# Revolutionizing Human Activity Recognition in Healthcare: Harnessing Red Deer for Feature Selection and Focal Loss-Based MLP for Classification


1st Nitesh Bharot
*Data Science Institute*
*University of Galway*
Galway, Ireland
nitesh.bharot@universityofgalway.ie

2nd John G. Breslin
*Data Science Institute*
*University of Galway*
Galway, Ireland
john.breslin@universityofgalway.ie

3rd Priyanka Verma
*Electronics and Computer Engineering*
*University of Limerick*
Limerick, Ireland
priyanka.verma@ul.ie



***Abstract*—Internet of Things (IoT) and Artificial Intelligence (AI) advancements have notably improved Human Activity Recognition (HAR) for healthcare, using sensor-based wearables to monitor daily and health activities. However, accuracy challenges arise in detecting specific movements like walking upstairs and walking downstairs due to limited training data and complex behaviours. Traditional HAR methods depend on large, accurately labelled datasets, but practical implementations often suffer from reduced accuracy when test subject data is scarce. Additionally, identifying key features for precise classification remains a critical task. In response, we present the Advanced Human Activity Recognition (AHAR) methodology. AHAR employs a bio-inspired feature selection technique to create an enriched feature-selected dataset. This dataset is then subjected to classification using the Multi-Layered Perceptron (MLP) model with focal_loss, which helps focus on weakly labelled data as well. When evaluated on the UCI-HAR dataset, our proposed methodology demonstrates significantly improved recognition accuracy by 2% compared to prevailing state-of-the-art techniques, thus providing a robust and reliant HAR system.**



***Index Terms*—Healthcare, HAR, UCI-HAR, Activity recognition, Artificial intelligence**


## I. Introduction

Human Activity Recognition (HAR) has appeared as a pivotal technology in the landscape of healthcare, leveraging the capabilities of automated systems to detect and classify human activities. This innovation holds particular significance in applications aimed at enhancing health outcomes, such as monitoring elderly individuals, supervising exercise routines, and facilitating rehabilitation processes [1]–[3]. The utility of HAR in these domains can range from predicting potential health issues among the elderly based on their daily activities to offering tailored exercise recommendations and aiding in the recovery of post-operative patients by providing detailed activity analyses. These applications underscore the potential of HAR to contribute to preventive health measures and personalized healthcare solutions significantly [4].

HAR methodologies can generally be categorized into two distinct types: vision-based HAR [5] and sensor-based wearable HAR [6]. Vision-based HAR, while cost-effective and straightforward to put into place, often struggles with issues related to environmental variables such as lighting, camera angles, and subject overlap, which can adversely affect the accuracy of activity classification [7]. Whereas, sensor-based wearable HAR, which is not susceptible to these environmental noises, offers a more reliable alternative and has thus captured the interest of the research community.

In sensor-based wearable HAR systems [8], data is collected from various motion sensors—like accelerometers, gyroscopes, and magnetometers—strategically placed on different parts of the participant's body [9], [10]. The data is preprocessed to eliminate noise and normalize the inputs, after which feature extraction and the classification of activities into categories such as walking, running, or stair climbing is performed. Historically, the development of these systems has involved both traditional Machine Learning (ML) techniques and more recent neural network approaches to handle the feature extraction and classification tasks [11], [12]. Despite the advancements, challenges remain, particularly with manual feature extraction which relies heavily on the selector's expertise and is both time-consuming and computationally expensive. Moreover, detecting certain movements, such as walking upstairs and downstairs, presents accuracy challenges due to the scarcity of training data and the complexity of the behaviours involved. While traditional methods for HAR rely on extensive a ing with limited test subject data.

Thus, this paper introduces the Advanced Human Activity Recognition (AHAR) methodology as a solution to handle the above challenges in HAR systems. AHAR utilizes a bioinspired approach for feature selection using red deer optimization, enhancing the dataset's quality. Also, using a Multi-Layer Perceptron (MLP) model with focal_loss for


This publication has received support from SFI under Grant 12/RC/2289-P2 (Insight).

classification purposes enables the model to better handle weakly labelled data. By focusing on enhancing the accuracy and efficiency of these systems, we aim to contribute to their practical applicability in real-world healthcare settings.

The remainder of this paper is structured as follows: Section II reviews the literature related to our topic, while Section III outlines our proposed methodology. In Section IV, we analyze the outcomes of our approach, and Section V offers conclusions and suggests path for future research.

## II. Related Work

This section reviews the current studies focusing on sensor-equipped wearable HAR systems that employ methods of feature extraction and classification. Methods based on feature extraction are a popular approach in sensor-based wearable HAR. These methods typically involve extracting relevant features from the sensor data and then using these features as input to a classification algorithm.

