Personalizing Human Physical Life Routines Recognition over Cloud-Based Sensor Data Via Machine Learning

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***Abstract*—**Pervasive computing is a growing research field that aims to acknowledge human physical life routines (HPLR) based on body-worn sensors such as MEMS (Micro-Electro-Mechanical Systems) sensors-based technologies. The use of these technologies for human activity recognition is progressively increasing. On the other hand, personalizing human life routines using numerous machine-learning techniques has always been an intriguing topic. In contrast, various methods have demonstrated the ability to recognize basic movement patterns. However, it still needs to be improved to anticipate the dynamics of human living patterns. This study presents state-of-the-art techniques for recognizing static and dynamic patterns and forecasting those challenging activities from multi-fused sensors. Furthermore, numerous MEMS signals are extracted from one self-annotated IM-WSHA dataset and two benchmarked datasets. First, raw data were processed with z-normalization and denoiser methods. Then, we adopted statistical, local binary pattern, auto-regressive model, and intrinsic time scale decomposition major features for feature extraction from different domains. Next, the acquired features are optimized using maximum relevance and minimum redundancy (mRMR). Finally, the artificial neural network is applied to analyze the whole system's performance. As a result, we attained a 90.27% recognition rate for the self-annotated dataset, while the HARTH and KU-HAR achieved 83% on nine living activities and 90.94% on 18 static and dynamic routines. Thus, the proposed HPLR system outperformed other state-of-the-art systems when evaluated with other methods in the literature.

***Keywords*—**Artificial intelligence, machine learning, gait analysis, local binary pattern, statistical features, micro-electro-mechanical systems, maximum relevance and minimum redundancy.

I. Introduction

HPLR recognition is becoming challenging for researchers in various practical domains such as pervasive computing, interactive learning, and pattern recognition. Such domains further involve various applications, including healthcare, security, surveillance, 3D interactive games, user-computer interaction, and fitness tracking [1]-[4]. Additionally, HPLR plays an essential role in user-to-user interaction and people skills, which provides vital information about a person, including identity, emotional state, and personality. Furthermore, a substantial amount of research is being conducted to advance the development of physical activity recognition via vision-based camera systems and body-worn MEMS sensors. In vision systems, different cameras are fixed at monitoring locations to automatically recognize physical activities based on the series of images [5], [6]. However, despite its advantages, vision-based systems have several limitations in some scenarios, such as continuous human movements over long-range distances, which requires uninterrupted monitoring of human activities [7]. On the other hand, MEMS-based inertial sensors have been gaining popularity as a feasible solution in different scenarios [8]. Therefore, the needs and demands for understanding and tracking human life routines via body-worn MEMS inertial sensors have progressed incrementally [9], [10].

During the last decade, the technological advancements of MEMS with embedded chips have progressed rapidly alongside developments simultaneously in information and communication technologies (ICTs). These MEMS devices, including accelerometers, gyroscopes, and magnetometers, are miniaturized for use in HPLR [11], [12]. Furthermore, the raw data acquired from these body-worn MEMS inertial sensors can be used in state-of-the-art systems that perceive and recognize human physical activities via pattern recognition and machine learning algorithms.

Body-worn sensors are more effective and suitable for continuous real-time monitoring in different scenarios, such as sports assistants, exercise monitoring, sleep quality analysis, heart rate monitoring, and elder care support [13]. For example, in sports assistants, these sensors provide speed tracking, energy level, and player's body fitness during physical training. Similarly, exercise tracking devices can keep track of particular workouts to conduct exercises more effectively. In the case of sleep quality analysis, inertial sensors can examine body movement patterns to determine your light and deep sleep. This information is essential in helping users recognize sleeping disorders as soon as possible for further treatment. The abovementioned applications promote the research for physical activity recognition via body-worn sensors. This paper uses three benchmark datasets, including our self-annotated benchmark dataset, IM-WSHA, for HPLR recognition. Annotated datasets like these have been shown to play a crucial role in promoting research across various data synthesis mechanisms [14], such as signal processing, wearable computing, computer vision, speech recognition, and pattern recognition. Additionally, we used a publicly accessible benchmark dataset named HARTH, collected under free-living

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settings, and KU-HAR, which captures heterogeneous life routines. The most important contributions of our study are:

- The proposed HPLR framework is based on multiple aspects, such as data acquisition from sensors, signal normalization, denoising, features engineering (such as statistical, LBP, ARM, AF, and ISD), feature selection, and classification.
- Features from multiple domains are utilized on the MEMS signal for a human daily life routine motion pattern. It assisted in determining the optimal results from the proposed HPLR proposed system.
- Maximum Relevance and Minimum Redundancy (mRMR) can distinguish important features precisely, which is enough to optimize the HPLR model's robustness and effectiveness.
- A comprehensive experimental analysis is conducted on two benchmark datasets (HARTH and KU-HAR) and one self-annotated dataset (IM-WSHA). Experimental results have shown that the proposed HPLR framework has achieved significant results compared to other state-of-the-art systems.

The remaining part of our work is organized as follows: Section II presents the background research and related work study. The proposed system methodology, including data acquisition, denoising, feature engineering, feature selection, and classification, is described in Section III. Section IV discusses the comparative analysis of our experimental results of three benchmark datasets. Finally, Section V reports the conclusion with future direction.

