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An optimization based deep learning approach for human activity recognition in healthcare monitoring

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ABSTRACT

Medical images are comprised of sensor measurements which help detect the characteristics of diseases. Computer-based analysis results in the early detection of diseases and suitable medications. Human activity recognition (HAR) is highly useful in applications related to medical care, fitness tracking, and patient data archiving. There are two kinds of data fed into the HAR system which are, image data and time series data of physical movements through accelerometers and gyroscopes present in smart devices. This study introduced crayfish optimization algorithm with long short term memory (COA-LSTM). The raw data is obtained from three datasets namely, WISDM, UCI-HAR, and PAMAP2 datasets; then, pre-processing helps in removal of unwanted information. The features from pre-processed data are reduced using principal component analysis and linear discriminant analysis (PCA-LDA). Finally, classification is performed using COA-LSTM where, the hyperparameters are fine-tuned with the help of COA. The suggested method achieves a classification accuracy of 98.23% for UCI-HAR dataset, whereas the existing techniques like convolutional neural network (CNN), multi-branch CNN-bidirectional LSTM, CNN with gated recurrent unit (GRU), ST-deep HAR, and Ensem-HAR obtain a classification accuracy of 91.98%, 96.37%, 96.20%, 97.7%, and 95.05%, respectively.

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1. INTRODUCTION

In recent decades, the medical systems on the basis of internet have a significant part in assessing the patient's data. Moreover, the efforts of researchers and scientist introduced vast number of technologies based on human healthcare system [1]. The patient's data is transferred as electronic records that involves the patient bio-data, type of disease and diagnosis details [2]. The algorithms based on machine learning (ML) and deep learning (DL) helps in mining the hidden data and these type of data is stored in a centralized location [3], [4]. Vast number of healthcare-related data is being generated globally, possessing unique characteristics [5]. This collected data is diverse in nature. Transporting patients from their residences to healthcare facilities for routine checkups poses challenges, such as travel time and waiting queues, increasing the likelihood of exposure to new diseases due to environmental factors [6]. Furthermore, the advancement of remote patient monitoring systems enables the continuous monitoring of vulnerable patients from a distance. Real-time monitoring by clinicians through these systems allows for comprehensive patient observation, facilitating quicker and more cost-effective disease diagnosis [7].

The data related to healthcare is splitted based on the systems related to health monitoring. For an example, the clinics maintain the patient data for a particular time period but it may have lost after the specified time [8], [9]. So, maintain the data relies as the main challenges which can be overwhelmed using ML and DL techniques. The ML techniques have constrained memory so that it cannot process large number of data [10]. So, the DL based techniques are vastly utilized in processing large data of patients and expressively helps in safeguarding the life of patients [11], [12]. Furthermore, DL offers distinct advantages over centralized learning approaches. It can train global-level models using distributed informational data and prioritizes privacy by disclosing only mathematical parameters and metadata concerning medical data [13]. Employing a collaborative technique, DL securely gathers individual information and provides it directly to clinicians or doctors for patient assessment [14]. The existing DL techniques faced issues related to interpretability and less transparency while predicting human activities. The misclassification occurs due to the inability of the model to map the feature dimensionalities [15]. Thus, this research utilized enhanced DL approach as a tool to solve the issues related to health monitoring and help both the doctor and patients. The recent research based on different ML and DL approaches for monitoring human activities are discussed.

Cruciani *et al*. [16] introduced a human activity recognition (HAR) framework based on feature learning and convolutional neural network (CNN). The use of a pre-trained CNN feature extractor was evaluated under realistic conditions. Different topologies and parameters were assessed to identify the best candidate models for HAR. The usage of CNN along with feature learning effectively recognized human activities by efficiently extracting the features. However, the suggested framework was not appropriate for large-scale datasets.

Challa *et al*. [17] introduced multi-branch CNN-bidirectional long short term memory (Bi-LSTM) for the recognition of human activities using data from wearable sensors. The multi-branch CNN-Bi-LSTM learned the local features as long-term dependencies. The various filter sizes utilized in this approach were capable of capturing the long-term dependencies of sequential data in an effective feature extraction. The batch normalization was performed after the dense layer that helped to normalize the output of extracted features, and Bi-LSTM with softmax activation function involves in classification task. However, the interpretability of the model was due to its less transparency during prediction.

Dua *et al*. [18] developed a deep neural network model that was based on CNN with a gated recurrent unit (GRU) to perform automatic extraction of features and classification. Initially, the data based on HAR was acquired, and a nominal pre-processing was performed. The suggested model utilized the advantageous properties of CNN and GRU. The extraction of features was performed using CNN, while GRU was used to capture the long-term dependencies. Moreover, the model consisted of three head architectures which helped to capture the local correlations with multi-size filters. However, the suggested framework mainly relied on the quality and diversity of training data that led to suboptimal results.