Li et al. [13] developed PSDRNN and tri-PSDRNN, integrating power spectral density (PSD) with deep recurrent neural networks (DRNNs) for enhanced human activity recognition on smartphones. These methods efficiently improve feature representation, surpass existing models in recognizing complex activities, and reduce computational demands, showing promise for resource-constrained devices. Whereas, Ahmed et al. [14] developed an innovative HAR system using smartphone sensors, combining power spectrum and linear discriminant analysis for efficient feature extraction and noise reduction. Tested on UCI-HAR and DU-MD datasets, their model outperformed traditional methods, suggesting benefits for applications like healthcare and security.

Addressing challenges related to sensor placement and orientation, reference [15] introduced coordinate transformation and principal component analysis combined with an online SVM to recognize activities with smartphones placed in various locations such as pants' pockets, shirt's pockets, and backpacks. Author in [16] proposed a novel windowing method aimed at reducing power consumption while efficiently segmenting data from a 3-axis accelerometer. They focused on extracting basic features such as mean, standard deviation, and the number of peaks to streamline HAR processes.

Yi et al. [17] propose a new method in HAR using a statistical feature extraction technique to simplify initial classification, thereby cutting computational needs for wearable devices. This system utilizes an optimized random forest and pruned, quantized convolutional neural networks, achieving high accuracy with reduced resource consumption. Concurrently, Javed et al. [18] introduce an explainable AI (XAI) approach to HAR within smart homes, focusing on healthcare and fitness applications. Their XAI-HAR system uses a novel feature selection method that sorts data into physical and statistical key features, improving outlier handling and class variance. It employs various models, including RF, CNN, and CNN-LSTM, with RF showing the highest effectiveness.

Despite these advancements, the reliance on manual feature extraction poses limitations due to its dependency on human expertise and the high computational cost associated with processing large feature sets. This highlights the ongoing challenge in HAR: balancing the accuracy achieved through sophisticated feature engineering with the practical constraints of computational resources and real-world applicability.

Deep et. al. [23] introduced a novel approach using deep learning (DL) methods, specifically a hybrid CNN-LSTM architecture. Tested on the UCI HAR dataset with accelerometer and gyroscope data, our method surpasses recent results of pure LSTM and bidirectional LSTM networks, demonstrating enhanced effectiveness in HAR tasks. Khan et. al. [22] introduced an attention-based multi-head model for HAR. This framework incorporates three lightweight convolutional heads, each employing one-dimensional CNNs to extract features from sensor data. Attention mechanisms enhance CNN's ability to automatically prioritize significant features while disregarding less relevant ones.

Integrating data from diverse sensors enables comprehensive monitoring of daily activities, but identifying key features and managing sensor weights remain challenging. [21] gives UC Fusion, which combines unique and common sensor features and addresses data heterogeneity through segmentation and transformation. Results demonstrate the effectiveness of the proposed approach in recognition of HAR tasks.

## III. Proposed Methodology

This section introduces the Advanced Human Activity Recognition (AHAR) technique, aimed at accurately identifying human activities. AHAR, depicted in Fig. 1, comprises two primary phases: the data modelling phase and the classification phase. Each phase integrates various techniques to comprehend the data better, ultimately facilitating accurate classification of activity labels. The stages of AHAR unfold as follows:

Initially, data from diverse sensors is combined to form sensor data, which is then preprocessed in the data modeling phase. After preprocessing, the data undergoes Red Deer Optimization (RDO) [19] based feature selection to identify crucial features for accurately identifying activity labels. These selected features generate feature-selected data, which is then partitioned into training and testing datasets. The training data is fed into the classification phase using the MLP model, which employs focal_loss and the Adam optimizer. To ensure robustness, the MLP model is validated with 10% of the training data and then tested on the testing data to assess its performance.

### A. Data Modeling Phase

This primary phase of AHAR focuses on preprocessing the sensor data using standard techniques, including standard scaling, mean imputation, and isolation forest. Following preprocessing, the data is subjected to RDO-based FS to get the most important features, resulting in the creation of feature-selected data.

