Design of Improved Metaheuristics with Machine Learning Driven Human Activity Recognition

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Abstract: ***Human Activity Recognition (HAR) is a significant area of research and application within the fields of computer vision, machine learning, and wearable technology. It involves the development of algorithms and models to automatically identify and classify human activities dependent upon data gathered in several sensors like accelerometers, gyroscopes, and even video cameras. The goal of HAR is to enable computers and systems to understand and interpret human actions and movements.In recent years, DL approaches have shown remarkable performance in HAR tasks. With this motivation, this study designs an improved metaheuristics with machine learning driven human activity recognition approach (IMML-HARA). The IMML-HARA technique focuses on the recognition and classification of human activities. In the presented IMML-HARA technique, Improved Chicken Swarm Optimization (ICSO) Algorithm for electing an optimal set of features. Moreover, the IMML-HARA technique offers the design of radial basis function (RBF) classifier for the identification of human activities into distinct activities. The performance of the IMML-HARA technique is tested on two benchmark HAR datasets. The experimental results indicate the betterment of the IMML-HARA method over other existing recent state of art approaches.***

Keywords: Machine Learning; Radial Basis Function; Chicken Swarm Optimization; Human Activity Recognition

1. Introduction

Recently, the scientific community pays more attention to the field of Human Activity Recognition (HAR) thus, a widespread real-world utilization in real-time applications, such as health monitoring of old people, monitoring by authorities, and biometric user identification [1]. Presently, numerous kinds of research implemented on HAR are growing quirkily as sensors that can be more extensively available, cost and power consumption is decreased, and owing to technological development in ML approaches [2]. Artificial Intelligence (AI) and Internet of Things (IoT) are shown live. The growth of HAR is allowed real-time applications in several real-time fields that consist of sports science, crime and violence recognition, strategic military applications [3], and medical field. Mathematical algorithms relying on human activity information, allow the recognition of different human activities like sitting, walking, standing, and running [5]. Fig. 1 depicts the overview of HAR.