Abdel-Basset *et al*. [19] introduced the supervised model to fine-grain the HAR and helped to enhance the efficiency in the applications related to internet of healthcare things (IoHT). The suggested model utilized LSTM to model the long-term temporal from raw data and feature extraction takes place using advanced residual network. The training data was fed to the layers of LSTM and convolutional layers, and then the performance of temporal fusion was enriched with the help of attention mechanisms. Finally, the adaptive squeezing CNN was used to perform an effective classification of HAR. However, the adaptive squeezing CNN was not able to be adjusted to the spatial dimensions of feature maps of various layers.

Bhattacharya *et al*. [20] developed ensemble-based DL approach to monitor health of elderly people. The suggested ensemble framework was the combination of CNN-net, CNNLSTM-net, convolutional LSTM-net, and stacked LSTM-net which was termed as Ensem-HAR. The classification model utilized ensemble-based 1D CNN and LSTM which performed stacked predictions to recognize the human activities. However, the suggested framework exhibited the highest rate of correlation, leading to misclassification.

Arikumar *et al*. [21] introduced federated learning person movement identification (FL-PMI) to auto-label data from wearable sensors. Bi-LSTM was used in classifying medical data for the proceeding stage. The FL-based edge servers need minimal memory and less cost for computation. Nonetheless, the interspace reward function was based on the distribution of data, and if it varied from assumptions, the model becomes less effective.

Andrade-Ambriz [22] introduced HAR using temporal architecture of CNN. The presence of spatio-temporal features in the suggested architecture helped to analyze and recognize the human activities. The suggested approach on the basis of 3D CNN and LSTM memory layer helped to leverage the features based on time motion. Moreover, the optimal design of the suggested approach aided in optimize the computational resources and helped to enhance the classification accuracy. However, the temporal CNN was only valid to capture long range dependencies in sequential data.

Overall, the existing approaches faced issues related to interpretability and less transparency while predicting human activities. The misclassification occured due to the inability of the model to map the feature dimensionalities. So, crayfish optimization algorithm with long short term memory (COA-LSTM) developed

in this research. The LSTM facilitated in classification and the hyper parameters were fine-tuned using COA which identified an optimal solution and provided better accuracy. The significant findings insisted in this study are presented as follows:
– This research introduces an effective classification technique known as COA-LSTM to recognize and classify the activities of patients.
– The hybrid approach based on principle component analysis-linear discriminant analysis (PCA-LDA) is utilized in the process of dimensionality reduction which helps to minimize the dimensionalities of the pre-processed data.
– The LSTM is used in recognizing the human activities and the hyperparameters of LSTM is fine-tuned using COA, facilitating to find an optimal solution and achieve better accuracy.

The rest of this research study is organized in the following manner: section 2 describes the proposed method of the research. The results and analysis of this research are mentioned in section 3 and finally, the conclusion of this research is listed in section 4.

2. HEALTH CARE MONITORING USING COA-LSTM WITH AN ATTENTION MECHANISM

Healthcare monitoring plays an important role in monitoring the health condition of patients. The data obtained from the wearable sensors of the patients are acquired and the pre-processing takes place to exclude the noises and redundant data. After this, the dimensionality reduction is performed to minimize the attributes of the large data, and the classification is performed using LSTM with an attention mechanism by fine-tuning the hyper-parameters using COA. The overall in healthcare monitoring using the proposed approach is depicted in Figure 1. The Figure 1 signifies the data collection layer, data storage layer, data analysis layer and the health monitoring phase.

