Automated Human Activity Recognition by Colliding Bodies Optimization-based Optimal Feature Selection with Recurrent Neural Network

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Abstract—In smart healthcare, Human Activity Recognition (HAR) is considered to be an efficient model in pervasive computation from sensor readings. The Ambient Assisted Living (AAL) in the home or community helps the people in providing independent care and enhanced living quality. However, many AAL models were restricted using many factors that include computational cost and system complexity. Moreover, the HAR concept has more relevance because of its applications. Hence, this paper tempts to implement the HAR system using deep learning with the data collected from smart sensors that are publicly available in the UC Irvine Machine Learning Repository (UCI). The proposed model involves three processes: (1) Data collection, (b) Optimal feature selection, (c) Recognition. The data gathered from the benchmark repository is initially subjected to optimal feature selection that helps to select the most significant features. The proposed optimal feature selection is based on a new meta-heuristic algorithm called Colliding Bodies Optimization (CBO). An objective function derived by the recognition accuracy is used for accomplishing the optimal feature selection. Here, the deep learning model called Recurrent Neural Network (RNN) is used for activity recognition. The proposed model on the concerned benchmark dataset outperforms existing learning methods, providing high performance compared to the conventional models.

Keywords: Human Activity Recognition, Smart Sensors, Optimal Feature Selection, Colliding Bodies Optimization, Recurrent Neural Network

1. Introduction

Human beings are capable of performing activities, along with walking and sewing when talking. However, there is a negative influence on daily human activities, bad postures, an unbalanced diet, and favoring a sedentary lifestyle towards technological development and more amount of resources availability. In order to identify the human activities, starting from the signal comparison with thresholds to the implementation of machine learning and deep learning algorithms, discrete methods have been introduced. By using various sensor readings, there is a rapid growth of the Internet of things (IoT) and Wireless sensor network (WSN) for HAR, which attains an enhanced probability [6] [7]. For effective activity recognition, the readings are gathered and interpreted from the sensors. The main aim of this activity recognition model alters detection by recognizing the unexpected change in measures like covariance and mean that denotes the change in an indoor environment [7]. By using a robust algorithm, accurate manipulation of these measures might do in a timeframe. In order to understand the requirement of the user and adjust according to the user circumstances, activity recognition is a crucial element that permits the applications related to a smart home. For helping various emergency-related wellbeing services and healthcare, HAR is very helpful for assistance. By monitoring various physical activities, it is attained for feasible real-time responders and nursing services in the domestic environment and care homes [6] [8]. However, introducing a scalable, robust, real-time indoor HAR model in a real-time environment...
frequently provides a difficult task because of the complexity of the indoor environment. The new technological developments and advancements of computer devices make use of smart home sensing models and stimulate the requirement for associated products and services [10]. In earlier researches, discrete classification models have been used like Support Vector Machine (SVM), Naive Bayes (NB), K Nearest Neighbor (KNN), Random Forest (RF), Conditional random fields (CRF), and Hidden Markov Model (HMM). In HAR, the famous deep learning algorithms used are Convolutional Neural Network (CNN), Long short-term memory (LSTM), Deep Neural Net (DNN), and Recurrent Neural Network (RNN). In order to address the HAR and human pose recognition task, CNN is used in most of the applications by convoluting across two or three dimensions for seizing an image’s spatial patterns [11] [9].

HAR has become a lively and challenging research field in the past years because of its applicability for various AAL domains and improving the demand for convenience services and home automation [12]. HAR has attained more interest in the ALL techniques in smart homes owing to the rapid increment of the world's aging population [12]. It is a challenging point in considering more count of observations in each second, the temporal nature of the observations, and the shortage of a clear procedure for relating accelerometer data for known movements [13]. Based on constant-size windows and training machine learning algorithms like ensembles of decision trees, conventional algorithms consist of handcrafting features from the time-series data. In this area, feature engineering is a complex task, which necessitates deep proficiency [14] [15].

The contribution of the entire paper is mentioned below:

- To introduce an effective HAR model using RNN with the developed CBO algorithm-based optimal feature selection.
- To recognize the human activities efficiently by deriving an objective function with maximum accuracy on two benchmark datasets like HAR dataset and WISDM dataset.