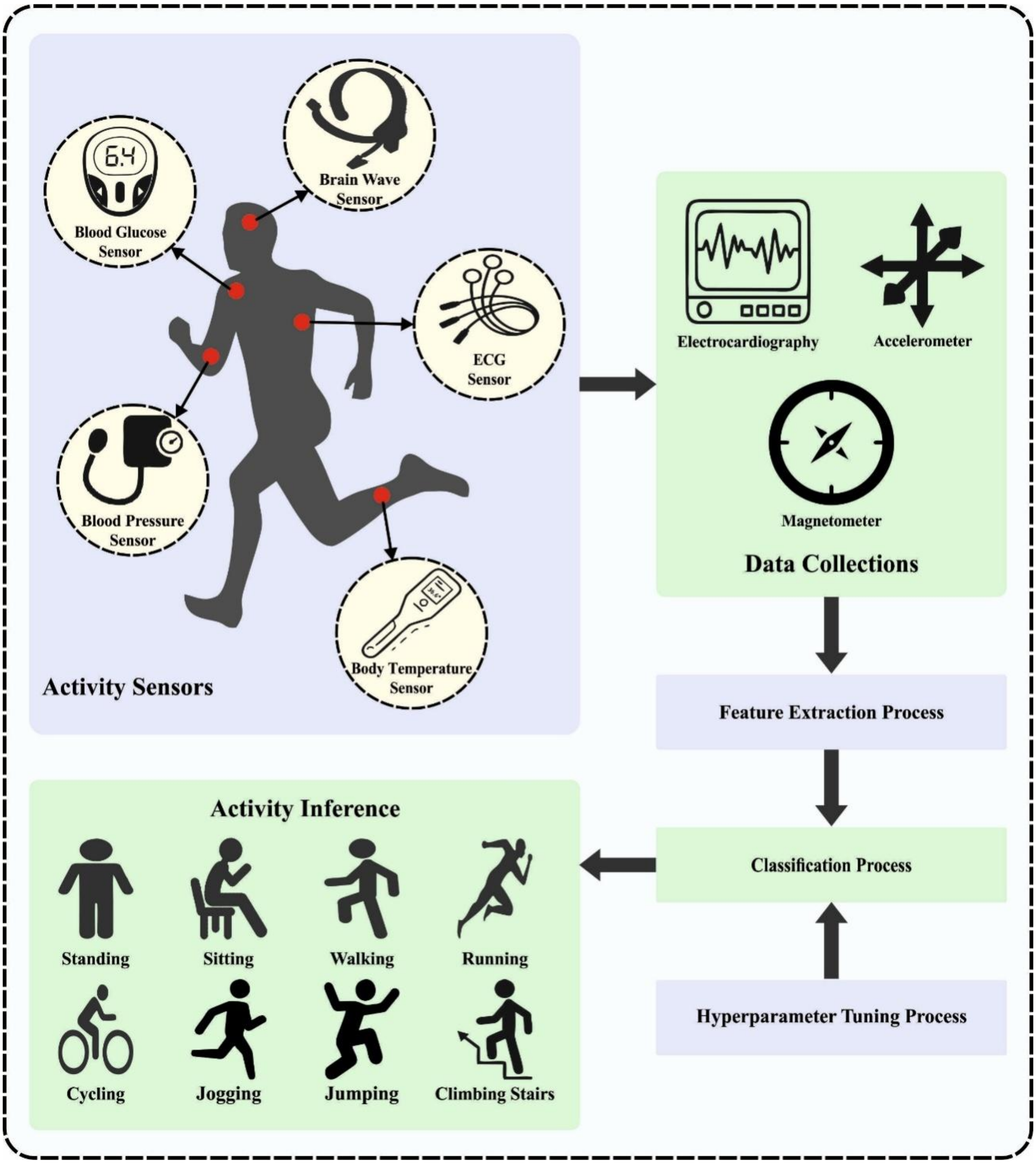

Figure 1: Overview of HAR

Several challenges in HAR arise, for example, biometric user identification can utilize HAR identification approaches for capturing the people activity patterns of an individual such as motion capture signs [5], as bio-metric is a science in which effective to identify person, relevant to their individual features for accessing devices without authorization is learned [6]. Now, the basic idea of bio-metric recognition primarily contains the physiological characteristics of a person [7]. Nevertheless, major problems regarding HAR and security are carried out by these physiological features that can be regarded as viable alternatives, working as a method for behavioral biometrics. At present, both technologies for processing sensor data and sensor technology is achieved a great deal [8]. Excellent performance of deep learning (DL) in image and speech recognition is supported for implementing DL in sensor based HAR, and authors demonstrated to be effective performance could be attained using DL method [9]. A 3-axis accelerometer is generally employed sensor in sensor based HAR. Therefore, incorporating the features of embedded and HAR technologies to study the application of HAR methods compared to convolutional neural networks (CNNs) on embedded platforms comprises a few real-world values to develop AI marginalization [10].

Basak et al. [11] present a DSwarm-Net framework, which utilizes swarm intellectual-based metaheuristic for HAR and DL method that uses 3D skeleton data for classifying the activities. After the method training, extraction of the deep factors is performed from the network’s pre-final layer. Also, the optimization of the attained feature representation is achieved by a nature-motivated metaheuristic, namely the ALO. Gao et al. [12] suggest a novel multi-branch CNN that employs a selective kernel mechanism for HAR. This suggested method utilizes an attention idea for performing the selection of kernel amongst several branches with diverse RFs in HAR. In [13], an approach that implemented Long Recurrent Convolutional Networks (LRCN) and

Convolutional LSTM (CLSTM) models for HAR in videos is presented. This approach utilized both LSTM and CNN techniques. These models can be utilized with Tensor Flow CNN chosen for LSTM and picture data networks for serial data.

The authors [14] presented a novel DL method for HAR by employing inertial sensors. Firstly, a portable device platform is constructed along with six inertial sensor units. Later, a DL approach namely the BiGRU-Inception (BiGRU-I) is constructed comprising 1 softmax, 3 Inception, and 1 Global Average Pooling (GAP) layer. Wensel et al. [15] proposed a dual transformer neural network called the Recurrent Transformer (ReT), an approach implemented for making anticipations on data serials, and the Vision Transformer (ViT), a transformer utilized for optimization in order to extract salient factors from the imageries. An elaborated model comparison with the contemporary RNN and CNN based HAR method is performed. Tasnim and Baek [16] present a novel hierarchy-based technique for selecting keyframes and adopting a 3D-CNN method for human activity categorization. This presented method employed the raw serial behalf of producing the dynamic imageries.