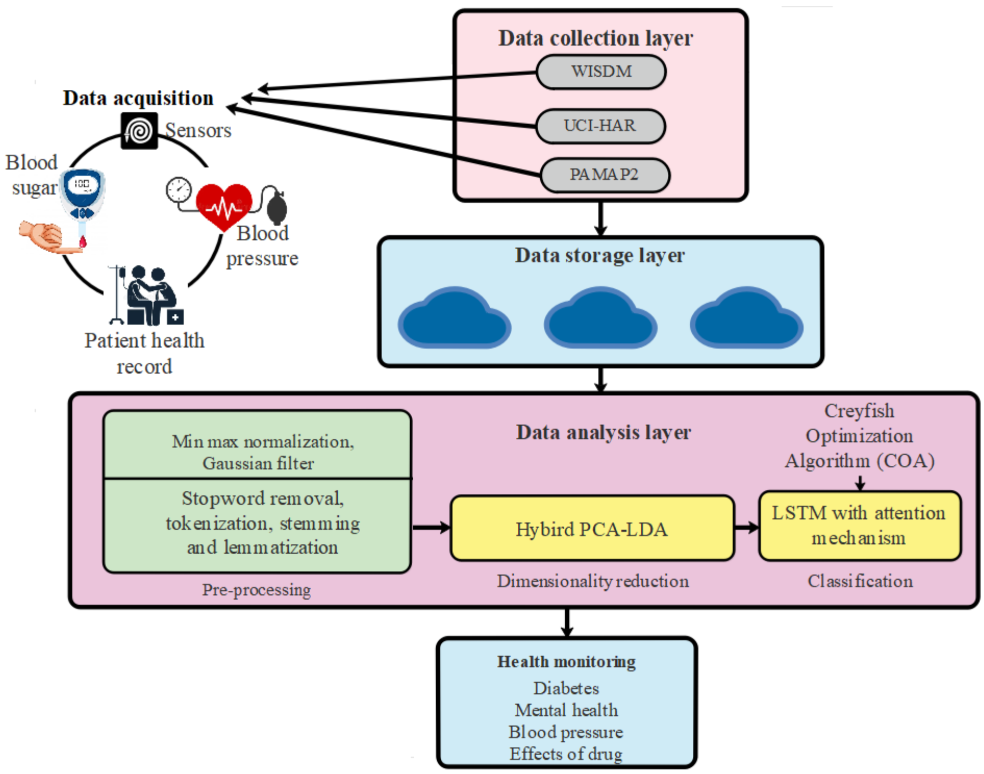

Figure 1. Overall process involved in healthcare monitoring using the proposed method

2.1. Data acquisition

This is initial stage where, the raw data is achieved using WISDM [23], UCI-HAR [24], and PAMAP2 [25] datasets. The datasets are comprised of the physical activities of the individuals and the rate of heartbeat, oxygen level and BP are obtained by using wearable sensors. The description of the aforementioned datasets utilized in this research is provided in this section.

- WISDM: the dataset is comprised of various activities based on various human activities such as sitting, standing, walking down and up, and jogging with a sampling of 20 Hz with the help of an accelerometer combined with smart mobiles with 36 participants listed above for each exercise with three features. The raw sensor data is segmented into fixed-size windows with an overlap of 50%.
- UCI-HAR dataset: the UCI-HAR dataset is comprised of activities like walking up and down, standing, and lying. The accelerometer and the gyroscope are used to collect the information installed on smartphones. There are about nine features collected based on the sampling rate of 50 Hz and 50% overlap. In total, 10299 samples are utilized in the dataset which is separated based on the user ID.
- PAMAP2 dataset: this is a kind of physical activity tracking dataset that includes various kinds of activities performed by nine participants. The participants perform different activities such as rope jumping, running, soccer, and so on. There are about three sensors positioned on the body of the participants and there are 52 features recorded at the sampling rate of 100 Hz. Moreover, researchers segmented sensor data at the fixed window size of 50% overlap.

2.2. Data storage phase

The data acquired from the aforementioned datasets helps to monitor the condition of the patient and offers significant information. The data obtained from those datasets is stored in a cloud storage platform and is accessable at any time from different locations. The data which is stored in this platform is fed into the analytic layer to perform further processing.

2.3. Data analytic phase

The data analytic phase is comprised of three stages such as pre-processing, dimensionality reduction, and classification. The raw data is pre-processed and fed into the stage of dimensionality reduction, then this data is fed into the stage of classification. The processes involved in fore mentioned stages are represented as follows:

2.3.1. Pre-processing

Before the phase of actual processing, the data is pre-processed to enhance the quality of data with the transformation of data and filtering stages. Moreover, the medical records of the patients are in the form of text which is pre-processed by employing stop word removal, tokenization, stemming, and lemmatization. The data transformation is performed using min-max normalization where, the data is transformed to a specified range. The min-max normalization is defined as the process of converting one value to another, within the range of (P, Q) and is mathematically represented in (1):

$$S = \frac{A - p_{min}}{A_{max} - p_{min}} \times (q - p) + p \tag{1}$$

where the value that needs to be normalized is referred to as A and the minimum value is represented as p_{min}. The lower and the upper limit is represented as p and q respectively, the maximum value is represented as A_{max}.