Regarding the paper’s organization, Section 2 shows the literature review of existing HAR models, and Section 3 describes the HAR using sensed data. Section 4 speaks about the steps utilized for the proposed HAR, and Section 5 discusses the experimental analysis, and Section 6 mentions the conclusion of the paper.

2. Literature Review

2.1 Related Works

In 2019 Alhameed et al. [1] have introduced an ambient HAR model using a multivariate Gaussian approach. In order to acquire more activity profiling, the classification model has augmented prior information from passive Radio-frequency identification (RFID) tags. Based on multivariate Gaussian, the developed model with maximum likelihood estimation was employed for feature learning. In the mock apartment environment, twelve sequential and concurrent experimental analysis were performed. By using a novel dataset of similar activity, the sampled activities were predicted, and more prediction accuracy has been acquired. The developed model was well suitable for a single and multi-dwelling environment. In 2020, Lizarazo et al. [2] have performed the classification of six human activities with bidirectional LSTM networks, which employed IMF representation of inertial signals. From the UCI repository, the inertial signals of 2.56s records were gathered from 30 subjects with the help of a smartphone. By using ICEEMDAN, inertial signals were assembled for considering them to a similar scale and were combined with the
IMF. The overall accuracy was acquired in classifying the six human activities. The results have proven that the developed ICEEMDAN was superior to conventional algorithms. In 2020, Fong et al. [3] have suggested a new data fusion model for merging data that were gathered from two sensors with the intent of improving the accuracy of HAR. In order to seize the complete details of body movements, Kinect has the ability, but the accuracy was based on the angle of view. For detecting basic movements, wearable sensors were primitive in collecting spatial information but reliable. The combination of data from the two types of sensors has enabled each other by their strength. A new technique with incremental learning using the decision table was combined with "swarm-based feature selection" that was introduced for acquiring fast and precise HAR. The test results have been shown that HAR accuracy was improved when a wearing sensor was utilized simultaneously. In 2020, Janko et al. [4] have suggested the analysis of the efficiency of components. For training conventional machine learning algorithms, a complex feature selection and extraction approaches were utilized. By using end-to-end architecture, the training of deep learning models was done for combining deep multimodal spectro-temporal. All the methods were combined to form the ensemble model with last predictions smoothed using HMM for the activities of temporal dependencies. With the help of test data, the developed model has attained a more F1 score. The results have shown that the developed model has attained the best HAR accuracy. In 2020, Bernardini et al. [5] have recommended various deep learning algorithms, which learned the human activities for classification. In order to model spatio-temporal sequences, LSTM was implemented. The suggested model was analyzed using the “Center for Advanced Studies in Adaptive Systems” dataset. The results have been indicated that LSTM-based models were superior to conventional deep learning and machine learning algorithms.

Table 1: Review of Traditional Human Activity Prediction or Recognition models

| Author [citation] | Methodology            | Features                                                                                   | Challenges                                                   |
|-------------------|------------------------|-------------------------------------------------------------------------------------------|--------------------------------------------------------------|
| Alhameed et al. [1] | Multivariate Gaussian | • It attained a detailed description of activity profiling.                                | • It becomes complicated to recognize complex activities.    |
|                   |                        | • It is applicable for single as well as multi-dwelling environments.                      |                                                              |
|                   |                        | • It provides an extensive sensing environment for the disabled, elderly, and carers.    |                                                              |
| Lizarazo et al. [2] | Bidirectional LSTM     | • It is creative with respect to the usage of the enhanced total ensemble empirical mode decomposition. | • The inference and learning seem to be very tough.         |
|                   |                        | • It enhances the system's observability.                                                   |                                                              |
| Fong et al. [3]   | Fast incremental learning | • The performance of the machine learning models was increased to five times.            | • The testing scenarios are not extended.                    |
|                   |                        | • The empirical data feeds to enhance the performance of                                  | • It does not include various angles of the field of view from aerial. |
2.1 Review