This study designs an improved metaheuristics with machine learning driven human activity recognition approach (IMML-HARA). The IMML-HARA technique focuses on the recognition and classification of human activities. In the presented IMML-HARA technique, Improved Chicken Swarm Optimization (ICSO) Algorithm for electing an optimal set of features. Moreover, the IMML-HARA technique offers the design of radial basis function (RBF) classifier for the identification of human activities into distinct activities. The performance validation of the IMML-HARA approach is tested on two benchmark HAR databases.

2. The Proposed Model

In the study, we have presented the IMML-HARA technique focuses on the recognition and classification of human activities. In the presented IMML-HARA technique, ICSO based feature selection and RBF using classification.

2.1 Feature selection using ICSO model

At this stage, ICSO algorithm for electing an optimal set of features.The traditional CSO technique considers the food source as a solution to the problem and the fitness values (FV) signify the quality of the food [17]. Individuals in the chicken flock are sorted according to theirFV, and the flock is split into different subgroups. Every subgroup was divided into 3 stages: roosters, hens and chicks, andN_r, N_h and N_c, are respectively the proportion of roosters, hens, and chicks.

In the search space, the rooster walks randomly and their location is updated, as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} * \left(1 + randn(0, \sigma^2)\right) \quad (1)$$

In Eq. (1),$x_{i,j}^{t}$ signifies the place of the i^{th}chickens at t^{th}iteration of j^{th} dimension search space. The individual with low FVs is chosen as the rooster. $randn(0,\sigma^2)$ denotes the uniformly distributed random integer. The computation of σ^2 is given below:

$$\sigma^2 = \begin{cases} 1, & f_i \leq f_k \\ exp\left(\dfrac{(f_k - f_i)}{|f_i + \varepsilon|}\right) & otherwise \end{cases} \quad (2)$$

The individual with best fitness is chosen as hen that moves following the rooster. The position of hen can be upgraded using the following expression:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S_1 * rand * \left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S_2 * rand * \left(x_{r2,j}^{t} - x_{i,j}^{t}\right) \quad (3)$$

In Eq. (3), $r1$ shows the individual rooster followed by i^{th}hens. The $r2$ is a random rooster or hen $(r2 \neq r1$. Evaluate the weights $S_1 = exp\left(\frac{f_i - f_{r1}}{abs\,(f_i) + \varepsilon}\right)$ and $S_2 = exp(f_{r2} - f_i)$. f_{r1} and f_{r2} are FV analogous to $r1$ and $r2$, correspondingly.

Excepting the roosters and hens, other individuals are determined by the chicks. The chick follows the movement of its mother, and the location of chick was updated, as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + PL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \quad (4)$$

In Eq. (4), $FL \in [0,2], x_{m,j}^{t}$ indicates the location of the i^{th}mother chicks.

The hierarchical structures of the CSO technique were determined by FVs that is simple but suffer from the drawback of the lower diversity of individual from the hierarchy. At first, the method freely splits the random population initialized into $0.5N_r$ group. Within every group, roosters (n_r), hens (n) and chicks (n) are carefully chosen according to the size of FVs. Next, various niches are presented from the group, with L as the radius and the hens as the center. Lastly, the hen summons chicks within the niche.

$$L = \frac{\alpha(ub_d - lb_d)}{N_h} \quad (5)$$

$$x_C = x_h + (2rand - 1) * L \quad (6)$$

Where α refers to the radius factor of niche. ub_d and lb_d denotes the upper and lower boundaries of the D-dimension space.

2.2 Classification of RBF method

Finally, anRBF classification for the identification of human activities into distinct activities.The fundamental structure of RBF comprises three different layers [18]. The initial layer is in charge of taking input patterns and presenting connection among the network and its environment. The next layer that is only hidden state from the network, employs the RBF. The correlation between the input as well as output of networks can be defined as follows:

$$y_{ij}(x) = \sum_{j=1}^{K} \sum_{i=1}^{N} W_{mj}\ G(\|x_i - c_m\|) + b + e_{ij} \quad (7)$$