The noises present in the medical data are removed using a Gaussian filter which is based on the Gaussian distribution function. The 2D Gaussian function is mathematically represented in (2):

$$G(x, y) = (1/(2 \times \pi \times \sigma^2)) \times e^{(-(\left(x^2 + \frac{y^2)}{2 \times \sigma^2}\right))} \tag{2}$$

where the value of the Gaussian function at coordinates (x, y) is represented as $G(x, y)$, the standard deviation function is represented as σ, and the spatial coordinates of the plane is x, y.

2.3.2. Dimensionality reduction using hybrid PCA-LDA

After pre-processing, dimensionality reduction which helps to diminish the attributes of the dataset. The PCA is applied to the training set to reduce the dimensionalities and the covariance matrix. The sorting is performed in descending order based on the corresponding eigenvalues. After this, top k eigenvector are selected which is based on lower dimensionality data. Then, the eigenvector and the eigenvalues of the covariance matrix are evaluated based on (3):

$$\sum v_i = \lambda_i v_i \tag{3}$$

where the ith eigenvalue is represented as λ_i and the respective eigenvector is represented as $v_i x$.

After reducing dimensionalities using PCA, the transformed dataset Q is obtained and is fed into LDA which helps to maximize class separability. In LDA, the within-class matrix (S_w) and between class matrix (S_b) is evaluated based on (4) and (5), respectively.

$$S_w = \sum_{c=1}^{C} \sum_{i=1}^{n_c} \left(z_{i,c} - \mu_c\right)\left(z_{i,c} - \mu_c\right)^T \tag{4}$$

$$S_b = \sum_{c=1}^{C} n_c (\mu_c - \mu)(\mu_c - \mu)^T \tag{5}$$

Where the number of data is denoted as n_c in class c, ith data in class c is represented as $z_{i,c}$ and the overall mean of data is represented as μ. The eigenvalues and the eigenvectors of the matrix are evaluated based on (6):

$$S_w^{(-1)} S_b v_i = \lambda_i v_i \tag{6}$$

After this, top p eigenvectors are selected, wherein the number of selected discriminant components is denoted as p. The finally reduced feature matrix is minimized by multiplying the PCA data transformed by eigenvectors of LDA, which is mathematically represented in (7):

$$X_{reduced} = Z_{LDA} \tag{7}$$

The hybrid PCA-LDA integrates the global variance by preserving characteristics of PCA along with the ability of LDA to create lower dimensional representation with class discriminative power.

2.3.3. Classification using COA-LSTM

The reduced dimensionalities are fed as the input to LSTM [26] for classifying the activities of patients. The LSTM architecture is comprised of a memory cell and 3 gate regulators where, the input elements' over processing are maintained in the memory cell. The LSTM is comprised of three gates such as input, output, and forget gates are represented as i_t, f_t and o_t. The input gate controls the information related to the memory cell. The output data from the memory cell C_t is managed by the output gate. The hidden state h_t is defined based on output and forget gate. The LSTM performs based on three gates and memory cells represented in (8) to (13):

$$i_t = \sigma(w_i \times [h_{t-1}, F_t] + b_i) \tag{8}$$

$$f_t = \sigma(w_f \times [h_{t-1}, F_t] + b_f) \tag{9}$$

$$o_t = \sigma(w_o \times [h_{t-1}, F_t] + b_o) \tag{10}$$

$$\tilde{C}_t = tanh(w_C \times [h_{t-1}, F_t] + b_C) \tag{11}$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{12}$$

$$h_t = tanh\, C_t . o_t \tag{13}$$

where the feature subset in a period t is represented as F_t and the weighted values are denoted as w_i, w_f, w_o, and w_C. The biases are represented as b_i, b_f, b_o, and b_C, the hyperbolic tangent and the sigmoid activation function are represented as $tanh$ and σ.

- Hyperparameter optimization using COA

The efficiency of LSTM classifier is on the basis of hyperparameters, so the selection of optimal hyperparameters plays a significant role in enhancing the efficiency of LSTM. So, this research performs an effective hyper-parameter optimization using COA [27] which helps to improve the accuracy of recognizing activities. COA is inspired by the activities of crayfish such as foraging, summer vacation, and competitive behavior. The exploitation stage is based on foraging and competition; the exploration stage is be based on summer resort.