HAR solves the problem of sequence classification of accelerometer data that are being stored by smartphones or specialized harnesses into well-known movements. However, it has various drawbacks like partial occlusion, viewpoint, appearance, background clutter, scale variations, and lighting. Very few features and challenges are listed in Table 1. Multivariate Gaussian [1] provides the disabled, elderly, and carers with an extensive sensing environment and applies for both single as well as multi-dwelling environments. The detailed description of activity profiling is also attained. Nevertheless, complex activities are very difficult to recognize. Bidirectional LSTM [2] enhances the observability of the system. The enhanced total ensemble empirical mode decomposition also provides a creative environment. Still, it seems very tough for inference as well as learning. Fast incremental learning [3] enhances the classification performance by the empirical data feeds, and it improves the performance of the learning approach to around five times. However, it does not benchmark the performance using several machine learning, and various angles of the field of views from aerial are not included. It also does not extend the testing scenarios. Classical machine learning [4] optimizes the energy consumption with the help of sensor settings, and the activities are also predicted on an unlabeled dataset. But, with the recent techniques like multimodal subspace clustering or two-stream network fusion, it does not get updated, and with different subjects and datasets for AR, the model was not evaluated. LSTM [5] does not require the methods of data augmentation, and it feels compatible with the highly unbalanced arrangement of the smart home dataset. It also enhances the generalization performance of the system. Still, the multi-user activity recognition was not implemented, and it also does not test several identical datasets. These challenges are inspired to find a novel method for recognizing or predicting human activity using machine learning with data from smart sensors.

3. Human Activity Recognition Using Sensed Data
3.1. Dataset adopted for Recognition

Here, two datasets, namely HAR and WISDM are utilized for analysis, and these datasets are downloaded from the UCI repository.

**HAR dataset**: The tests have been performed with 30 volunteers whose age is in between 19 to 48 years of age. Each and every person has performed six activities like “walking, walking upstairs, walking downstairs, sitting, standing, and laying” who is wearing a smartphone on the waist. To label the data manually, the simulations have been recorded in the video format. The acquired datasets are split into 70% of the data is considered training, and 30% for testing. The feature vector is acquired from each window by calculating the variables from the frequency and time domain.

**WISDM dataset**: The collection of gyroscope and accelerometer sensor data is done from smartwatch and smartphone at a rate of 20Hz. This is acquired from 51 test subjects as they conduct 18 activities for 3 minutes apiece. In a discrete directory, the sensor data for each device and the sensor type is maintained. There are 51 files with respect to 51 test subjects in each directory. The entry format of each data is similar.

3.2. Proposed Model

In the earlier contributions, HAR is enabled in some applications like healthcare, improved manufacturing, and smart homes. Activity recognition is essential for handling recorded data, thus permits the computing models for monitoring, analyzing, and assisting their daily life. The usage of smart sensors in the current healthcare models helps health professionals and patients to automatically monitoring human activities. In personal healthcare monitoring, smartphones and smart body sensors are rapidly employed. The wearable sensor technology is a significant improvement in smart sensor technologies. Moreover, there is more interest in machine learning algorithms, and it plays a significant role in HAR. The proposed HAR model is represented in Fig. 1.

![Proposed HAR Model Diagram](image-url)
In the proposed HAR model, the two datasets, such as HAR and WISDM, are collected from the UCI repository using smart sensors. The developed model includes Data collection, Optimal feature selection, and Recognition. The data acquired from the standard repository is given to perform optimal feature selection, which is helpful for selecting the essential features. Based on the developed CBO algorithm, the optimal feature selection is determined. In order to perform the optimal feature selection, an objective function derived using the recognition accuracy is employed. For effective Recognition of human activities, a deep learning model named RNN is employed. The main objective of the proposed HAR model is to maximize accuracy. In order to attain maximized accuracy, the classification of the data is done.