In Eq. (7), $m = 1,2,\dots,M$, $M+1$ specifies the amount of hidden neurons' add bias (b), x_K specifies the input patterns, y_{ij} indicates the i,j-th component of resultant matrix $Y_{N,K}$, N shows the count of data (observations); K represents the amount of outputs. If M is specified as the RBF center (the amount of hidden neurons), w mj refers to m,j-th component of the weight matrices $W_{M+1,K}$, c_m symbolizes the square centroid matrices $M \times M$, and $E_{N,K}$ shows the matrix of residuals of e_{ij}, consequently $Y_{N,K}(x) = d_{ij}$ considers the process output:

$$d_{ij} = GiV \quad (8)$$

An unbiased estimator for the weight, represented as W, is presented for the well-established outcomes of multi-variate ordinary least square:

$$W = (\acute{G}G)^{-1}\acute{G}Y \quad (9)$$

In Eq. (9), G can be attained by the distance $\|x_i - c_m\|$ through the RBF in Gaussian form:

$$G(\|xi - c_m = exp(-\|x_i - c_m\|^2) \quad (10)$$

Euclidean distance $\|x_{NM} - c_{MM}\|$ was substituted with Mahalanobis distance attained by the following expression:

$$r = \sqrt{(x_i - c_m)\sum^{-1}(x_i - c_m)} \quad (11)$$

In Eq. (11), Σ indicates the global covariance matrix for the input pattern:

$$G = \begin{bmatrix} G(x1 - c_1) & G(x_1 - c_2) & \dots & G(x1 - c_m) \\ G(x_2 - c_1) & G(x_2 - c_2) & \dots & G(x_2 - c_m) \\ \vdots & \vdots & \ddots & \vdots \\ G(x_N - c_1) & G(x_N - c_2) & \dots & G(x_N - c_m) \end{bmatrix} \quad (12)$$

The distance between χ_j and c_i, and the RBF is a function that can monotonically decrease or increase its response dependent upon the distance from the fixed point called as center or centroid as:

$$\varphi(r) = exp(-r^2) \quad (13)$$

3. Result Analysis

The IMML-HARAmethodology is examined on two databases namely UCI HAR database and USC HAD database. The UCI HAR databaseincludes 10299 instances with 6 classes. Besides, the USC HAD database comprises 420 samples with six classes.

The recognition outcome of the IMML-HARAmethod is examined on the UCI HAR database as represented in Table 1 and Fig. 2. The resultimplied that the IMML-HARA approach reaches effectual outcomes on 6 classes. On 70% TRP, the IMML-HARA approach resulted in average $accu_y$ of 96.41%, $sens_y$ of 89.10%, $spec_y$ of 97.83%, F_{score} of 89.21%, and MCC of 87.07%. Afterwards, on 30% TSP, the IMML-HARA system resulted in average $accu_y$ of 96.19%, $sens_y$ of 88.49%, $spec_y$ of 97.71%, F_{score} of 88.53%, and MCC of 86.27%.

Table 1: Recognition outcome of IMML-HARA approach on UCI HAR database

UCI HAR Database					
Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	**MCC**
Training Phase (70%)					
Walking	96.53	91.05	97.63	89.79	87.71
Walking Upstairs (WU)	96.35	84.55	98.43	87.42	85.36
Walking Downstairs (WD)	97.31	89.66	98.52	90.11	88.56
Sitting (Si)	96.50	88.34	98.14	89.39	87.30
Standing (St)	95.73	92.16	96.56	89.09	86.51
Lying (Sl)	96.02	88.82	97.71	89.44	86.99
Average	**96.41**	**89.10**	**97.83**	**89.21**	**87.07**
Testing Phase (30%)					
Walking	96.02	88.74	97.48	88.14	85.75
Walking Upstairs (WU)	95.92	82.94	98.21	85.91	83.60
Walking Downstairs (WD)	97.28	90.00	98.43	90.00	88.43
Sitting (Si)	96.05	88.19	97.85	89.28	86.87
Standing (St)	95.73	91.68	96.59	88.26	85.74
Lying (Sl)	96.15	89.39	97.69	89.63	87.26
Average	**96.19**	**88.49**	**97.71**	**88.53**	**86.27**