a. Population initialization

Every individual crayfish is assigned as the matrix of $1 \times dim$. Each column matrix presents a solution to the problem and in the set of variables, each variable relies on the upper and lower boundaries. The initialization of COA creates a random group of candidate solution X in search space. The candidate solution X is based on population size N and the dimension dim. The initialization of the population in COA algorithm is mathematically represented in (14):

$$X = [X_1, X_2, \dots, X_N] = \begin{bmatrix} X_{1,1} & \cdots & X_{1,j} & \cdots & X_{1,dim} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots & X_{i,dim} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ X_{N,1} & \cdots & X_{N,j} & \cdots & X_{N,dim} \end{bmatrix} \quad (14)$$

where the position of the initial population is represented as X, the number of the population is represented as N and the dimension of the population is denoted as dim. The position of the individual i at jth dimension is denoted as $X_{i,j}$ and the value of $X_{i,j}$ is obtained from (15):

$$X_{i,j} = lb_j + (ub_j - lb_j) \times rand \quad (15)$$

where the random number is represented as $rand$; lower and the upper bound of the dimension j is represented as lb_j, ub_j respectively.

b. Behavior of crayfish based on varying temperature

Any variation in the temperature affects the behavior of crayfish and pushes them to enter various stages. The change in temperature is represented in (16) when the temperature exceeds $30\,^{\circ}\mathrm{C}$, the crayfish selects a cool place for summer vacation.

$$temp = rand \times 15 + 20 \quad (16)$$

Where the temperature of the crayfish is located is represented as $temp$.

The quantity of feeding is affected by the change in temperature and the temperature between $25\,^{\circ}\mathrm{C}$ is optimistic. The mathematical model for the intake of crayfish is represented in (17):

$$p = C_1 \times \left(\frac{1}{\sqrt{2\times\pi}\times\sigma} \times exp\left(-\frac{(temp-\mu)^2}{2\sigma^2}\right)\right) \quad (17)$$

where the temperature that is suitable for crayfish is represented as μ. The intake of crayfish fish varying temperatures is denoted as σ and C_1.

c. Exploration stage

If the value of $temp > 30$, the temperature value is higher. During this time phase, the crayfish selects a place for summer vacation with minimal temperature. The new cave (place) selected by the crayfish is represented as X_{shade} which is represented in (18):

$$X_{shade} = (X_G + X_L)/2 \quad (18)$$

where the optimal position is represented as X_G which is acquired from a number of iterations and the optimal position of the present population is denoted as X_L. The population of crayfish fights for the cave in a randomized manner when the value of $rand < 0.5$, there are no crayfish competing for the cave. The crayfish enters the cave based on (19):

$$X_{i,j}^{t+1} = X_{i,j}^{t} + C_2 \times (rand) \times (X_{shade} - X_{i,j}^{t}) \quad (19)$$

where the iteration number at the present position is represented as t and the iteration number at the next generation is represented as $t+1$. The C_2 is the kind of decreasing curve which is represented in (20):

$$C_2 = 2 - \left({}^{t}/_{T}\right) \quad (20)$$

where the maximum number of iterations is represented as T. During the stage of exploration, the crayfish enters the cave which offers an optimal solution to the individuals and helps to enhance the exploitation ability of COA with a better convergence rate.

d. Exploitation stage

In a case where, the value of $temp > 30$ and $rand \geq 0.5$, the other crayfish present in the population were also interested in the cave, this case leads to a fight among them. The behavior of crayfish fighting for the cave is represented in (21):

$$X_{i,j}^{t+1} = X_{i,j}^{t} - X_{z,j}^{t} + X_{shade} \quad (21)$$

where the randomized individual of the crayfish population is represented as z and it is obtained through (22):

$$z = round\big(rand \times (N-1)\big) + 1 \quad (22)$$

In the stage of exploitation, the crayfish fight with each other for their caves. The crayfish X_i adjust the position based on the other crayfish. The behavior of crayfish in adjusting the position helps to expand the range of searching which helps to enhance the exploring capability of COA.

e. Foraging stage

When the value of $temp \leq 30$, it is considered a probable solution to feed the crayfish. During this time, the crayfish moves toward food and find food, the crayfish tend to judge the size of their food. The location of the food X_{food} is represented in (23):

$$X_{food} = X_G \quad (23)$$

The size of the food is denoted as Q and it is evaluated using (24):

$$Q = C_3 \times rand \times \left({fitness_i}/{fitness_{food}} \right) \quad (24)$$

where the food factor is represented as C_3, the fitness value of the ith crayfish is represented as $fitness_i$ and the fitness value for the location of food is represented as $fitness_{food}$. When $Q > (C_3 + 1)/2$ means the size of the food is much bigger. Same time, crayfish tear the food with their claw foot which is mathematically represented in (25):

$$X_{food} = exp\left(-\frac{1}{Q}\right) \times X_{food} \quad (25)$$

The food obtained by the crayfish is based on the intake of food and the foraging activity is represented in (26):

$$X_{i,j}^{t+1} = X_{i,j}^{t} + X_{food} \times p \times (cos(2 \times \pi \times rand)) - sin(2 \times \pi \times rand)) \quad (26)$$

