate Feedback. Getmob. Mob. Comput. Commun. 21, 22–25.
[12] Huang J, Xu X, Zhang T. (2017). Emotion classification using deep neural networks and emotional patches. In: 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 958–962
[13] Kamble KS, Sengupta J. (2021). Ensemble machine learning-based affective computing for emotion recognition using dual-decomposed EEG signals. IEEE Sensors J 22:2496–2507
[14] Pandeya YR, Lee J. (2021). Deep learning-based late fusion of multimodal information for emotion classification of music video. Multimed Tools Appl ,80:2887–2905
[15] Shirke B, Wong J, Libut JC, George K, Oh SJ (2020). Brain-IoT based Emotion Recognition System. In: 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), pp. 0991–0995
[16] Harisu Abdullahi Shehu; Will Browne; Hedwig Eisenbarth. (2021). Particle Swarm Optimization for Feature Selection in Emotion Categorization. IEEE Congress on Evolutionary Computation (CEC)
[17] Nakisa, B., Rastgoo, M. N., Tjondronegoro, D., & Chandran, V. (2018). Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors. Expert Systems with Applications, 93, 143–155.

[18] Pratibha Sonawane, Jagdish Helonde, Prakash Burade. (2022). Feature Selection of EEG Signals using Cat Coyote optimization algorithm (CCOA) with Classification", International Conference on Futuristic Technologies (INCOFT)
[19] Gaganjot Kaur, Meenu Gupta, Rakesh Kumar. (2023). Swarm Intelligence-Based Feature Selection Algorithm of EEG Classification for Brain Emotion Detection: A Review. IEEE 8th International Conference for Convergence in Technology (I2CT)
[20] Qingke Zhang, Xianglong Bu, Junqing Li, Huaxiang Zhang. (2023). An efficient Optimization State-based Coyote Optimization Algorithm and its applications", Applied Soft Computing.Volume 147. 110827
[21] Luefeng Chen, Min Li, Wanjuan Su,Min Wu, Kaoru Hirota, Witold Pedrycz.(2021).Adaptive Feature Selection-Based AdaBoost-KNN With Direct Optimization for Dynamic Emotion Recognition in Human–Robot Interaction", IEEE Transactions on Emerging Topics in Computational Intelligence . Volume: 5, Issue: 2.
[22] Rajawat, Aparna,Pandey, Mahendra Kumar (2017). [IEEE 2017 7th International Conference on Communication Systems and Network Technologies (CSNT) - Nagpur, India (2017.11.11-2017.11.13)] 2017 7th International Conference on Communication Systems and Network Technologies (CSNT) - Efficient feature extraction using hybrid
[23] Jun Liu;Yanjun Feng;Hongxia Wang; (2021). Facial Expression Recognition Using Pose-Guided Face Alignment and Discriminative Features Based on Deep Learning. IEEE Access, (), –. doi:10.1109/access.2021.3078258
[24] Devi, Bhagyashri; Jain Preetha, M.Mary Synthuja (2020). [IEEE 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI) - Tirunelveli, India (2020.6.15-2020.6.17)] 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI) (48184) - Algorithmic Study on Facial Emotion Recognition model with Optimal Feature Selection via Firefly Plus Jaya Algorithm, 882–887.
[25] Christina Brester; Maxim Sidorov; Eugene Semenkin. (2014). Acoustic emotion recognition two ways of features selection based on self-adaptive multi-objective genetic algorithm. 11th International Conference on Informatics in Control, Automation and Robotics (ICINCO).