4. Steps Utilized for Proposed Human Activity Recognition

4.1 Data Normalization

Data normalization is a process in which the data in the database is appropriately arranged, which is used for altering the numerical values in the dataset to a common scale without distorting the ranges. By the frequency of occurrence, the data normalization procedure is defined. With this concept, the record-level normalization produces the data representation related to the record, and it is generally observed between the same record set for an entity. In the normalized record, the field level normalization selects the value for each field, which occurs often. Let \( am = 0 \) and \( bm = 0 \) be the two variables, where the maximum and minimum normalized values are indicated by \( am \) and \( bm \), respectively. The data normalization is mathematically represented in Eq. (1).

\[
DT_{u}^{\text{norm}} = (am - bm) \cdot \left( \frac{DT_{u} - DT_{\text{min}}}{DT_{\text{max}} - DT_{\text{min}}} \right) + bm \tag{1}
\]

In the above equation, the term \( DT_{u}^{\text{norm}} \) represents the normalized data, and the term \( DT_{u} \) denotes the value or data that to be normalized. The maximum and minimum values related to each record is denoted as \( DT_{\text{max}} \) and \( DT_{\text{min}} \), correspondingly.

4.2 Optimal Feature Selection by Colliding Bodies Optimization

From the normalized data, the optimal features are selected. The employment of optimal feature selection is to decrease the dimensionality of the data for developing the best classification model. The results of classification are impacted using optimal feature selection approaches. If optimal feature selection is good, there is a positive effect on classification in proposed HAR. With the help of developed CBO-RNN, the optimal feature selection is performed. The solution encoding of optimal feature selection is given in Fig. 2.

![Solution encoding of proposed human activity recognition](image)

Fig. 2. Solution encoding of proposed human activity recognition
From the above figure, the optimal features are denoted as $DT^{\text{opt}}$, in which the number of features is indicated by $NF$. The objective function of the proposed HAR is to maximize the accuracy, which is attained by the proposed CBO-RNN. The objective function of the proposed model is denoted in Eq. (2).

$$obj = \arg\max_{\mu_{\text{acc}}}$$

The numerical formula for computing the accuracy is specified in Eq. (3).

$$A = \frac{Tps + Fps}{Tps + Fps + Tne + Fne}$$

In the above equation, the term $Tps$ denotes true positive of the elements, $Tne$ denotes true negative, $Fps$ indicates false positive, and $Fne$ indicates the false negative.

CBO [16] is a population-based evolutionary algorithm that uses the concept of the laws of the collision of two objects. In order to find a maximum or minimum of functions, CBO employs simple formulation and does not depend on any internal parameter. Each solution candidate $x_i$ includes the count of variables, and it is assumed as the CB. The massed objects include stationary and moving objects, in which the stationary objects are followed by moving objects, and the collision will occur among the object pairs. It is performed for enhancing the moving object’s position and pushing stationary objects towards the best position. Based on new velocities, the novel positions of CBs are updated using collision laws. The process of conventional CBO is given below.

1. By initializing the population in the search space at random, the initial positions of CBs are defined as shown in Eq. (4). Here, the initial value vector of $i^{th}$ CB is given by $X_i^0$. "The minimum and maximum allowable values vectors of variables are denoted as $X_{\text{min}}$ and $X_{\text{max}}$, respectively. Moreover, the random number is given by $\text{rnd}$, which lies from 0 to 1, and the count of CBs is given by $N$.

$$X_i^0 = X_{\text{min}} + \text{rnd}(X_{\text{max}} - X_{\text{min}}), i = 1, 2, \cdots, N$$

2. For each CB, the magnitude of the body mass is given by Eq. (5). In this, the objective function value of the agent $i$ is denoted as $f_i(b)$, and the population size is denoted as $N$. The objective function $f_i(b)$ is replaced by $\frac{1}{f_i(b)}$ for maximization.

$$mg_b = \frac{1}{\sum_{i=1}^{N} \frac{1}{f_i(b)}}, b = 1, 2, \cdots, N$$
3. The CB’s objective values are allotted in ascending order. The sorted CBs are similarly split into two groups.