When the value of $Q \leq (C_3 + 1)/2$, the crayfish move towards the direction of food and it is represented in (27):

$$X_{i,j}^{t+1} = \left(X_{i,j}^{t} - X_{food}\right) \times p + \times\, rand \times X_{i,j}^{t} \quad (27)$$

At the stage of foraging, the crayfish performs various types of foraging based on the size of the food. Whenever the size of the food is too large, crayfish vary in their path of detecting food. In the foraging stage, the COA approach in detecting optimal solutions helps to enhance the convergence ability during the exploitation stage. Thus, the usage of COA helps in fine-tuning the hyper-parameters of the classifier and results in better results outcome.

3. RESULTS AND ANALYSIS

Here, the experimental results achieved while evaluating suggested method with publicly available datasets such as WISDM, UCI-HAR, and PAMAP2. The design and simulation COA-LSTM are performed in MATLAB R2020b and system is configured with i7 processor, 8 GB RAM, and Windows 11 operating system. The proposed COA-LSTM is effective in classifying the human activities in medical monitoring applications and is evaluated by considering the performance metrics such as accuracy, precision, recall and F-1 score. In (28) to (31) are used to evaluate the aforementioned performance metrics, respectively:

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \quad (28)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (29)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (30)$$

$$F1\ score = 2 \times \frac{(precision \times recall)}{(precision + recall)} \quad (31)$$

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

3.1. Performance analysis

Here, the performance of the proposed classifier is evaluated based on three different datasets such as WISDM, UCI-HAR, and PAMAP2. The efficiency of the proposed COA-LSTM is evaluated with existing classifiers such as capsule network (Caps Net), recurrent neural network (RNN), GRU, LSTM, and COA-LSTM. Table 1 to 3 depicted experimental results obtained while evaluating the proposed approach with the existing classifiers for WISDM, UCI-HAR, and PAMAP2 datasets, respectively. Similarly, the performance of the optimization algorithm used in hyper-parameter optimization is evaluated with butter fly optimization (BOA), grey wolf optimization (GOA), and firefly optimization algorithm (FOA), which is depicted in Table 4 for WISDM, UCI-HAR, and PAMAP2 datasets, respectively.

Table 1. Evaluation of classifiers for the WISDM dataset

Classification models	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Caps Net	97.63	91.23	94.66	92.91
RNN	95.87	93.78	94.92	94.35
GRU	98.03	94.62	95. 32	94.97
LSTM	97.88	94.89	96.89	95.88
COA-LSTM	99.21	98.43	98.89	98.66

Table 2. Evaluation of classifiers for the UCI-HAR dataset

Classification models	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Caps Net	94.45	94.45	95.29	94.87
RNN	96.56	95.59	95.45	95.52
GRU	96.88	96.05	96.84	96.44
LSTM	97.67	95.11	96.10	95.60
COA-LSTM	98.23	97.65	97.73	97.69

Table 3. Evaluation of classifiers for the PAMAP2 dataset

Classification models	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Caps Net	95.01	98.43	94.98	96.67
RNN	94.99	96.24	96.44	96.34
GRU	96.90	97.21	97.12	97.16
LSTM	97.62	97.85	97.73	97.79
COA-LSTM	98.89	98.10	98.44	98.27

Table 4. Experimental analysis of optimization techniques used in hyperparameter optimization

		WISDM dataset		
Optimization techniques	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
BOA	97.01	90.89	93.56	92.89
FOA	96.99	92.55	92.67	92.61
GOA	95.80	92.10	94.39	93.23
COA	98.23	93.58	95.38	94.47
		UCI-HAR dataset		
BOA	94.01	91.50	90.00	90.74
FOA	95.99	90.36	91.04	90.70
GOA	92.90	89.12	91.54	90.31
COA	96.62	92.58	93.44	93.01
		PAMAP2 dataset		
BOA	94.01	94.88	93.90	94.39
FOA	94.99	95.02	92.89	93.94
GOA	93.90	96.13	92.67	94.37
COA	95.62	96.45	94.38	95.40

3.1.1. Evaluation of different classifiers

Here, the efficiency of the existing classification models is assessed with proposed model for three different datasets. Table 1 depicted shows the result when the evaluation is performed with WISDM dataset. The results from Table 1 exhibits COA-LSTM obtained better outcome in overall metrics when compared with the existing ones. For example, the accuracy of COA-LSTM is 99.21% which is comparably higher than Caps Net, RNN, GRU, and LSTM.