II. Related Work

Extensive research has been conducted on the HPLR system, resulting in the development of numerous techniques based on various considerations [14]. Consequently, several orthogonal parameters can be employed to categorize the proposed techniques. General classification requirements are based on the following type of information: i) data used to build the system, ii) the machine learning method to analyze the augmented signal, and iii) the type of sensors utilized to capture the augmented signal to be filtered. The data used to develop the classifiers split the technique into three primary classes: data-driven, knowledge-driven, and hybrid.

A. Human Activity Recognition (HAR) Personalization over RGB Systems

In RGB systems, numerous researchers have implemented RGB-based frameworks, primarily utilized in health and security-based systems for tracking and recognizing 3D locomotion and behaviors of humans.

Ni et al. [15] introduced an intelligent home tracking system with a benchmark database based on integrating an RGB camera and a depth sensor. In addition, this dataset intends to stimulate additional research on HAR via multi-fused sensors. Furthermore, two feature extraction methods for activity tracking have been designed that fuse color and depth information conventionally. In another study, Crispim-Junior et al. [16] present and thoroughly evaluate a fully operational, knowledge-based model for recognizing the human routines of elderly individuals. In addition, the approach integrates a constraint-based taxonomy language for modeling daily life activities with a strong pipeline for detecting and monitoring individuals based on color-depth data. Furthermore, the introduced method significantly surpasses and permits the modeling and tracking of prolonged and challenging scenarios characteristic of real-world settings. However, the main limitation of this work is the ambiguity at the low-level data and conceptual level, how to combine numerous sensor data effectively, and how to enable the autonomous detection of cognitive diseases using behavioral data.

Wu et al. [17] combined different benchmark RGB-D databases to design a large-scale HAR dataset. In addition, a two-tier hierarchical-based system is introduced for the massive dataset. All human life routines are classified into seven fundamental activities, subdivided into various sub-activities. Furthermore, they analyzed three handcrafted feature methods on the acquired dataset. The evaluation result has shown lower results on publicly integrated datasets which highlights the concerns of the massive dataset.

Moreover, the three handcrafted features incorporated only depth information, disregarding the RGB signals. Gu et al. [18] employed a deep model to categorize human action routines. Initially, they abstract the depth MHIs for the HAR datasets, and then ResNet-101 is catered to the model. The experimental evaluation on two benchmark datasets indicated that a deep learning framework might learn the distinct features of human life routines. This study analysis demonstrated that MHIs could provide robust locomotion patterns for recognition. In addition, the deep learning framework can extract unique features from this. However, additional work is required to tackle the real-time processing issue in the domain of HAR.

Sharif et al. [19] provided an innovative method for enhancing human monitoring and life-log recognition. The proposed approach is comprised of two significant components. In the first phase, new uniform and EM segmentation are fused to detect multiple persons in provided video sequences. Then, abstracted textured and shape features were integrated based on their vector size. The proposed method has demonstrated visual and empirical accuracy. However, this study has a few constraints, such as occlusions, which are not tackled; thus, this concern must be addressed in future development.

Additionally, using saliency to optimize the segmentation can be a better choice. Wu et al. [20] presented the SVM and HMM hybrid framework for human physical activity recognition. Initially, the author introduced combined features involving kinematic features, structural features, and different coordinate features. The significant experimental evaluation revealed that the SVM and HMM model is more accurate and feasible than the individual performance of SVM or HMM. The hybrid framework has attained a better recognition rate when compared with other systems. Nevertheless, there are a few things that could be improved in this work. First, data involved in the training were not occluded by an artifact, as the method does not account for occlusion problems. Next, some human activities require additional context information beyond human posture.

B. HAR Personalization over Inertial-Based Systems

This section mainly emphasizes wearable inertial-based systems for HPLR. In the context of wearable sensors, MEMS inertial sensors have significantly contributed to the convenience and personalization of human daily life routines and motion recognition. In their attempts to develop human locomotion wearable gadgets, experts have incorporated a multi-fused inertial sensor to identify improved methods for quantifying and interpreting skeletal movements. Specifically, inertial sensors, including accelerometers, gyroscopes, and magnetometers, have played a vital role in collecting and analyzing human motion data.

In this context, Ahmed et al. [21] proposed a hybrid feature selection method that accurately detects various human locomotion activities. These data are recorded from an inertial-based smartwatch sensor. The introduced hybrid framework combines the filter and wrapper techniques which have figured significantly in extracting optimal features. Next, the acquired optimal characteristics are employed for validation tests via the support vector machines (SVMs). Furthermore, the hybrid system framework achieved significant results compared to other methods. This research can categorize input data; however, fusion with the IoT system will allow this model to use controllers and other gadgets for further analysis and development in the real world. Sunken et al. [22] utilized an SVM classifier to recognize human locomotion patterns. They used the USC-HAD dataset to extract six different features. The appropriate features are evaluated using random combinations of the statistical features. The optimal hyperparameters are attained using a grid search optimization technique. The proposed system achieved better results on one benchmark dataset. This research utilized only one benchmark dataset. More benchmark HAR datasets can also be employed with other techniques in this context.