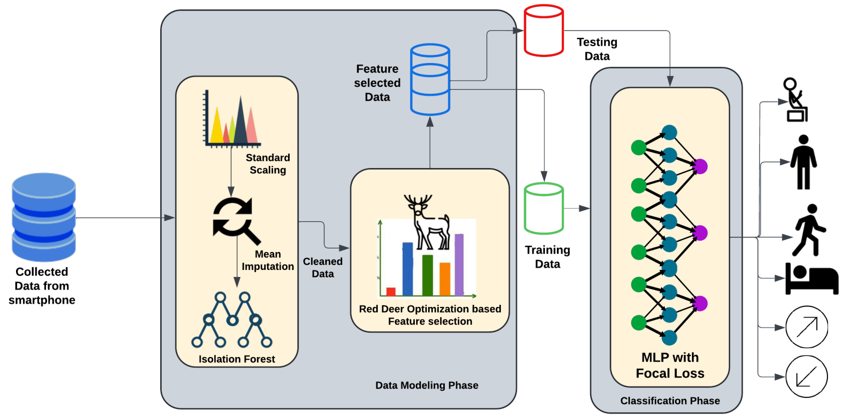


Fig. 1. Proposed AHAR methodology

*1) Standard scaling:* AHAR utilizes a standard scaler as a preprocessing technique. Standard scaler modifies data by removing the mean and dividing by the standard deviation, thereby standardizing each feature to have a mean of zero and a standard deviation of one. The formula for a standard scaler is:

$$X_{new} = \frac{X - \mu}{\sigma} \tag{1}$$

Where: $X_{new}$ represents the standardized value, X denotes the original value, $\mu$ is the feature's mean, and $\sigma$ is the feature's standard deviation.

*2) Mean imputation:* Mean imputation is a widely used method for addressing missing data, where missing entries are replaced with the mean of the observed values for a particular feature. This approach involves calculating the average value of the feature throughout the dataset and using it to substitute the missing values. It maintains the general distribution of the data and avoids introducing bias, provided that the missing values are missing completely at random.

*3) Isolation forest:* Isolation forest adopts a unique approach by explicitly targeting anomalies rather than characterizing normal data points. It leverages decision trees for this purpose, where partitions are formed by randomly selecting features and splitting values. Given that outliers are typically rare and distant from regular observations in feature space, they necessitate fewer splits to isolate them closer to the tree's root. Hence, anomalies are identified with shorter average path lengths, requiring fewer partitions compared to normal points. This methodology aligns with the inherent nature of outliers, making isolation forests effective in anomaly detection tasks. Like other methods used to detect outliers, a score to identify anomalies is necessary for making decisions. In the context of an isolation forest, this score is defined as follows:

$$s(o, n) = 2^{-\frac{E(P(o))}{A(n)}} \tag{2}$$

where $P(o)$ is the path length for observation $o$, $A(n)$ indicates the average path length from an unsuccessful search in a Binary Search Tree, and $n$ refers to the count of external nodes.

*4) Red deer optimization-based feature selection:* RDO is an evolutionary algorithm inspired by the mating and fighting behaviour of red deer, a common antelope found in various regions, including Europe and Asia. In a red deer group, comprised of stags (males) and hinds (females), a stag is chosen as the leader responsible for mating and caring for the hinds in the group, known as a harem. Stags compete for leadership by roaring loudly, with the one producing the highest-pitched roars often becoming the commander. This behaviour ensures the production of offspring with increased fitness across generations. RDO, proposed by Fathollahi-Fard et al. [19], mimics this behaviour to optimize solutions.

RDO for feature selection process, as indicated by step 2 of Algorithm 1 begins by initializing the population of red deer, which includes both stags (males) and hinds (females), along with defining the maximum number of generations for the optimization process. An initial population is generated, where each deer represents a potential solution vector, with a binary variable indicating feature selection. The population is then divided into stags and hinds. A random stag is chosen as the commander. During each iteration, the fitness of each stag is evaluated based on its feature selection accuracy and the proportion of features selected. The fitness function combines these aspects, assigning higher fitness to solutions with better accuracy and fewer features selected. If a neighboring deer has a better fitness score, the current stag is replaced. The position of each deer is updated based on random values and the defined bounds of the search space. The best stag becomes the new commander and mates with hinds to generate offspring, introducing new solutions into the population. There is also a probability of stags fighting, where the winner replaces the current commander if it has better fitness. The algorithm continues until the maximum number of generations is reached or the optimal solution is found. The best solution represents the optimal set of features for the given dataset. Utilizing RDO, the number of features in the UCI-HAR (selected for

**Algorithm 1** Proposed Methodology

**Input:** Sensor Data $S_d$
**Output:** Classifier $C_f$

Data Modeling Phase

1: Apply Data Preprocessing;
$X = S_d.iloc[:, : -1]$
$y = S_d.iloc[:, -1]$
$X = StandardScalar().fit\_transform(X)$
$X.fill\_na(Mean(X))$
$I_f = IsolationForest()$
$I_f$.fit(X,y)
Outlier = $I_f$.predict_Outliers
$D = (X, y), drop(Outliers, axis = 0)$