- The lower half CBs are termed as stationary CBs. These CBs are good agents that are stationary, and these bodies velocity is 0 before collision based on Eq. (6).

\[ v_{l_i} = 0, i = 1,2,\ldots,\frac{N}{2} \]  \hspace{1cm} (6)

- The upper half CBs are called as moving CBs, which will move to the lower half CBs. The velocity of these bodies is given by the position of the body prior to the collision, as shown in Eq. (7).

\[ v_{l_i} = X_i - X_{i-N/2}, i = \frac{N}{2} + 1,\ldots, N \]  \hspace{1cm} (7)

In the above equation, the velocity and position vector of \( i^{th} \) CB is given by \( v_{l_i} \) and \( X_i \), respectively. The \( i^{th} \) CB pair position of \( X_i \) in the last group is given by \( X_{i-N/2} \).

4. In each group, the velocities of CBs are analyzed using Eq. (6) and Eq. (7), and the velocity before the collision. By using Eq. (8), the velocity of each moving CBs after the collision is acquired.

\[ v'_{l_i} = \frac{\left( mg_i - \varepsilon mg_i \frac{N}{2} \right) v_{l_i}}{mg_i + \varepsilon mg_i \frac{N}{2}}, i = \frac{N}{2} + 1,\ldots, N \]  \hspace{1cm} (8)

In Eq. (8), the velocity of \( i^{th} \) moving CB before and after the collision is given by \( v_{l_i} \) and \( v'_{l_i} \), respectively. The \( i^{th} \) CBs mass is given by \( mg_i \). The mass of \( i^{th} \) CB pair is denoted as \( mg_{i-N/2} \). Once the collision is done, the velocity of each stationary CB is denoted in Eq. (9).

\[ v'_{l_i} = \frac{\left( mg_i + \varepsilon mg_i \frac{N}{2} \right) v_{l_i}}{mg_i + \varepsilon mg_i \frac{N}{2}}, i = \frac{N}{2} + 1,\ldots, N \]  \hspace{1cm} (9)

In the above equation, the moving CB pair before and stationary CB after collision’s velocity is given by \( v_{l_i} \) and \( v'_{l_i} \), respectively. The value of the COR parameter is denoted as \( \varepsilon \).

5. By using the generated velocities after collision in the stationary CB’s position, the new locations of CBs are analyzed. Eq. (10) represents the new locations of each moving CBs. Here, the \( i^{th} \) moving CBs new position and velocity after a collision is denoted as \( X_i^{\text{new}} \) and \( v_i' \),
respectively. The old position of the $i^{th}$ stationary CB pair is given by $X_{i,\frac{N}{2}}$. The new locations of stationary CBs are acquired using Eq. (11).

$$X_{i,\frac{N}{2}}^{new} = X_{i,\frac{N}{2}} + \text{rnd} \cdot v_{i}^{l}, i = \frac{N}{2} + 1, \cdots, N$$ (10)

$$X_{i,\frac{N}{2}}^{new} = X_{i} + \text{rnd} \cdot v_{i}^{l}, i = 1, \cdots, \frac{N}{2}$$ (11)

In Eq. (8) the random vector is uniformly distributed, and the value ranges from -1 to 1, and the element-by-element multiplication is given by $\circ$.

6. Until the termination criterion is reached, the optimization procedure is repeated from step 2. Termination criteria mean the count of maximum iteration is fulfilled. The status of the body and its numbering is modified in two successive iterations.

4.3 Recurrent Neural Network-based Recognition

RNN [17] is a dynamic model, which is computationally powerful, and it is used in many temporal processing methods and applications. This is trained for providing any target dynamics until the degree of precision is offered. RNN is one of the categories of ANNs, where the links among the nodes generate the directed graph with the information growth. This is similar to the time series data operation effectively, and therefore the results found to be best when the earlier and present data is defined. LSTM is one type of RNN that consists of three gate units, such as input, output, and forget gates and a memory cell unit. The specific type of LSTM called GRU is considered, which is employed for building the model of RNN for enhancing the performance. It combines both forget and output gates into one update gate $U_{up}$, where the interpolation is used for attaining the current result. Assume $g_{a} \leftarrow DT_{a}^{up}$ as the $a^{th}$ input feature and the earlier hidden state is denoted as $d_{a-1}$. The update and reset gates are denoted in Eq. (12) and Eq. (13), respectively. Here, the activation function is denoted as $Acv$, which is the logistic sigmoid function.