Tian et al. [23] proposed a novel approach for acquiring data from smartphone-based inertial sensors comprising accelerometers and gyroscopes. In addition, this study combines temporal features and wavelet coefficients to obtain accuracy-enhancing features. Xu et al. [24] introduced a unique approach to human activity monitoring by fusing 3-IMU sensors. In addition, multi-fused feature extraction from HHT was used to improve human activity detection. Finally, Subasi et al. [37] adopted data mining techniques in an IoT-based healthcare system to propose ubiquitous HAR. The proposed framework uses a dataset containing body motion and vital signs data for ten individuals with various profiles while conducting twelve life routines. The evaluation result demonstrated that the suggested system performs better and is efficient, robust, and dependable in providing m-Healthcare facilities during various activities.

III. System Design

This part presents a proposed methodology of the HPLR system with state-of-the-art methods and results. The proposed HPLR framework has employed the three-axis IMU data combined as input to the system. The initial phase comprised a preprocessing engine involving varied inertial signal data from accelerometers, gyroscopes, and magnetometers. First, these signals are enhanced through normalization, smoothing, and filtering techniques to reduce random noise emitted by abrupt movements. Further, we utilized different feature extraction techniques from different domains to retain better inertial signal values. Next, we determine the minimal optimized set of features using the maximum relevance and minimum redundancy (mRMR) approach that can distinguish important features precisely. Finally, we supplemented the feed-forward neural network, such as ANN, on the optimized feature sets of the HPLR classification framework. Fig. 1 displays the complete system architecture of the proposed HPLR framework.

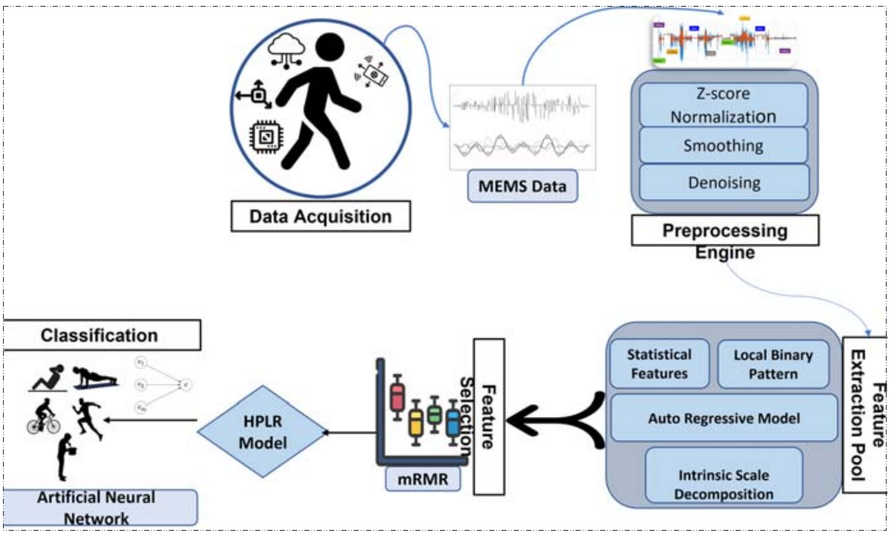

Fig. 1 Detailed overview of the proposed architecture via mRMR and ANN

A. Pre-processing of Raw Data

Initially, we acquired data from one self-annotated dataset named IM-WSHA and two benchmark datasets, such as HARTH and KU-HAR datasets. All these datasets involve data from multi-fused inertial sensors. Inertial sensors combine data from accelerometers, gyroscopes, and magnetometers. However, there is the possibility of random variation in human motion that can generate sudden noise and impact the strength of the signal. As a result, to preserve the inertial signal strength, we apply z-score normalization [25] and median filter techniques to smooth the data for further processing.

A Z-score-based normalization is an arithmetic estimation of a number's association with the group's mean. In addition, Z-scores are generally calculated via the standard deviations (SD) of a set of data from their respective averages. As a result, the z-score indicates that the score is equivalent to the group's mean score. On the other hand, we utilized a third-order median filter, which is used as a denoising setup that handles the unwanted motion of IMU data without compromising essential data.

$$Zscore = \frac{(Y-\mu)}{\sigma} \tag{1}$$

where μ and σ are the mean and SD of the sample group, respectively.