2: Apply Red Deer Optimization for Feature Selection
(i) Initialize the population size of $P$ (Red Deer population), $S_P$ (Stag population in $P$), $H_P$ (Hind population in $P$) & $max_g$ (maximum number of generations)
(ii) Generate initial Red Deer population $P$
(iii) Based on Equation:
$$E = \begin{cases} 1 & if\, v < 0.5 \\ 0 & \text{otherwise} \end{cases}$$
$v$ - Continuous Random Variable between 0 & 1
$E$ is a discrete format of the solution vector
Separate $P$ into $S_P$ & $H_P$
(iv) Choose a random deer form $S_P$ as Commander $r$
(v) While iteration $\leq max_g$ or $f_i$(r) = 1 do
- The fitness of each deer $r_i$ in $S_P$ is compared with fitness of its neighbouring deers $r_n$
If $f_i(r_n) > f_i(r_i)$
$r_i = r_n$ (Replace $r_i$ with $r_n$ in $S_p$
The fitness function is:
$f_i(r_i) = v_1 * (1 - a) + (1 - v_1) * \sigma$
$v_1$ = random value in the range [0,1]
$\sigma = \frac{no.of features selected}{Total no.of features}$
a = accuracy of random forest
$$r = \begin{cases} r_i + v_1 * ((B_U - B_L) * v_2) + B_L & if\, v_3 \geq 0.5 \\ r_i - v_1 * ((B_U - B_L) * v_2) + B_L & if\, v_3 < 0.5 \end{cases}$$
$B_U$ and $B_L$ are upper and lower bounds of search space (Max. number of attributes that can be selected and min. number that need to be selected)
$v_1, v_2, v_3 \in [0, 1]$
- The best deer from $S_P$ is selected as commander $(r)$
- $r$ will be meeting with 80% of hinds in $H_p$ to generate offsprings
offspring = $\frac{r+h_i}{2} + (B_U - B_L) * V_4$
$h_i \in H_P$, $V_4$ = Continuous random variable
- $r$ will fight with random stag from $S_P$ with the probability of 5%
- replace $r$ with winning stag
- Return $r$

3: $X = X.select(r, axis = 1)$

4: X_train, y_train, X_test, y_test = train_test_split $(X, y, test\_size = 0.3)$
where X represents the sample and y represents its target class

5: Classifier = MLP_Model()
Classifier.compile(optimize='adam', loss='categorical_focal_crossentropy', metrics = ['accuracy'])
Classifier.fit(X_train, y_train, epochs =200, validation_split=0.1)

6: y_pred = Classifier.predict(X_test)

7: Metrics(y_pred, y_test)

8: Return Classifier

TABLE I
MODEL DESCRIPTION

| Layer | Shape | Parameters |
|---|---|---|
| Dense | (None, 50) | 11600 |
| Dense_1 | (None, 100) | 5100 |
| Dense_2 | (None, 50) | 5050 |
| Dense_3 | (None, 6) | 306 |

evaluation) is reduced to 231 from the 561 actual features. These selected features help to better classify human activities with the proposed methodology.

### B. Classification Phase

In the secondary phase of AHAR, which is the classification phase, the feature-selected training data undergoes processing through a focal_loss based MLP classifier described in Table I. This classifier is designed to handle the task of accurately categorizing the data into respective activity labels. MLP offers distinct advantages over traditional ML techniques by excelling in capturing non-linear relationships between features and target variables, a capability essential for handling complex datasets where linear models fall short.

Additionally, by reducing the impact of well-classified examples, focal_loss allows the MLP model to concentrate more on learning from difficult instances, such as minority class samples or hard-to-distinguish examples in the case of multi-class classification. By prioritizing the correct classification of difficult instances, the model becomes more resilient to noise, outliers, and variations in the data distribution.

The focal_loss function $L_{\text{focal}}(p, y)$ is defined as:

$$L_{\text{focal}}(p, y) = -(1-p)^{\gamma} \cdot \log(p) \cdot y - p^{\gamma} \cdot \log(1-p) \cdot (1-y) \quad (3)$$

In this expression, $p$ denotes the predicted probability of the correct class, $y$ stands for the actual label, which can be either 0 or 1, and $\gamma$ is the focusing parameter that adjusts the extent to which easier examples are given less weight.

This formulation emphasizes hard-to-classify examples by down-weighting easy examples based on the value of $\gamma$. When $\gamma > 0$, the model reduces the loss associated with examples that are classified correctly (where $p \approx 0$ or $p \approx 1$), thereby enabling the model to concentrate more on examples that have been misclassified. As $\gamma$ increases, the effect of down-weighting becomes more pronounced, giving the loss function its focal nature.