Similarly, the performance of the classifiers is evaluated for the UCI-HAR dataset. Table 2 depicts outcome based on classification approach with existing classifiers. The result of the classifier evaluated for UCI-HAR is presented in Table 2. The outcome exhibits COA-LSTM achieved better outcome performance metrics. For instance, COA-LSTM achieved classification accuracy of 98.23%, which is comparably higher than the existing classification approaches. Finally, efficiency of the classifier is evaluated for PAMAP2 dataset and the experimental evaluation of results is depicted in Table 3.

The overall results from Tables 1 to 3 show the efficiency of the proposed classification model. The proposed approach exhibits better results in overall metrics for all three datasets when compared with Caps Net, RNN, GRU, and LSTM. The classification accuracy of the proposed classifier model for WISDM, UCI-HAR, and PAMAP2 is 99.21%, 98.23%, and 98.89%, respectively. The proposed model eliminates the vanishing gradients during the time of modeling long-term dependencies. The hyperparameter optimization takes place using COA enhances the classification and effectively fine-tunes the hyperparameters, which helps to increase the classification efficiency of LSTM. The graphical depiction for the classifier's efficiency for WISDM dataset is depicted in Figure 2.

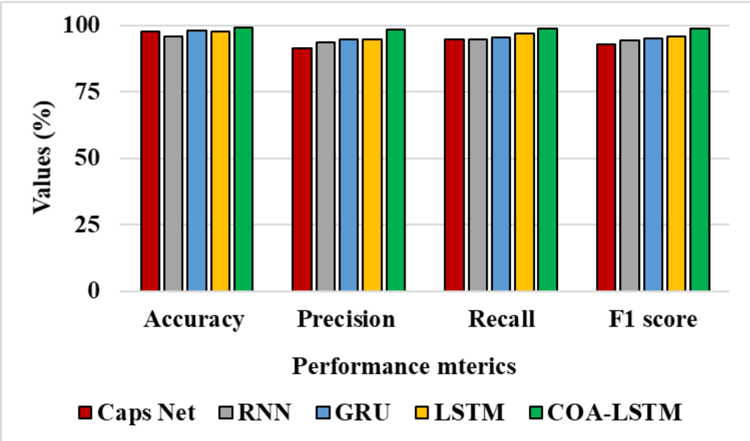

Figure 2. Graphical representation for evaluation of classifier in WISDM dataset

3.1.2. Evaluation of optimization algorithms in hyperparameter optimization

In this subsection, the performance of the optimization techniques used for hyperparameter optimization is evaluated for three datasets utilized in this research. The existing optimization techniques like butterfly optimization algorithm (BOA), FOA, and grasshopper optimization algorithm (GOA). Table 4 shows the experimental results achieved while assessing proposed approach with existing ones.

The overall results from Table 4 show that COA utilized in this research shows better performance in optimizing the hyperparameters with better accuracy. For example, the accuracy of the COA algorithm for the WISDM dataset is 98.23% which is relatively better than existing optimization techniques. The better result of COA is due to behavior of crayfish in adjusting the position, helps to expand the range of searching which helps to enhance the exploring capability of COA.

3.2. Comparative analysis

Here, the efficiency of COA-LSTM classification approach is assessed with existing techniques listed in related works. The existing techniques like CNN [16], multi-branch CNN-Bi LSTM [17], CNN-GRU [18], ST-deep HAR [19], and Ensem-HAR [20] are used to evaluate the efficiency of the proposed approach. Table 5 depicts the comparative results of the proposed approach when it is evaluated with existing techniques.

The COA-LSTM obtains better classification results for all three datasets. For instance, the proposed approach obtains a classification accuracy of 98.23% for UCI-HAR dataset whereas CNN, multi-branch CNN-Bi LSTM, CNN-GRU, ST-deep HAR, and Ensem-HAR obtain classification accuracy of 91.98%, 96.37%, 96.20%, 97.7%, and 95.05%, respectively. The outcome of COA-LSTM is due to the usage of LSTM in eliminating the vanishing gradients during the time of modeling long-term dependencies. The hyper-parameter optimization performed using COA enhances the classification and effectively fine-tunes the hyperparameters which help to increase the classification efficiency of LSTM. The comparative graph of the proposed approach for the UCI-HAR dataset is presented in Figure 3.