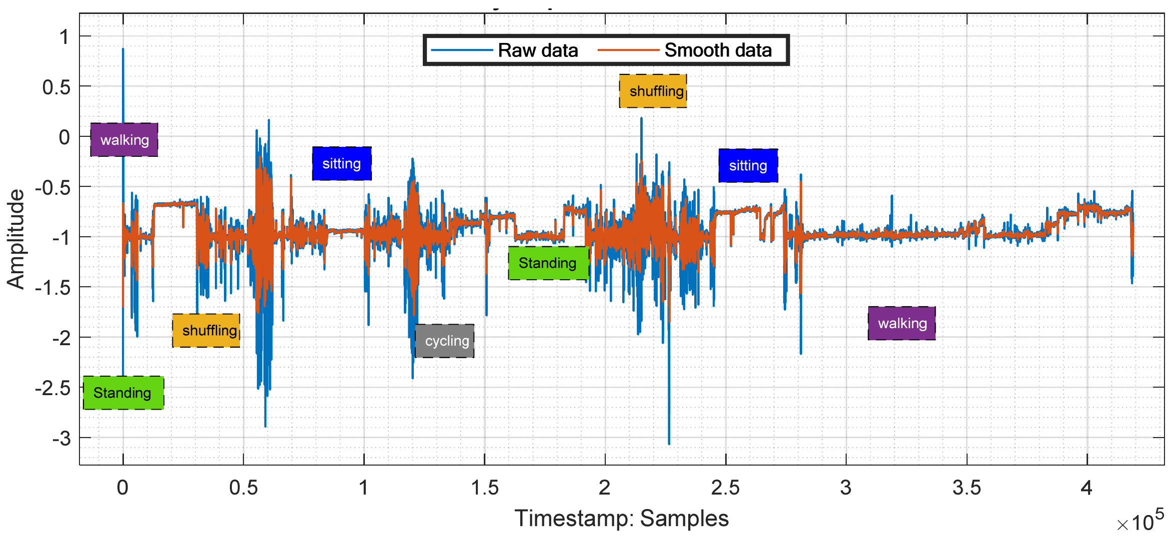

Fig. 2 Preprocessing Engine: IMU signal with raw data and smooth (normalized and filtered) data for nine human life routines on the HARTH dataset

B. Feature Extraction Pool

Examining and evaluating sensor data characteristics is vital to establish a representation that precisely represents its aspect. In addition, there is no detailed framework in HPLR that enables the expert-driven development of a generic feature representation that would elaborate the intrinsic process that HAR tackles. Consequently, the sophisticated HAR features comprise more or less comprehensive, commonly heuristic-driven interpretations of the unprocessed signal.

1. Statistical-Based Features

We employ the statistical measures described in [26]. In this context of inertial signal, we incorporated variance, mean, energy, skewness, and kurtosis features. The mean is the averaged IMU reading in a specific time interval, whereas the variance indicates the augmented signal's strength. Energy reflects the inertial signal periodicity.

2. Local Binary Pattern

The LBP feature is extensively used in image sequences for feature acquisition. In addition, LBP is effective as a local visual feature descriptor. It can efficiently acquire spatial structure and precisely analyze local patterns. Our study evaluated the acquired augmented signals, and features were abstracted via the 1D-LBP technique.

In our work, the 1D-LBP is designed by comparing each signal value to its existing and next neighbors. The binary result acquired from the evaluation is then transformed to a decimal number to generate 1D-LBP labels for each value. To generate a binary string, the neighbor was picked up to point. Next, the center point (Pc) was selected to the p/2 both before and after the center value. These steps are carried out at every location along the signal. Signals with a frequency range of 0 to 255 were generated by using this approach. These are known as binary patterns.

$$x = P_i - P_c \tag{2}$$

$$\text{LBP (IMU)} = \sum_{i=0}^{r} S_{IMU}\,(x)2^{i} \tag{3}$$

$$S_{IMU}\begin{cases}1, & x \geq \text{ threshold}\\ 0, & x < \text{ threshold}\end{cases}$$

where 'x' represents the neighbors and centroid.

3. Auto-Regressive Model

The autoregressive (AR) model is employed to represent the time series inertial signals of the two benchmark datasets comprising different static and dynamic activities [27]. The AR model of a stochastic process is determined as follows:

$$x(t) = \sum_{i=1}^{n} a(j)x(t-j) + \varepsilon(t), \quad (4)$$

where 'a' denotes the model's coefficients, 'n' represents the order of the model, and $\varepsilon(t)$ shows the resultant uncorrelated error.

The inertial signal was subjected to AR and partial AR to evaluate this. In addition, these methods are a measurement of how closely an inertial signal sets a time-shifted version.

4. Intrinsic Time Scale Decomposition (ITD)

The ITD approach was developed to address several shortcomings of the empirical mode decomposition method (EMD). ITD is an adaptable and data-driven technique. Additionally, it can decompose a sophisticated inertial signal into numerous proper rotation components and a residual. Compared to the EMD method's shifting method, a benchmark operator R is developed to abstract an inertial signal from a signal and verify that the residue is a proper rotation. Thus, the inertial X_a can be shown as:

$$X_a = \mathcal{L}X_a + (1-\mathcal{L})X_a = R_a + H_a \quad (5)$$

where 'L_a = $\mathcal{L}X_a$' implies the baseline inertial signal. H_a represents a valid rotation.

C. Maximum Relevance and Minimum Redundancy (mRMR)

The mRMR feature selection technique is widely used in various research disciplines. It intends to attain significant classification performance by minimizing feature repetition and maximizing feature relevance to the main class [28]. In addition, the algorithm is a filter-based technique for selecting features that integrate minimum redundancy and maximum relevance into a single function (see Fig. 3). Using an iterative selection technique, these conditions are merged by computing the mutual information to determine the degree of relevance and redundancy [9]. For example, the mutual information from feature f_a associated with f_b can be shown as:

$$I(f_a; f_b) = \sum_{i,j} p(i,j) log\left(\frac{p(i,j)}{p(i)p(j)}\right) \quad (6)$$

where x indicates all the probabilities of f_a values and j represents all the probabilities of f_b values. Then, the minimum redundancy can be demonstrated as:

$$minR(F), R = \frac{1}{|f|^2}\sum_{x_a, x_b \in F} I(x_a, x_b) \quad (7)$$

where 'F' is the predicted feature subset, |F| can be represented as 'm', which indicates the total number of features in F. Next, the maximum relevance can be presented as:

$$maxG(F, c), G = \frac{1}{|F|}\sum_{x_a \in F} I(x_b, c) \quad (8)$$

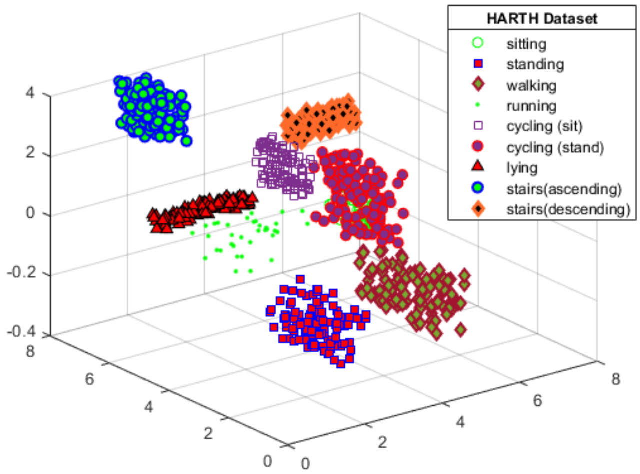

Fig. 3 mRMR based optimized features for static and dynamic activities

D. Classification: Artificial Neural Network (ANN)

The ANN is proven to be a sophisticated and better framework applied to image and scene data. ANN is a model for managing data that replicates the function of the human brain's nervous system. In addition, ANNs are adaptable algorithms that can learn to solve challenging problems based on training data involving a collection of input-output pairs [29]. They can be incorporated to do tasks such as classification and prediction.

An ANN comprises neurons, which are interconnected processing units that generate an output. Two sorts of neural network learning approaches exist supervised learning and unsupervised learning. During the training stage, sets of pairs are submitted to the network. The entire network is trained repeatedly to achieve the required Mean Squared Error (MSE) and best generalize test inputs. Finally, we serve the optimized features vector to ANN for classification. Fig. 4 shows the model diagram of ANN.

IV. Experimental Evaluation and Settings

This section provides a detailed overview of the three databases incorporated into the HPLR system. The experimental result and evaluation of these datasets are conducted to assess the performance of our HPLR system.

A. Dataset Description

The self-annotated IM-WSHA [30] has been acquired using three triaxial IMU sensors (MPU-9250) from 10 individuals with a balance gender ratio. The sensors were incorporated into the participant's wrist, chest, and thigh regions. It has been designed to monitor human personal locomotion in intelligent home environments during life routine activities, such as cooking, drinking, walking, exercising, reading a book, and many others. Each activity's total variable time for data acquisition is 45-60 seconds.

The second benchmark (Human Activity Recognition Trondheim dataset) HARTH dataset [31] involves data from two accelerometers (Triaxial Axivity AX3). Additionally, the database was acquired from 22 participants placed on the lower back and thigh regions. The activities comprise walking, shuffling, running, cycling, etc.

The third benchmark KU-HAR [32] database includes samples from 18 distinct activity categories. These data were acquired from 90 volunteers aged between 18 and 34 years by attaching smartphones to their waists. The collected data include the signals of a triaxial accelerometer and gyroscope.

B. Experimental Evaluation on Self-Annotated IM-WSHA Dataset

In our self-annotated dataset, we employed a three-fold cross-validation strategy to assess the performance of our system. Fig. 5 presented the confusion matrix with 11 primary and complex routines of daily living, where a 90.27% mean recognition rate is achieved.