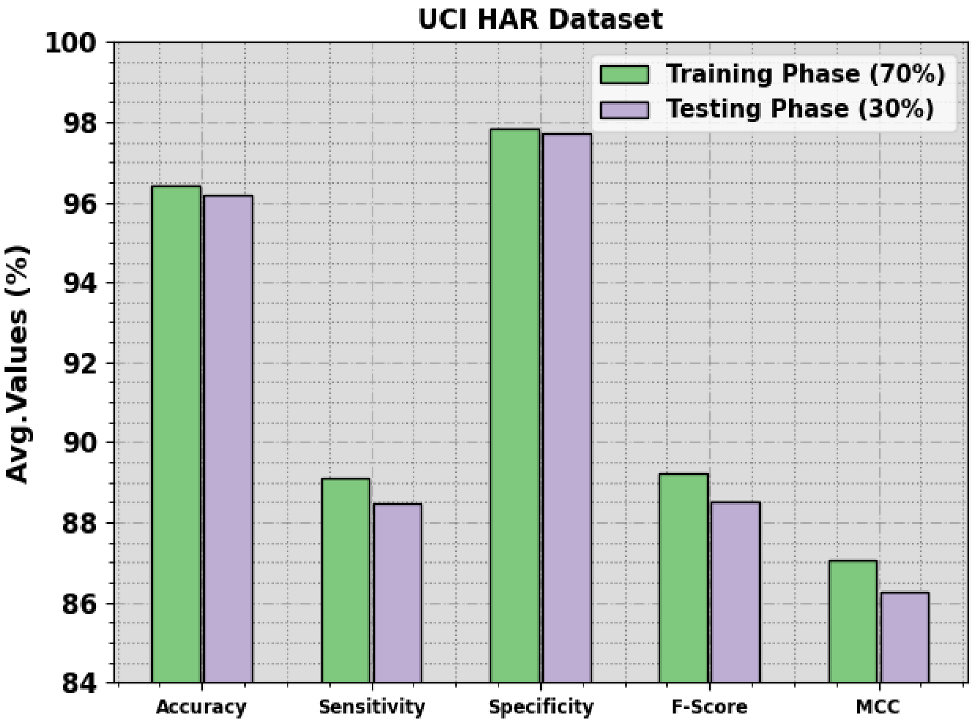

Figure 2: Average of IMML-HARA approach on UCI HAR database

The recognition result of the IMML-HARA approach is examined on the USC HAD database as depicted in Table 2 and Fig. 3. The outcome stated that the IMML-HARA approach reaches effective outcomes on six classes. On 70% TRP, the IMML-HARAsystem resulted in average $accu_y$ of 96.37%, $sens_y$ of 89.02%, $spec_y$ of 97.84%, F_{score} of 88.80%, and MCC of 86.84%. Furthermore, on 30% TSP, the IMML-HARA approach resulted in average $accu_y$ of 96.03%, $sens_y$ of 87.94%, $spec_y$ of 97.62%, F_{score} of 87.75%, and MCC of 85.47%.

Table 2: Recognition outcome of IMML-HARA approach on USC HAD database

USC HAD Database					
Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	**MCC**
Training Phase (70%)					
Walking Left (WL)	96.94	97.78	96.79	90.72	89.23
Walking Downstairs (WD)	97.96	94.44	98.75	94.44	93.19
Running Forward (RF)	94.56	88.64	95.60	82.98	79.99
Standing (St)	95.24	82.35	97.94	85.71	82.96
Sleeping (Sl)	95.24	76.60	98.79	83.72	81.44
Elevating Up (EU)	98.30	94.34	99.17	95.24	94.21
Average	**96.37**	**89.02**	**97.84**	**88.80**	**86.84**
Testing Phase (30%)					
Walking Left (WL)	98.41	96.00	99.01	96.00	95.01
Walking Downstairs (WD)	95.24	81.25	97.27	81.25	78.52
Running Forward (RF)	93.65	80.77	97.00	84.00	80.15
Standing (St)	96.83	84.21	99.07	88.89	87.23
Sleeping (Sl)	95.24	91.30	96.12	87.50	84.68
Elevating Up (EU)	96.83	94.12	97.25	88.89	87.23
Average	**96.03**	**87.94**	**97.62**	**87.75**	**85.47**