$$U_{a} = Acv\left(wm^{up}d_{a} + wm^{up}d_{a-1}\right)$$ (12)

$$R_{a} = Acv\left(wm^{reg}g_{a} + wm^{reg}d_{a-1}\right)$$ (13)

In the above equations, the weight matrix is given by $wm^{e} = \{wm^{up}, wm^{up}, wm^{reg}, wm^{reg}\}$ that must be tuned for error minimization among actual and measured output. The hidden unit’s candidate state is measured by Eq. (14).

$$d_{a} = \tan\left(wm^{ed}e_{a} + wm^{dd}(d_{a-1} \otimes R_{a})\right)$$ (14)
In Eq. (14) the term \( \otimes \) represents the element-wise multiplication; the hidden activation function of the candidate state is denoted as \( \tilde{d}_{a} \), and the linear interpolation \( d_{a-1} \) is given by \( d_{a} \) of GRU, and the numerical equation is given in Eq. (15).

\[
d_{a} = (1 - \theta_{p}) \otimes \tilde{d}_{a} + \theta_{p} \otimes d_{a},
\]

(15)

In the proposed HAR, the objective is to maximize the recognition accuracy with the optimal features.

5. Result and Discussion

5.1 Experimental Setup

The presented HAR was implemented using Python, and the analysis was carried out. The datasets named UCI-HAR and WISDM were considered for the experiment. The maximum number of iterations considered for the experiment was 25, and the population size was considered as 10. The analysis of the proposed CBO-RNN was compared over conventional meta-heuristic algorithms like PSO-RNN [18], FF-RNN [19], and CBO-RNN [16], and the performance of RNN was compared over NN [23], DT [20], KNN [21], SVM [22] concerning the performance measures like "accuracy, sensitivity, specificity, precision, FPR, FNR, NPV, FDR, F1 score, and MCC".

5.2 Analysis of Diverse heuristic-based Optimal Feature Selection

The analysis of the proposed and the traditional meta-heuristic algorithms for optimal feature selection with respect to learning percentage for UCI-HAR and WISDM datasets is shown in Fig. 3. In Fig. 3 (a), the accuracy of the developed CBO-RNN is acquiring the best results in recognizing the human activities when compared over conventional algorithms for the UCI-HAR dataset. The accuracy of the improved CBO-RNN at learning percentage 85 is 2.2% better than PSO-RNN and 3.4% superior to FF-RNN. Table II and Table III show the overall analysis of the developed CBO-based optimal feature selection over the traditional algorithms for UCI-HAR and WISDM datasets through RNN-based classification. In Table II, the accuracy of the implemented CBO-RNN is 1.4% improved than PSO-RNN, and 2.6% improved than FF-RNN. From Table III, the accuracy of the suggested CBO-RNN is 1.4% better than PSO-RNN, 1.7% better than FF-RNN. Thus, the developed CBO-based optimal feature selection has attained the best results in recognizing human activities.
Table II. Different Heuristic-Based Optimal Feature Selection For Har Using UCI-HAR Dataset

| Algorithms   | Accuracy | Sensitivity | Specificity | Precision | FPR    | FNR    | NPV    | FDR    | F1 score | MCC    |
|--------------|----------|-------------|-------------|-----------|--------|--------|--------|--------|----------|--------|
| PSO-RNN      | 0.889443 | 0.8902      | 0.889292    | 0.616593  | 0.110708 | 0.1098 | 0.889292 | 0.383407 | 0.728556 | 0.679592 |
| FF-RNN       | 0.879008 | 0.888385    | 0.877132    | 0.591184  | 0.122868 | 0.111615 | 0.877132 | 0.408816 | 0.709935 | 0.658454 |
| CBO-RNN      | 0.901996 | 0.909256    | 0.900544    | 0.646452  | 0.099456 | 0.090744 | 0.900544 | 0.353548 | 0.755656 | 0.71239 |