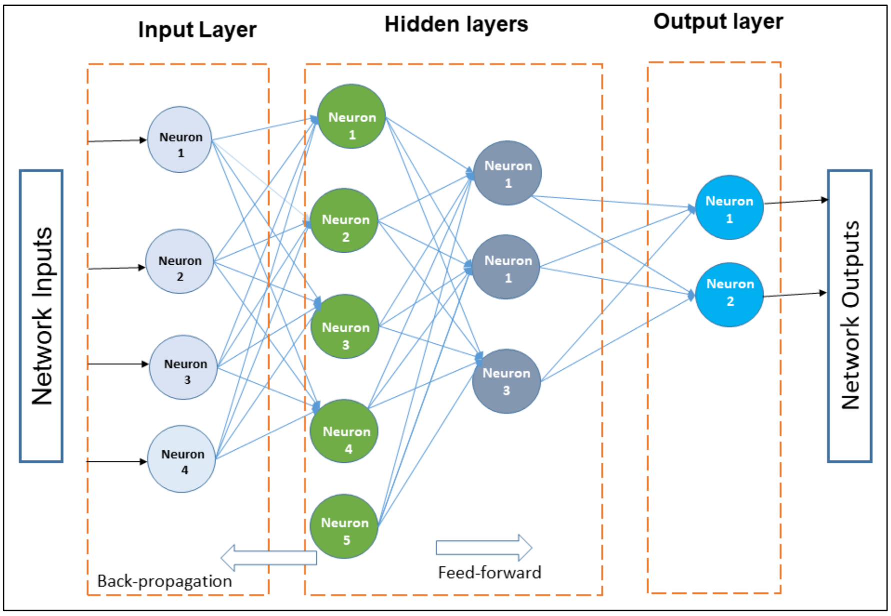

Fig. 4 The model overview and diagram of Artificial Neural Network

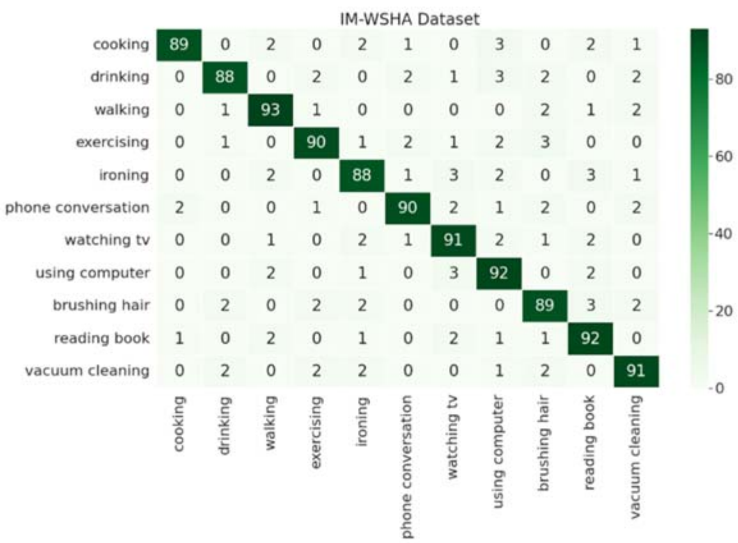

Fig. 5 Confusion Matrix of 11 physical life routines activities on the IM-WSHA dataset via ANN

TABLE I
HUMAN INTERACTION COMPARISON RESULTS OF THE PROPOSED METHOD WITH OTHER STATE-OF-THE-ART METHODS OVER IM-WSHA DATASET

Frameworks	IM-WSHA (%)
Bag of features [33]	84.50
MS-DLD system [34]	87.15
Sensor level fusion [35]	89.50
Proposed HPLR	90.27

Table I shows the comparison of the proposed system over benchmark dataset IM-WSHA.

C. Experimental Evaluation of HARTH Dataset

During experiments, it was found that interactions involved repetitive tasks, so we merged a few activities. In particular, shuffling, transport (standing), and standing are merged into the same locomotion activity into standing. Likewise, sitting and transport (sitting) are combined into sitting. The classification findings for the HARTH datasets are presented as a confusion matrix in Fig. 6, indicating an attained recognition rate of 83% over nine physical activities.

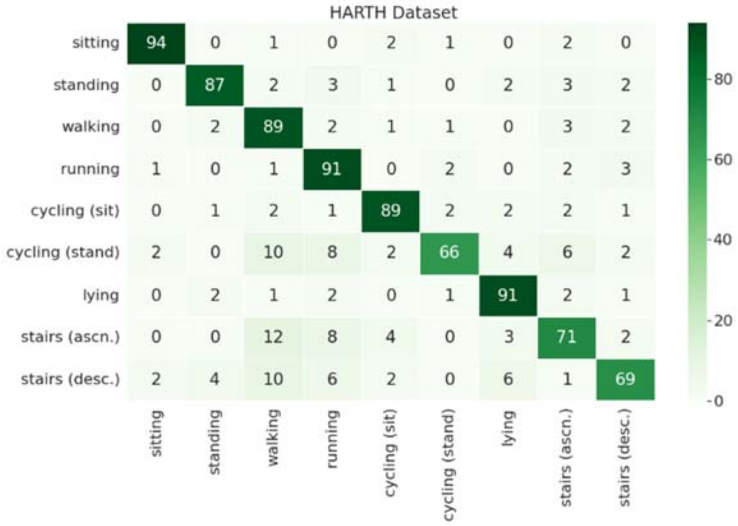

Fig. 6 Confusion Matrix of nine human locomotion activities on the HARTH dataset via ANN

D. Experimental Evaluation of KU-HAR Dataset

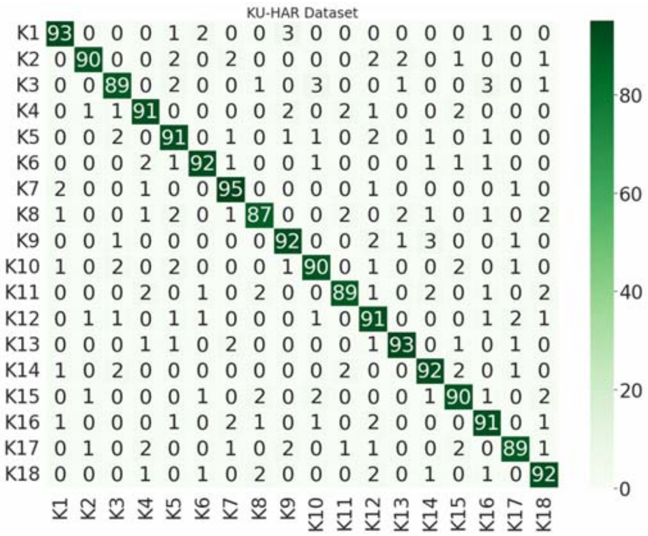

Fig. 7 Confusion Matrix of AAMAZ dataset over 11 actions: K1 = Stand, K2 = Sit, K3 = Talk-sit, K4 = Talk-stand, K5 = Stand-sit, K6 = Lay, K7 = Lay-stand, K8 = Pick, K9 = Jump, K10 = Push-up, K11 = Sit-up, K12 = Walk, K13 = Walk-backward, K14 = Walk-circle, K15 = Run, K16 = Stair-up, K17 = Stair-down, K18 = Table-tennis

TABLE II
HUMAN INTERACTION COMPARISON RESULTS OF THE PROPOSED METHOD WITH OTHER STATE-OF-THE-ART METHODS OVER KU-HAR AND HARTH DATASETS

Frameworks	HARTH (%)	KU-HAR (%)	Frameworks
SVM [31]	78.66	Random Forest [36]	89.50
		RF [32]	89.67
	-	-	-
Proposed HPLR	83	90.94	90.94

In the context of the KU-HAR dataset, Fig. 7 depicts an average accuracy of 90.94% over 18 static and dynamic activities. Similarly, Table II compares our proposed HPLR system with other state-of-the-art methods.