TABLE II
MODEL PARAMETERS

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Total Parameters | 22056 | Trainable params | 22056 |
| Non-trainable params | 0 | Activation | relu |
| Learning_rate | 0.001 | Beta_1 | 0.9 |
| Beta_2 | 0.999 | Epsilon(for adam optimizer) | 1e-08 |
| Validation_split | 0.1 | Shuffle | true |
| $\gamma$ | 2 | | |

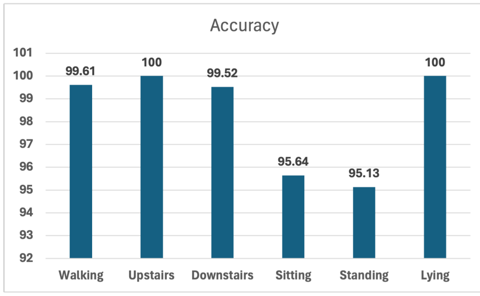


Fig. 2. Accuracy for individual class

## IV. EXPERIMENTAL RESULTS AND EVALUATION

### A. Experimental Setup

Experiments are carried out on a workstation featuring an Intel i5 CPU, 16 GB of RAM, and an NVIDIA 1650 GPU with 4GB of memory. The experiments utilize Python for coding within the TensorFlow framework for machine learning. The training setup includes 200 epochs, using the Adam optimizer with a learning rate of 0.001, and focal_loss is applied. Additional model parameters are outlined in Table II. The proposed method is evaluated using the UCI-HAR dataset [20], which is a well-known dataset for activity recognition. It gathers activity data from 30 volunteers wearing waist smartphones equipped with accelerometers, magnetometers, and gyroscope sensors. This dataset captures signals at a frequency of 50Hz while participants engage in six activities: standing, sitting, lying down, walking, walking downstairs, and walking upstairs. The UCI-HAR dataset contains 7352-2947 train-test samples which are combined, processed, and redistributed to training (7207) and testing(3090) samples.

### B. Results and Evaluation

Fig. 2 presents the individual accuracies achieved by the proposed approach in identifying the six different activities such as walking, walking upstairs, walking downstairs, sitting, standing, and lying. It can be observed that the proposed approach performs well, consistently achieving high accuracies ranging from 95% to 100% for each activity.

Further, to evaluate the proposed approach over a number of epochs, the model's performance generally improves, with fluctuations observed at certain epochs as observed in Fig. 3. Initially, at 10 epochs, the training accuracy stands at 96.44%, gradually increasing to 99.32% by the 75th epoch. The validation accuracy follows a similar trend, starting at 97.23% and peaking at 97.78% by the 75th epoch. However,

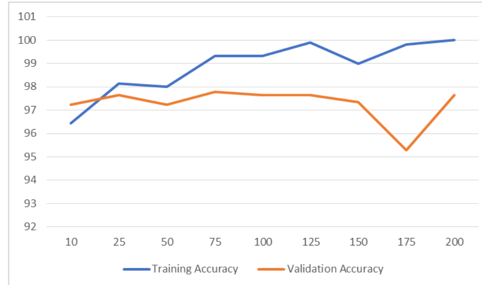


Fig. 3. AHAR training and validation accuracy

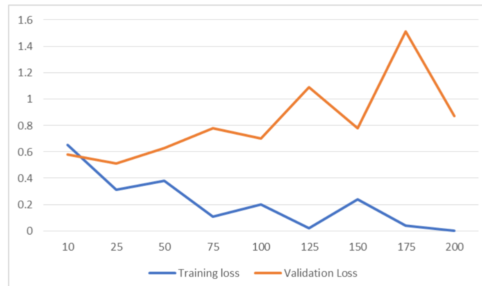


Fig. 4. AHAR training and validation loss

beyond this point, fluctuations occur, with slight decreases observed in validation accuracy at epochs 150 and 175. Despite these fluctuations, the model maintains high accuracy levels, reaching 100% training accuracy and 97.64% validation accuracy by the 200th epoch. These observations shed light on how the model learns and its capacity to adapt to new, unseen data, with the validation accuracy serving as a crucial metric for evaluating its performance.

Along with that, the training and validation loss values of a model across different epochs during the training process is depicted in Fig. 4. The training loss, which measures the error between predicted and actual values on the training dataset, exhibits fluctuations throughout epochs. Initially, at 10 epochs, the training loss is 0.65, decreasing to 0.11 by the 75th epoch before slightly increasing to 0.20 by the 100th epoch. Subsequently, the loss decreases significantly to 0.02 by the 125th epoch, fluctuating thereafter but remaining relatively low. Conversely, the validation loss, indicating the model's performance on unseen data, experiences fluctuations with increasing epochs. It begins at 0.58 and decreases to 0.51 by the 25th epoch, subsequently fluctuating before peaking at 1.51 by the 175th epoch. Notably, the validation loss decreases to 0.87 by the 200th epoch, indicating improved generalization despite fluctuations. Overall, monitoring both training and validation loss provides insights into the model's learning dynamics and generalization performance during training.