Table 5. Comparison of COA-LSTM with existing techniques for UCI-HAR, WISDM, and PAMAP2

Methods	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F-1 score (%)
CNN [16]	UCI-HAR	91.98	93.79	91.98	93.02
Multi-branch CNN-Bi LSTM [17]	UCI-HAR	96.37	NA	NA	96.31
	WISDM	96.05	NA	NA	96.04
	PAMAP2	94.29	NA	NA	94.27
CNN-GRU [18]	UCI-HAR	96.20	NA	NA	96.19
	WISDM	97.21	NA	NA	97.22
	PAMAP2	95.27	NA	NA	95.24
ST-deep HAR [19]	UCI-HAR	97.7	NA	NA	97.5
	WISDM	98.90	NA	NA	98.32
Ensem-HAR [20]	UCI-HAR	95.05	NA	NA	NA
	WISDM	98.70	NA	NA	NA
	PAMAP2	97.45	NA	NA	NA
COA-LSTM	UCI-HAR	98.23	97.65	97.73	97.69
	WISDM	99.21	98.43	98.89	98.66
	PAMAP2	98.89	98.10	98.44	98.27

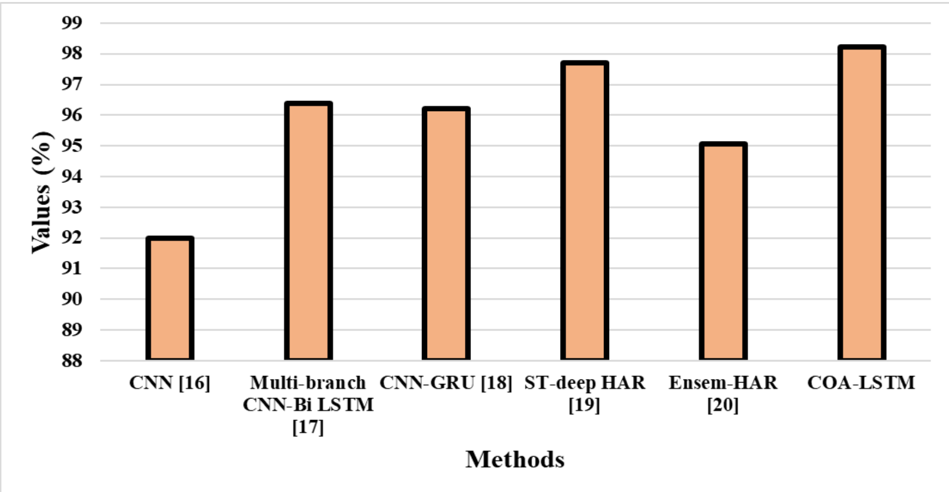

Figure 3. Comparison graph for classification accuracy in the UCI-HAR dataset

3.3. Discussion

In this section, the advantages of the proposed work along with the outcome of proposed approach are described. The results of COA-LSTM is evaluated with three datasets such as WISDM, UCI-HAR, and PAMAP2. The analysis is performed for the proposed approach when it is assessed with different techniques such as CNN, Multi-branch CNN-Bi LSTM, CNN-GRU, ST-deep HAR, and Ensem-HAR. For example, the classification efficiency of the proposed approach for UCI-HAR dataset is 98.23% whereas the existing classification techniques listed in related works such as CNN [16], multi-branch CNN-Bi LSTM [17] CNN-GRU [18], ST-deep HAR [19], and Ensem-HAR [20] have obtained classification accuracies of 91.98%, 96.37%, 96.20%, 97.7%, and 95.05%. Thus, the proposed approach secures better results in overall performance metrics than the existing ones. The reason behind this is due to the classification efficiency of LSTM is optimized by tuning the hyperparameters using the COA where, the position of the crayfish is adjusted to expand the searching range which helps to achieve better convergence and classification accuracy. However, the usage of LSTM is only applicable to the fixed length that relies as the major limitation while dealing with irregular time series data.

4. CONCLUSION

This research introduced an effective DL-based classification approach based on LSTM with COA for hyperparameter optimization to recognize the activities of patients. This research makes use of three publicly available datasets such as WISDM, UCI-HAR, and PAMAP2 to assess effectiveness of COA-LSTM. The acquisition data is pre-processed by normalization and Gaussian filter. After this stage, the dimensionality of the features is reduced using hybrid PCA-LDA. Finally, the classification is performed using the proposed COA-LSTM which provides better classification efficiency. The COA relies as a reason to fine-tune the hyperparameters and helps to achieve better classification accuracy. The classification accuracy of the proposed approach for UCI-HAR dataset is 98.23% which is comparably higher than the existing approaches like CNN (91.98%), multi-branch CNN-Bi LSTM (96.37%), CNN-GRU (96.20%), ST-deep HAR (97.7%), and Ensem-HAR (95.05%). In the future, hybrid optimization techniques can be implemented in advanced DL models to improve the classification results.

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