V. DISCUSSION

A comparison of the proposed system to other state-of-the-art systems revealed that the performance of our HPLR system had outperformed other existing methods. Our application of the HPLR architecture generated sensor data with significant accuracy. Initially, we attached three triaxial IMU sensors to various body sites to obtain more accurate information regarding the orientation and rotation of different body parts. Initially, we employed z-score normalization and denoising techniques to smooth the data for data preprocessing. In addition, by utilizing various cues in distinct domains (such as statistical, LBP, ARM, and ISD descriptors), the HPLR system yields improved performance. Next, the attained features are optimized using maximum relevance and minimum redundancy (mRMR) to pick essential features. Additionally, routine human activities are classified using ANN, which achieves a greater mean recognition rate than other standard approaches.

VI. CONCLUSIONS

The sensor-based HPLR analysis has substantially gained attention due to the accessibility of pervasive devices. This research analyzes the utilization and incorporation of multi-fused sensors for recognizing indoor and outdoor activities. We have proposed a HPLR Recognition system using an artificial neural network (ANN) optimized with mRMR. The experimental evaluation was assessed using one self-annotated dataset and two benchmark datasets. The evaluation of the proposed HPLR systems with other existing systems shows better performance.

The proposed HPLR system applies to many real-world applications, including smart home systems, activity recognition, surveillance system, and healthcare.

REFERENCES

[1] Feng, Z.; Mo, L.; Li, M. A Random Forest-based ensemble method for activity recognition. In Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, Italy, 25–29 August 2015; pp. 5074–5077.

[2] Yang, D.; Huang, J.; Tu, X.; Ding, G.; Shen, T.; Xiao, X. A wearable activity recognition device using air-pressure and IMU sensors. IEEE Access 2018, 7, 6611–6621.

[3] Uddin, M.T.; Uddin, M.A. A Guided Random Forest based Feature Selection Approach for Activity Recognition. In Proceedings of the 2nd Int'l Conf. on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh, 21–23 May 2015.

[4] Sabatini, A.M. Estimating Three-Dimensional Orientation of Human Body Parts by Inertial/Magnetic Sensing. Sensors 2011, 11, 1489-1525.

[5] Rodriguez, C.; Fernando, B.; Li, H. Action Anticipation by Predicting Future Dynamic Images. In Proceedings of the European Conference on Computer Vision (ECCV), Munich, Germany, 8–14 September 2018.

[6] Gholami, S.; Noori, M. You Don't Need Labeled Data for Open-Book Question Answering. Appl. Sci. 2022, 12, 111.

[7] Casson, A.J.; Galvez, A.V.; Jarchi, D. Gyroscope vs. accelerometer measurements of motion from wrist PPG during physical exercise. ICT Express 2016, 2, 175–179.

[8] Mustafa, Z., Nsour, H., & ud din Tahir, S. B. (2023). Hand gesture recognition via deep data optimization and 3D reconstruction. *PeerJ Computer Science*, *9*, e1619.

[9] Wang, J.; Xu, Z. Spatio-temporal texture modelling for real-time crowd anomaly detection. Comput. Vis. Image Underst. 2016, 144, 177–187.

[10] Wang, K.; He, J.; Zhang, L. Attention-based Convolutional Neural Network for Weakly Labeled Human Activities Recognition with Wearable Sensors. IEEE Sens. J. 2019, 19, 7598–7604.

[11] Xiao, Q.; Song, R. Human motion retrieval based on statistical learning and bayesian fusion. PLoS ONE 2016, 11, e0164610.

[12] Bhargavi, D.; Coyotl, E.P.; Gholami, S. Knock, knock. Who's there?--Identifying football player jersey numbers with synthetic data. arXiv 2022, arXiv:2203.00734.

[13] Lara, O.D.; Labrador, M.A. A survey on human activity recognition using wearable sensors. IEEE Commun. Surveys Tutor. 2013, 15, 1192–1209.

[14] Chen, L.; Hoey, J.; Nugent, C.D.; Cook, D.J.; Yu, Z. Sensor-based activity recognition. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. 2012, 42, 790–808.

[15] Ni, B.; Wang, G.; Moulin, P. RGBD-HuDaAct: A Color-Depth Video Database for Human Daily Activity Recognition. In Consumer Depth Cameras for Computer Vision; Springer: London, UK, 2013; pp. 193–208.

[16] Crispim-Junior, C.F.; Gómez Uría, A.; Strumia, C.; Koperski, M.; König, A.; Negin, F.; Cosar, S.; Nghiem, A.T.; Chau, D.P.; Charpiat, G.; Bremond, F. Online Recognition of Daily Activities by Color-Depth Sensing and Knowledge Models. Sensors 2017, 17, 1528.