Table III. Different Heuristic-Based Optimal Feature Selection For Har Using WISDM Dataset

| Algorithms   | Accuracy | Sensitivity | Specificity | Precision | FPR    | "FNR'" | NPV    | FDR    | F1 score | MCC    |
|--------------|----------|-------------|-------------|-----------|--------|--------|--------|--------|----------|--------|
| PSO-RNN      | 0.884846 | 0.899563    | 0.88398     | 0.313229  | 0.11602 | 0.100437 | 0.88398 | 0.686771 | 0.464662 | 0.490129 |
| FF-RNN       | 0.882258 | 0.870451    | 0.882952    | 0.304326  | 0.117048 | 0.129549 | 0.882952 | 0.695674 | 0.45098  | 0.472052 |
| CBO-RNN      | 0.897784 | 0.887918    | 0.898365    | 0.339455  | 0.101635 | 0.112082 | 0.898365 | 0.660545 | 0.491143 | 0.511057 |

5.3 Analysis over Various Classifiers

In Fig. 4, the analysis of various classifiers with respect to learning percentage using UCI-HAR and WISDM datasets is shown. The optimal features by CBO are used for performing the Recognition by all classifiers. For the WISDM dataset, the accuracy of the presented RNN when considering the learning percentage as 75 is 2.1% advanced than NN, 5.5% advanced than SVM and KNN, and 9.1% advanced than DT. The overall performance analysis of the developed and the conventional classifiers using two datasets is shown in Table IV and Table V. In Table IV, the accuracy of the proffered RNN is 7.9% improved than DT, 6.4% advanced than KNN, 5.7% advanced than SVM, and 2.4% advanced than NN using UCI-HAR dataset. Table V shows the overall performance analysis of the proposed CBO-RNN and the conventional classifiers for the WISDM dataset. The accuracy of the
presented RNN is attaining the best HAR. It is 7.3% progressed than DT, 6.5% progressed than KNN, 4.1% progressed than SVM, and 2.2% progressed than NN. Hence, it is confirmed that the suggested RNN is performing well in recognizing human activities with CBO-based optimal features.

![Accuracy vs Learning Percentage for different algorithms](image1)

![Accuracy vs Learning Percentage for different algorithms](image2)

Fig 4: Analysis on diverse machine learning algorithms for HAR concerning Accuracy using (a) UCI-HAR dataset, and (b) WISDM

Table IV. Different Machine Learning Algorithms For Har Using UCI-HAR Dataset

| Algorithms | Accuracy | Sensitivity | Specificity | Precision | FPR   | FNR   | NPV   | FDR   | F1 score | MCC    |
|------------|----------|-------------|-------------|-----------|-------|-------|-------|-------|----------|--------|
| DT [20]    | 0.835451 | 0.842105    | 0.83412     | 0.5038    | 0.16588| 0.157895| 0.83412| 0.4962 | 0.630435 | 0.562152|
| KNN [21]   | 0.847701 | 0.850272    | 0.847187    | 0.5267    | 0.152813| 0.149728| 0.847187| 0.4733 | 0.650469 | 0.586123|
| SVM [22]   | 0.853297 | 0.856624    | 0.852632    | 0.537585  | 0.147368| 0.143376| 0.852632| 0.462415| 0.660602 | 0.598505|
| NN [23]    | 0.880067 | 0.869328    | 0.882214    | 0.596142  | 0.117786| 0.130672| 0.882214| 0.403858| 0.707272 | 0.652996|
| RNN [17]   | 0.901996 | 0.909256    | 0.900544    | 0.646452  | 0.099456| 0.090744| 0.900544| 0.353548| 0.755656 | 0.71239 |

Table V. Different Machine Learning Algorithms For Har Using WISDM Dataset

| Algorithms | Accuracy | Sensitivity | Specificity | Precision | FPR   | FNR   | NPV   | FDR   | F1 score | MCC    |
|------------|----------|-------------|-------------|-----------|-------|-------|-------|-------|----------|--------|
| DT [20]    |          |             |             |           |       |       |       |       |          |        |
| KNN [21]   |          |             |             |           |       |       |       |       |          |        |
| SVM [22]   |          |             |             |           |       |       |       |       |          |        |
| NN [23]    |          |             |             |           |       |       |       |       |          |        |
| RNN [17]   |          |             |             |           |       |       |       |       |          |        |
5.4 Effect of Optimal Feature Selection