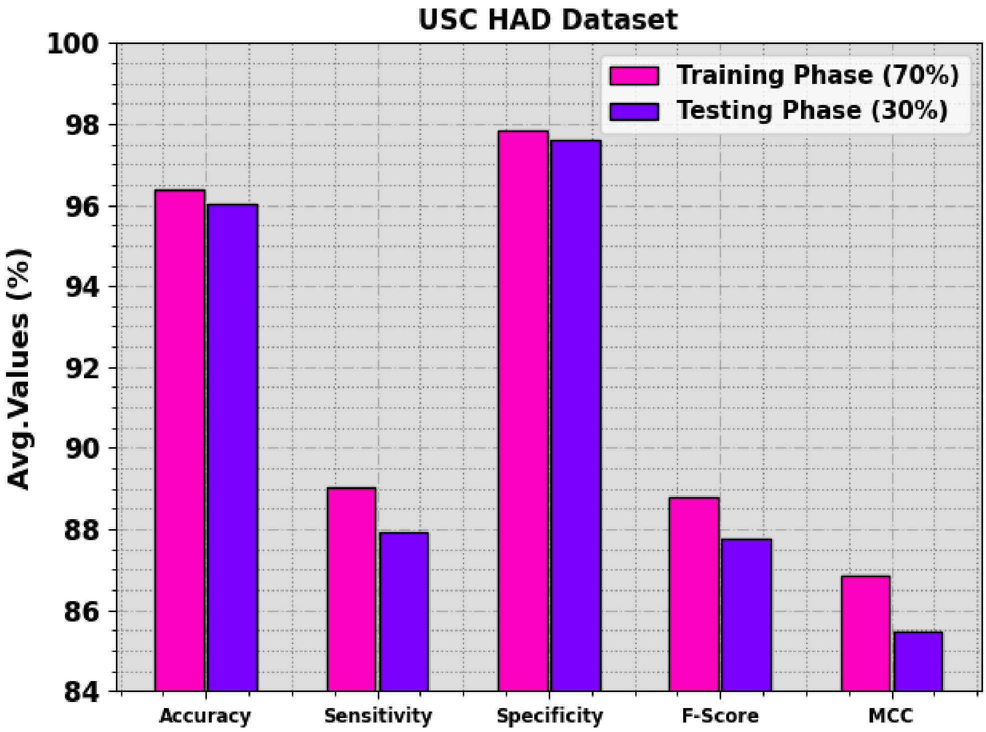

Figure 3: Average of IMML-HARA approach on USC HAD database

The comparative statement of the IMML-HARA methodology with recent DL systems are established in Table 3.

Table 3: $Accu_y$ outcome of IMML-HARA approach with other systems on two databases

Methods	UCI HAR Database	USC HAD Database
CNN	89.45	85.26
LSTM	89.67	83.08
CNN-LSTM	87.33	87.41
Conv. LSTM	90.85	84.86
RHAR-EODELM	95.95	95.92
The Proposed Model	96.41	96.37

In Fig. 4, the activity recognition analysis of the IMML-HARAmethod with existing systems on the UCI HAR database is reported. The result inferred that the IMML-HARA approach produces higher $accu_y$ of 96.41%. Also, the CNN, LSTM, CNN-LSTM, Conv. LSTM, and RHAR-EODELM methods accomplish lesser$accu_y$ values of 89.45%, 89.67%, 87.33%, 90.85%, and 95.95% correspondingly.

In Fig. 5, the activity recognition outcome of the IMML-HARAmethodology with existing approaches on the USC HAD database is reported. The outcome signified that the IMML-HARA method produces improved$accu_y$ of 96.37%. In the meantime, the CNN, LSTM, CNN-LSTM, Conv. LSTM, and RHAR-EODELM approaches gained reduced $accu_y$ values of 85.26%, 83.08%, 87.41%, 84.86%, and 95.92% respectively.