To show the effectiveness of the overall AHAR (RDO + MLP + focal_loss) model, it is compared with MLP + focal_loss and MLP only model for various metrics of different models. The accuracy metric, which indicates the overall correctness of the model's predictions, is highest for the "RDO

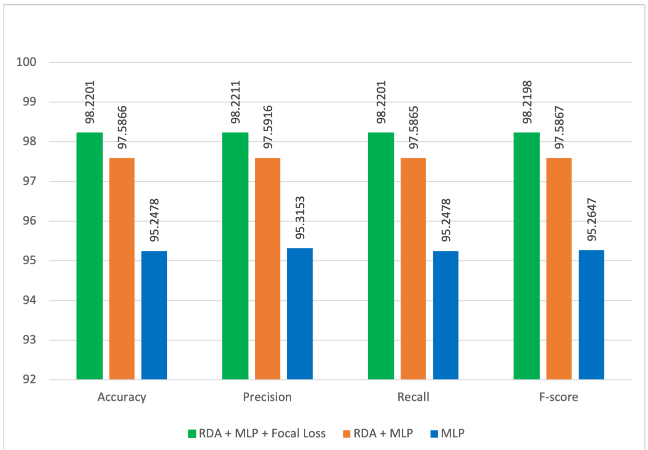


Fig. 5. AHAR comparative analysis

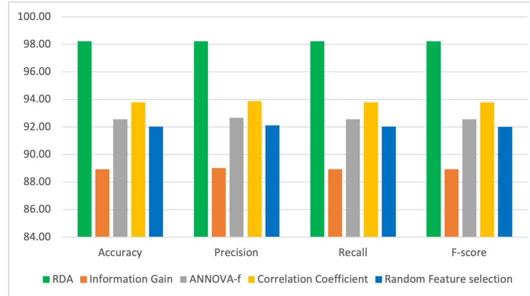


Fig. 6. RDO comparison with other feature selection techniques

TABLE III
AHAR COMPARISON WITH ML MODELS

| Model | Precision | Accuracy | F-score | MAE |
|---|---|---|---|---|
| **Proposed** | **98.2211** | **98.2201** | **98.2198** | **1.8770** |
| RF | 93.3975 | 93.0414 | 93.0277 | 8.0788 |
| DT | 83.2109 | 81.4324 | 80.8861 | 19.8914 |
| SVC | 96.4642 | 96.3680 | 96.3620 | 4.1752 |
| Perceptron | 94.2254 | 93.7542 | 93.7273 | 7.6714 |
| SGD | 94.6338 | 94.3992 | 94.4210 | 6.2112 |
| KNN | 89.5791 | 89.1039 | 89.0528 | 13.7814 |
| LR | 96.3253 | 96.3000 | 96.2977 | 4.1752 |

+ MLP + focal_loss" model (proposed AHAR) at 98.2201%. Additionally, AHAR achieves high precision, recall, and F-score values, all hovering around 98.22%. The "RDO + MLP" model follows closely with an accuracy of 97.5866% and similarly high precision, recall, and F-score values, around 97.59%. In comparison, the standalone "MLP" model exhibits slightly lower performance across all metrics, with an accuracy of 95.2478% and precision, recall, and F-score values around 95.32%. These numeric values offer deeper insights into the concise understanding and effectiveness of the AHAR methodology.

Moreover, to demonstrate the reason behind choosing red deer for feature selection, it is compared with other state-of-the-art feature selection techniques as shown in Fig. 6. The RDO method achieves the highest scores across all metrics, with an accuracy of 98.22% and precision, recall, and F-score values also at 98.22%. In contrast, information gain demonstrates lower performance with an accuracy of 88.93% and precision, recall, and F-score values around 89.03%. Similarly, ANOVA-f and correlation coefficient methods exhibit higher performance compared to information gain but lower than RDO, with accuracy scores of 92.57% and 93.79%, respectively. Random feature selection also shows moderate performance with an accuracy of 92.02% and precision, recall, and F-score values around 92.12%. These results highlight the effectiveness of the RDO feature selection method in improving classification performance, outperforming other methods considered in this evaluation. The advantages of RDO over other feature selection methods lie in its ability to balance exploration and exploitation within the search space effectively. By mimicking the social and competitive behaviors of red deer, RDO ensures a thorough search for optimal feature subsets, leading to higher accuracy and better overall performance. Its dynamic population update mechanism and fitness-based selection process allow it to adaptively refine solutions, outperforming static methods like information gain and ANOVA-f. Additionally, RDO's robust handling of diverse datasets makes it a versatile and powerful tool for feature selection in various ML tasks.