The effect of optimal feature selection on both UCI-HAR and WISDM is shown in Fig. 5. From Fig. 5 (a), the accuracy of the optimized feature at learning percentage 85 is 2.2% superior to all features. Moreover, the overall analysis of with and without optimized features for both the datasets is shown in Table VI and Table VII. From Table VI, the accuracy of the optimized feature is 1.8% enhanced than all features. In Table VII, the accuracy of the optimized features is attaining the best results for HAR. It is 1.5% better than all features. Therefore, it has been confirmed that the developed CBO-RNN is giving the best results in recognizing human activities.

| Method | Accuracy 75% | Accuracy 80% | Accuracy 85% | Accuracy 80% | Accuracy 85% | Accuracy 80% | Accuracy 85% |
|--------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| DT [20] | 0.836568     | 0.825328     | 0.837229     | 0.829741     | 0.162771     | 0.837229     | 0.770259     | 0.359429     | 0.379715     |
| KNN [21] | 0.842956     | 0.845706     | 0.842795     | 0.240381     | 0.157205     | 0.842795     | 0.759619     | 0.374356     | 0.397702     |
| SVM [22] | 0.862203     | 0.863173     | 0.862146     | 0.269178     | 0.138504     | 0.862146     | 0.730822     | 0.410381     | 0.434202     |
| NN [23]  | 0.877972     | 0.861718     | 0.878928     | 0.295115     | 0.121072     | 0.878928     | 0.704885     | 0.439658     | 0.4602       |
| RNN [17] | 0.897784     | 0.887918     | 0.898365     | 0.339455     | 0.101635     | 0.898365     | 0.660545     | 0.491143     | 0.511057     |

Fig 5: Effect of optimal feature selection for HAR concerning Accuracy using (a) UCI-HAR dataset, and (b) WISDM

Table VI. Overall Analysis Of With And Without Optimized Features For HAR Using UCI-HAR Dataset
| Algorithms | Accuracy | Sensitivity | Specificity | Precision | FPR    | FNR    | NPV    | FDR    | F1 score | MCC    |
|------------|----------|-------------|-------------|-----------|--------|--------|--------|--------|----------|--------|
| All Features | 0.885209 | 0.878403    | 0.88657     | 0.607659  | 0.11343| 0.121597| 0.88657| 0.392341| 0.718367| 0.666647|
| Optimized Feature | 0.901996 | 0.909256    | 0.900544    | 0.646452  | 0.099456| 0.090744| 0.900544| 0.353548| 0.755656| 0.71239|

Table VII. Overall Analysis Of With And Without Optimized Features For HAR Using WISDM Dataset

| Algorithms | Accuracy | Sensitivity | Specificity | Precision | FPR    | FNR    | NPV    | FDR    | F1 score | MCC    |
|------------|----------|-------------|-------------|-----------|--------|--------|--------|--------|----------|--------|
| All features | 0.884441 | 0.89083     | 0.884065    | 0.311292  | 0.115935| 0.10917| 0.884065| 0.688708| 0.461364| 0.485418|
| Optimized Feature | 0.897784 | 0.887918    | 0.898365    | 0.339455  | 0.101635| 0.112082| 0.898365| 0.660545| 0.491143| 0.511057|

6. Conclusion

This paper has tended to develop a novel HAR model with a deep learning algorithm by gathering the data from smart sensors, which was publicly available in the UCI repository. Initially, the data was given to the optimal feature selection that helped in selecting the most relevant features. This optimal feature selection was done by the developed CBO algorithm. In order to accomplish the optimal feature selection, an objective function was derived by recognition accuracy. Further, RNN was employed for recognizing the activity. From the analysis, the accuracy of the developed CBO-RNN was acquired best results in recognizing the human activities when compared over conventional algorithms for the UCI-HAR dataset. Hence, it is confirmed that the developed CBO-RNN was efficient in recognizing human activities when compared to the existing methods.

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