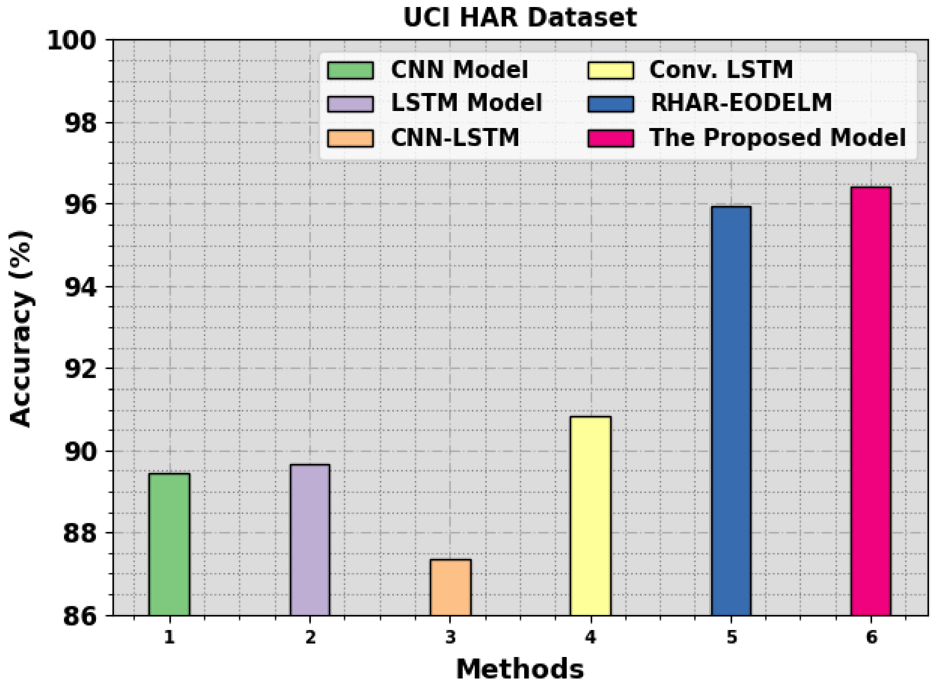

Figure 4: $Accu_y$ outcome of IMML-HARA approach on UCI HAR database

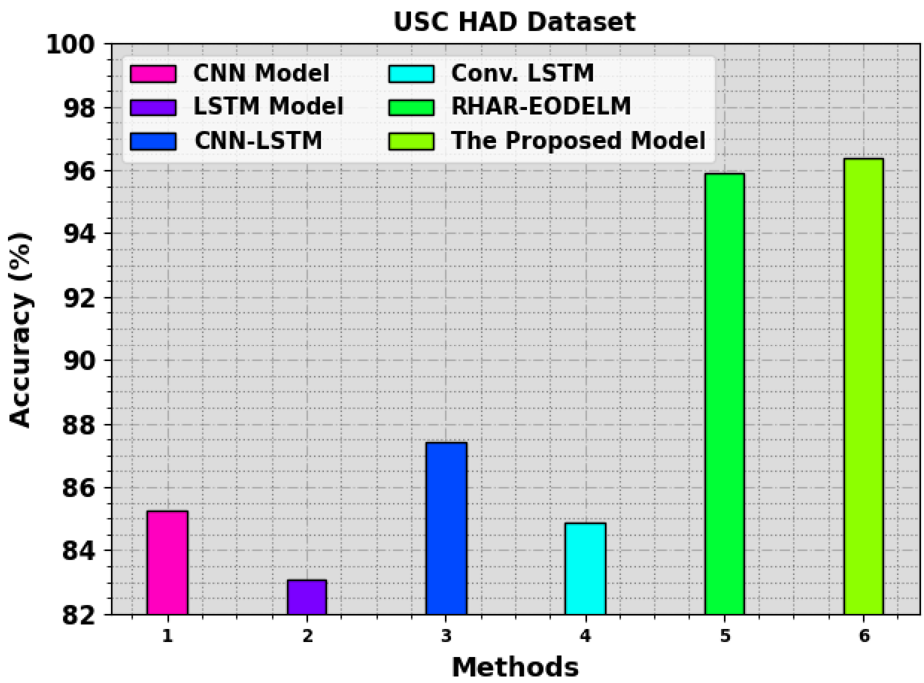

Figure 5: $Accu_y$ outcome of IMML-HARA approach on USC HAD database

4. Conclusion

In the study, we have presented the IMML-HARA technique focuses on the recognition and classification of human activities. In the presented IMML-HARA technique, ICSO Algorithm for electing an optimal set of features. Moreover, the IMML-HARA technique offers the design of RBF classifier for the identification of human activities into distinct activities. The performance validation of the IMML-HARA technique is tested on two benchmark HAR datasets.