[17] Wu, H.; Ma, X.; Zhang, Z; Wang, H; Li, Y. Collecting public RGB-D datasets for human daily activity recognition, Int. J. Adv. Robot. Syst., 14, 2017.

[18] Gu, Y.; Ye, X.; Sheng, W. Depth MHI Based Deep Learning Model for Human Action Recognition. In Proceedings of the 2018 13th World Congress on Intelligent Control and Automation (WCICA), Changsha, China, 4–8 July 2018; pp. 395–400.

[19] Sharif, M.; Khan, M.A.; Akram, T.; Younus, M.J.; Saba, T.; Rehman, A. A framework of human detection and action recognition based on uniform segmentation and combination of Euclidean distance and joint entropy-based features selection. EURASIP J. Image Video Process. 2017, 2017, 89.

[20] Wu, H.; Pan, W.; Xiong, X.; Xu, S. Human activity recognition based on the combined svm&hmm. In Proceedings of the 2014 IEEE International Conference on Information and Automation (ICIA), Hailar, China, 28–30 July 2014; pp. 219–224.

[21] Ahmed, N.; Rafiq, J.I.; Islam, M.R. Enhanced Human Activity Recognition Based on Smartphone Sensor Data Using Hybrid Feature Selection Model. Sensors 2020, 20, 317.

[22] Elkerdawi, S.M.; Sayed, R.; ElHelw, M. Real-time vehicle detection and tracking using Haar-like features and compressive tracking. In Proceedings of the ROBOT2013: First Iberian Robotics Conference; 2014; pp. 381–390.

[23] Miller, N.; Thomas, M.A.; Eichel, J.A.; Mishra, A. A hidden Markov model for vehicle detection and counting. In Proceedings of the 2015 12th Conference on Computer and Robot Vision; 2015; pp. 269–276.

[24] Sun, D.; Watada, J. Detecting pedestrians and vehicles in traffic scene based on boosted HOG features and SVM. In Proceedings of the 2015 IEEE 9th International Symposium on Intelligent Signal Processing (WISP) Proceedings; 2015; pp. 1–4.

[25] Laopracha, N.; Sunat, K.; Chiewchanwattana, S. A novel feature selection in vehicle detection through the selection of dominant patterns of histograms of oriented gradients (DPHOG). IEEE Access 2019, 7, 20894–20919.

[26] Girshick, R.; Donahue, J.; Darrell, T.; Malik, J. Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the Proceedings of the IEEE conference on computer vision and pattern recognition; 2014; pp. 580–587.

[27] Ramasamy Ramamurthy, S.; Roy, N. Recent trends in machine learning for human activity recognition—A survey. WIREs Data Min. Knowl. Discov. 2018, 8, e1254.

[28] Peng, H.; Long, F.; Ding, C. Feature selection based on mutual information: Criteria of max-dependency, max-relevance, and min-redundancy. IEEE Trans. Pattern Anal. Mach. Intell. 2005, 27, 1226–1238.

[29] Abdolrasol, M.G.M.; Hussain, S.M.S.; Ustun, T.S.; Sarker, M.R.; Hannan, M.A.; Mohamed, R.; Ali, J.A.; Mekhilef, S.; Milad, A. Artificial Neural Networks Based Optimization Techniques: A Review. Electronics 2021, 10, 2689.

[30] Tahir, S.B.U.D. Intelligent Media-Wearable Smart Home Activities (IM-WSHA). 2020. Available online: http://portals.au.edu.pk/imc/Pages/Datasets.aspx (accessed on 10 Feb 2022).

[31] Logacjov, A.; Bach, K.; Kongsvold, A.; Bårdstu, H.B.; Mork, P.J. HARTH: A Human Activity Recognition Dataset for Machine Learning. Sensors 2021, 21, 7853.

[32] Sikder, N.; Nahid, A.-A. KU-HAR: An open dataset for heterogeneous human activity recognition. Pattern Recognit. Lett. 2021, 146, 46–54.

[33] Shloul, T.; Javeed, M.; Gochoo, M.; Alsuhibany, S.; Ghadi, Y.; Jalal, A.; Park, J. Student's Health Exercise Recognition Tool for E-Learning Education. Intell. Autom. Soft Comput. 2022, 35, 149–161.

[34] Y. Y. Ghadi et al., MS-DLD: Multi-Sensors Based Daily Locomotion Detection via Kinematic-Static Energy and Body-Specific HMMs," IEEE Access, 10, 2022, 23964-23979.

[35] Webber, M.; Rojas, R.F. Human Activity Recognition with Accelerometer and Gyroscope: A Data Fusion Approach. IEEE Sens. J. 2021, 21, 16979–16989.

[36] Abid, M.H.; Nahid, A.-A. Two Unorthodox Aspects in Handcrafted-Feature Extraction for Human Activity Recognition Datasets. In Proceedings of the 2021 International Conference on Electronics, Communications and Information Technology (ICECIT), Khulna, Bangladesh, 14–16 September 2021; pp. 1–4.

[37] Subasi, A., Radhwan, M., Kurdi, R., & Khateeb, K. (2018, February). IoT based mobile healthcare system for human activity recognition. In *2018 15th learning and technology conference (L&T)* (pp. 29-34). IEEE.