A comparison of AHAR with various ML models is also made and is shown in Table III. AHAR exhibits the highest performance across all metrics, with precision, accuracy, and F-score values at 98.2211%, 98.2201%, and 98.2198%, respectively. Among the other models, the Support Vector Classifier (SVC) also demonstrates strong performance, with precision, accuracy, and F-score values around 96.46%. Perceptron and Stochastic Gradient Descent (SGD) models achieve similar performance levels, with precision, accuracy, and F-score values above 94%. However, Decision Tree (DT) and K-Nearest Neighbors (KNN) models exhibit comparatively lower performance, with precision, accuracy, and F-score values ranging from 83% to 89%. The Logistic Regression (LR) model shows performance similar to SVC, with precision, accuracy, and F-score values around 96%. These results highlight the superior performance of the proposed AHAR model compared to traditional ML approaches across various metrics. Comparing Mean Absolute Error (MAE) values across different models, AHAR exhibits the lowest MAE at 1.8770, indicating superior prediction accuracy. SVC and LR show comparable MAE at 4.1752, while DT and KNN display the highest MAE values, signifying larger prediction errors.

A comparison of AHAR with various Deep Learning (DL) models is shown in Table IV. AHAR model achieves the highest scores across all metrics, with accuracy, precision, recall, and F-score values all at 98.22%. Among the DL models, UC Fusion [21] demonstrates the closest performance to the AHAR, with accuracy, precision, recall, and F-score values around 96.84%. Multi-head CNN [22] also shows strong performance, with scores around 95.38%. CNN-LSTM [23] and CNN [24] exhibit slightly lower performance, with scores

TABLE IV
AHAR COMPARISON WITH DL MODELS

| Model | Accuracy | Precision | Recall | F-score |
|---|---|---|---|---|
| **Proposed** | **98.22** | **98.22** | **98.22** | **98.22** |
| CNN [24] | 92.71 | 92.93 | 92.86 | 92.62 |
| CNN-LSTM [23] | 93.40 | 92.20 | 93.55 | 93.48 |
| Multi-head CNN [22] | 95.38 | 95.46 | 95.41 | 95.36 |
| UC Fusion [21] | 96.84 | 96.35 | 96.22 | 96.27 |

ranging from 92.20% to 93.40%. Overall, the AHAR model outperforms DL models in this comparison, demonstrating its effectiveness in HAR.

## V. CONCLUSION AND FUTURE WORK

This work provides a comprehensive analysis comparing the AHAR methodology with various ML and DL models. Across multiple metrics, including accuracy (of 98.22%), precision, recall, and F-score, AHAR consistently outperforms traditional ML models and DL architectures. Its superior performance underscores its efficacy in accurately identifying human activities. This study underscores AHAR's potential as a robust solution for real-world applications requiring precise HAR, such as healthcare monitoring and smart environment management. Furthermore, the insights gleaned from this study pave the way for further advancements, encouraging exploration into AHAR's scalability, adaptability to diverse datasets, and integration into real-world systems. By harnessing AHAR's capabilities, researchers and practitioners can revolutionize activity recognition paradigms, enhancing the efficiency and effectiveness of numerous domains reliant on human activity analysis. In future work, we will make use of data from sensors placed at multiple body locations to enhance the generalizability of the proposed approach. Moreover, we will also train the proposed model on wider range of activities relevant to medical applications.

## ACKNOWLEDGMENT

This publication has received support from SFI under Grant 12/RC/2289-P2 (Insight). To facilitate Open Access, the author has placed a CC BY public copyright license on any Author Accepted Manuscript that results from this submission.

## REFERENCES

[1] A. Hussain, S. U. Khan, N. Khan, M. Shabaz, and S. W. Baik, "AI-driven behavior biometrics framework for robust human activity recognition in surveillance systems," Engineering Applications of Artificial Intelligence, 127, 107218, 2024.

[2] I. Bisio, A. Delfino, F. Lavagetto, and A. Sciarrone, " Enabling IoT for in-home rehabilitation: Accelerometer signals classification methods for activity and movement recognition," IEEE Internet of Things Journal, vol. 4, pp. 135–146, 2016.

[3] D. Tao, Y. Wen, and R. Hong, "Multicolumn bidirectional long short-term memory for mobile devices-based human activity recognition," IEEE Internet of Things Journal, vol. 3, pp. 1124–1134, 2016.

[4] J. Chen, C. Yi, H. Du, D. Niyato, J. Kang, J. Cai, and X. Shen, "A revolution of personalized healthcare: Enabling human digital twin with mobile AIGC," IEEE Network, 2024.

[5] A. Ray, M. H. Kolekar, R, Balasubramanian, and A. Hafiane, "Transfer learning enhanced vision-based human activity recognition: A decade-long analysis," International Journal of Information Management Data Insights, Elsevier, vol. 3, pp. 100142, 2023.