References

[1] Durga, K.M.L., Jyotsna, P. and Kumar, G.K., 2022, April. A Deep Learning based Human Activity Recognition Model using Long Short Term Memory Networks. In *2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)* (pp. 1371-1376). IEEE.

[2] Nair, R., Ragab, M., Mujallid, O.A., Mohammad, K.A., Mansour, R.F. and Viju, G.K., 2022. Impact of wireless sensor data mining with hybrid deep learning

for human activity recognition. *Wireless Communications and Mobile Computing*, *2022*.

[3] Oluwalade, B., Neela, S., Wawira, J., Adejumo, T. and Purkayastha, S., 2021. Human activity recognition using deep learning models on smartphones and smartwatches sensor data. *arXiv preprint arXiv:2103.03836*.

[4] Gu, F., Chung, M.H., Chignell, M., Valaee, S., Zhou, B. and Liu, X., 2021. A survey on deep learning for human activity recognition. *ACM Computing Surveys (CSUR)*, *54*(8), pp.1-34.

[5] Mazzia, V., Angarano, S., Salvetti, F., Angelini, F. and Chiaberge, M., 2022. Action Transformer: A self-attention model for short-time pose-based human action recognition. *Pattern Recognition*, *124*, p.108487.

[6] Wan, S., Qi, L., Xu, X., Tong, C. and Gu, Z., 2020. Deep learning models for real-time human activity recognition with smartphones. *Mobile Networks and Applications*, *25*(2), pp.743-755.

[7] Zhang, S., Li, Y., Zhang, S., Shahabi, F., Xia, S., Deng, Y. and Alshurafa, N., 2022. Deep learning in human activity recognition with wearable sensors: A review on advances. *Sensors*, *22*(4), p.1476.

[8] Chen, K., Zhang, D., Yao, L., Guo, B., Yu, Z. and Liu, Y., 2021. Deep learning for sensor-based human activity recognition: Overview, challenges, and opportunities. *ACM Computing Surveys (CSUR)*, *54*(4), pp.1-40.

[9] Mekruksavanich, S. and Jitpattanakul, A., 2022. Multimodal Wearable Sensing for Sport-Related Activity Recognition Using Deep Learning Networks. *Journal of Advances in Information Technology Vol*, *13*(2).

[10] Zhou, X., Liang, W., Kevin, I., Wang, K., Wang, H., Yang, L.T. and Jin, Q., 2020. Deep-learning-enhanced human activity recognition for Internet of healthcare things. *IEEE Internet of Things Journal*, *7*(7), pp.6429-6438.

[11] Basak, H., Kundu, R., Singh, P.K., Ijaz, M.F., Woźniak, M. and Sarkar, R., 2022. A union of deep learning and swarm-based optimization for 3D human action recognition. *Scientific Reports*, *12*(1), p.5494.

[12] Gao, W., Zhang, L., Huang, W., Min, F., He, J. and Song, A., 2021. Deep neural networks for sensor-based human activity recognition using selective kernel convolution. *IEEE Transactions on Instrumentation and Measurement*, *70*, pp.1-13.

[13] Ganta, S., Desu, D.S., Golla, A. and Kumar, M.A., 2023, January. Human Action Recognition using Computer Vision and Deep Learning Techniques. In *2023 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA)* (pp. 1-5). IEEE.

[14] Tong, L., Ma, H., Lin, Q., He, J. and Peng, L., 2022. A novel deep learning Bi-GRU-I model for real-time human activity recognition using inertial sensors. *IEEE Sensors Journal*, *22*(6), pp.6164-6174.

[15] Wensel, J., Ullah, H. and Munir, A., 2023. ViT-ReT: Vision and Recurrent Transformer Neural Networks for Human Activity Recognition in Videos. *IEEE Access*.

[16] Tasnim, N. and Baek, J.H., 2022. Deep Learning-Based Human Action Recognition with Key-Frames Sampling Using Ranking Methods. *Applied Sciences*, *12*(9), p.4165.

[17] Zhang, Y., Wang, L. and Zhao, J., 2023. PECSO: An Improved Chicken Swarm Optimization Algorithm with Performance-Enhanced Strategy and Its Application. *Biomimetics*, *8*(4), p.355.

[18] Khan, S., 2023. Short-Term Electricity Load Forecasting Using a New Intelligence-Based Application. *Sustainability*, *15*(16), p.12311.