[6] K. K. Sahoo, R. Ghosh, S. Mallik, A. Roy, P. K. Singh, and Z. Zhao, "Wrapper-based deep feature optimization for activity recognition in the wearable sensor networks of healthcare systems," Scientific Reports, Nature Publishing Group UK London, vol. 13, pp. 965, 2023.

[7] Y. Chen, and C. Shen, "Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition," IEEE Access, vol. 5, pp. 3095-3110, 2017.

[8] P. Verma, J. G. Breslin, D. O'Shea, and R. K. Pateriya, "A stacked ensemble method with adaptive attribute selection to detect ddos attack in cloud-assisted wban,"International Conference on Machine Learning, Image Processing, Network Security and Data Sciences, Springer, pp. 329–344, 2022.

[9] L. M. Amugongo, A. Kriebitz, A. Boch, and C. Lutge, "Operationalising AI ethics through the agile software development lifecycle: a case study of AI-enabled mobile health applications," AI and Ethics, Springer, vol. 12, pp. 1–18, 2023.

[10] N. Hnoohom, S. Mekruksavanich, and A. Jitpattanakul, "Physical activity recognition based on deep learning using photoplethysmography and wearable inertial sensors," Electronics, MDPI, vol. 12, pp. 693, 2023.

[11] L. Baroudi, K. Barton, S. M. Cain, and K A. Shorter, "Classification of human walking context using a single-point accelerometer," Scientific Reports, Nature Publishing Group UK London, vol. 14, pp. 3039, 2024.

[12] Y. A. Andrade-Ambriz, S. Ledesma, M. A. Ibarra-Manzano, M. I. Oros-Flores, and D. L. Almanza-Ojeda, "Human activity recognition using temporal convolutional neural network architecture" Expert Systems with Applications, Elsevier, vol. 191, pp. 116287, 2022.

[13] X. Li, Y. Wang, B. Zhang, and J. Ma, "PSDRNN: An efficient and effective HAR scheme based on feature extraction and deep learning," IEEE Transactions on Industrial Informatics, vol. 16, pp. 6703–6713, 2020.

[14] R. Bhuiyan, N. Ahmed, M. Amiruzzaman, and M. R. Islam, "A robust feature extraction model for human activity characterization using 3-axis accelerometer and gyroscope data," Sensors, MDPI, vol. 20, pp. 6990, 2020.

[15] Z. Chen, Q. Zhu, Y. C. Soh, and L. Zhang, "Robust human activity recognition using smartphone sensors via CT-PCA and online SVM", IEEE transactions on industrial informatics, vol. 13, pp. 3070–3080, 2017.

[16] I. Bisio, F. Lavagetto, M. Marchese, and A. Sciarrone, "Smartphone-based user Activity Recognition Method for Health Remote Monitoring Applications," PECCS, pp. 200–205, 2012.

[17] M. K. Yi, W. K. Lee, S. O. Hwang, "A human activity recognition method based on lightweight feature extraction combined with pruned and quantized CNN for wearable device," IEEE Transactions on Consumer Electronics, 2023.

[18] J. A. Rehman, H. U. Khan, M. K. B. Alomari, M. U. Sarwar, M. Asim, A. S. Almadhor, M. Z. Khan, "Toward explainable AI-empowered cognitive health assessment," Frontiers in Public Health, vo. 11, pp. 1024195, 2023.

[19] A. M. Fathollahi-Fard, M. Hajiaghaei-Keshteli, and R. Tavakkoli-Moghaddam, " Red deer algorithm (RDO): a new nature-inspired meta-heuristic," Soft computing, Springer, vol. 24, pp. 14637–14665, 2020.

[20] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine," Ambient Assisted Living and Home Care: 4th International Workshop, IWAAL 2012, Vitoria-Gasteiz, Spain, pp. 216–223, 2012.

[21] K. Liu, C. Gao, B. Li, and W. Liu, "Human activity recognition through deep learning: Leveraging unique and common feature fusion in wearable multi-sensor systems," Applied Soft Computing, Elsevier, vol. 151, pp. 111146, 2024.

[22] Z. N. Khan, and J. Ahmad, "Attention induced multi-head convolutional neural network for human activity recognition," Applied soft computing, Elsevier, vol. 110, pp. 107671, 2021.

[23] S. Deep, and X. Zheng, "Hybrid model featuring CNN and LSTM architecture for human activity recognition on smartphone sensor data,"2019 20th international conference on parallel and distributed computing, applications and technologies (PDCAT), pp. 259–264, 2019.

[24] S. Wan, L. Qi, X. Xu, C. Tong, and Z. Gu, "Deep learning models for real-time human activity recognition with smartphones," Mobile Networks and Applications, Springer, vol. 25, pp. 743–755, 2020.