

Received 10 August 2022, accepted 20 September 2022, date of publication 22 September 2022,
date of current version 29 September 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3208686

RESEARCH ARTICLE

Complex Human Activity Recognition Using a Local Weighted Approach

TUNÇ AŞUROĞLU 

Faculty of Medicine and Health Technology, Tampere University, 33720 Tampere, Finland

e-mail: tunc.asuroglu@tuni.fi

ABSTRACT Due to the life expectancy increase, there will be a workforce shortage in elderly care sector in forthcoming years. Ambient Assisted Living (AAL) systems can cope with this issue. A subset of AAL, Human activity recognition (HAR) provides an efficient way to tackle this issue. It can help with evaluating general health and welfare of elderly by automatically tracking their activities. Lifelogging and home diary applications will reduce the load on physicians and caregivers. On the other hand, complex activities play a vital role as they have high level semantic characteristics that truly represent daily life of the user. The main objective is to track these high-level semantic motions with low-cost single sensor systems with efficient machine learning frameworks. To achieve this objective, a framework is proposed to predict complex human activities from a single sensor using a machine learning approach. Time and frequency features are extracted from PAAL ADL Accelerometry Dataset and fed to Locally Weighted Random Forest (LWRF) machine learning algorithm. This algorithm is a hybrid structure that utilizes local weighting by introducing neighboring samples on Random Forest tree building phases. Proposed approach achieved 91% accuracy for HAR and 91.3% for gender recognition, outperforming other machine learning algorithms and previous study on the same dataset. This is the first study that utilize a local weighted approach for accelerometer signal domain. For prospective application, proposed framework can be embedded in lifelogging and home diary applications in home environments to track mental status of elderlies.

INDEX TERMS Accelerometers, activity recognition, ambient assisted living, machine learning, wearable sensors.


I. INTRODUCTION

In recent years, world life expectancy is increased due to advancements on healthcare, this situation results in an elevation of elderly population in society [1]. With the reduction of birth rates all around the world, the ageing population gains a larger proportion in living societies. In approximately 30 years, 16% of all human population will be over 65 years of age [1]. This situation can cause a workforce shortage on elderly care sector. Workforce shortages can lead to overtime work and workload increase of care workers. Also, this issue can affect the quality of assistance in healthcare facilities. To tackle this problem, Ambient Assisted Living (AAL) technologies are introduced [2]. With the introduction of assistive technologies, humans can take better care of

the elderly. These technologies can help on rehabilitation, monitor chronic diseases, tracking cognitive impairment and mild dementia in older adults [3].

AAL is the combination of several aspects, these are context awareness, internet of things, machine learning and sensor technologies [4]. All of these aspects are combined to provide a better life quality for elderly and enable them to live their life independently. A subset of AAL, Human activity recognition (HAR) is a perfect combination of these aspects. HAR, which involves analyzing data from different sensor sources to identify characteristics related to a person's activity, is a crucial component of AAL. It can be utilized to promote proactive behavior or even basic cooperation between the person and the environment [2].

Recognition of daily activities via HAR is a good approach for evaluating general health and welfare in elderly people. This evaluation can be done by asking the question "Is the

The associate editor coordinating the review of this manuscript and approving it for publication was Lei Shu .

user conducting his or her normal activities at the usual times?'. This approach can aid elderly in lifelogging and home diary applications. By looking at automated activity logs, physicians or caregivers can check the validity of activities and afterwards detect certain dementia related diseases before they begin to manifest [5]. Likewise, users can check their activity diaries and see what activities they have done. Since there are no available treatment for dementia related diseases, an HAR system that collects data for long durations in a home setting can help doctors or caregivers to analyze progression of mental decline [5].

There are mainly two ways to conduct HAR, these are vision-based and sensor-based approaches. In vision-based approach, image and video data are analyzed from optical sensors to detect activities. Research area of this approach is limited with security related and interactive applications [6]. There are several negative sides of this approach. First, the performance is greatly dependent on external conditions. Bad lighting conditions of measurement areas can greatly affect the performance of the vision-based system. Also, concerning privacy, these systems cannot be installed on private spaces like bathrooms and bedrooms [7]. Lastly, users should always stay in visual range of optical systems. Because of these drawbacks, interest in vision-based approaches is declining in literature.

As vision-based approaches are losing its popularity, sensor-based approaches take the lead on HAR research. In recent years, sensor-based approaches have gained a vast majority in research due to the advancements of microsensor technologies [8]. Sensor based approaches mainly consist of wearable sensors. These wearable sensors can be Inertial Measurement Units (IMU), pressure sensors and global positioning system (GPS) sensors [2]. Applications that can be done with sensor-based approaches are fitness and motion tracking, daily activity monitoring, virtual reality and medical rehabilitation [9]. Sensor based approaches can be considered as two types: Multi sensor based and single sensor-based systems. As the name suggests, multi sensor-based systems can increase activity recognition performance by combining multiple sensor data, however it is not applicable for long term use in daily life. The reason behind this issue is that one sensor malfunction can cause activity recognition system to collapse if the system dependent on frameworks that use sensor fusion [10]. Also, dealing with multiple sensors increases the computational costs due to processing of aggregated data from fused sensors. For these aforementioned drawbacks, recent studies are mainly focused on single sensor-based systems [11]. But single sensor systems are not perfect either. The main drawback with single sensor approaches is the limitation of available concurrent data [10]. So, studies are mainly focused on finding a robust and effective feature extraction and machine learning algorithm to overcome this drawback. Therefore, it poses a challenge to researchers to do human activity recognition analysis using only one sensor.

Human activities can be considered as a combination of simple and complex activities [9]. Simple activities are

defined by actions that repeats itself and possess a single body pose. Example simple activities are sitting, running, walking. Simple activities lack the capability of reflecting the daily life of users because behaviors of users are made of combination of several activities. Complex activities on the other hand, are the combination of simple activities. For example, eating a meal can be considered as a complex activity because it involves sitting and can contain several different hand motions while eating a meal. Example complex activities are cleaning, cooking, writing and eating [9]. These activities usually have high level semantic characteristics that truly represent daily life of the user. In order to create an AAL system for the care of the elderly, it is necessary to examine complex activities instead of focusing on simpler ones because complex activities contain more information about daily life of a user [12]. But to be able to find appropriate features is another challenge in complex HAR tasks [13]. Machine learning approaches can become insufficient to make accurate predictions without a prior knowledge on which features have the most representative power [14]. Ranking of features can provide this insight. With the help of ranking approaches, relevant features can be identified easily for recognition tasks [15]. Another research direction for these complex activities is to find robust machine learning frameworks that can cope with limited sample size. Due to their nature, these activities can have small motion cycles and therefore they have small number of samples. These limited sample size data can have a negative effect on prediction capability of machine learning approaches [5].

To this end, a framework is proposed to predict complex human activities from a single sensor using a local weighted machine learning approach. The main challenge is, instead of using multiple sensor data, use a robust framework that combines single sensor data and machine learning algorithms to predict complex daily living activities. For this purpose, an open access dataset called "PAAL ADL Accelerometry dataset" is selected for this study. The dataset includes simple movements and complex daily living activities. Also, it has the highest number of daily living activities among accelerometer-based open access datasets so far [5]. Several time and frequency domain features are extracted from a single accelerometer sensor and fed to a hybrid machine learning algorithm called Locally Weighted Random Forest (LWRF) to predict human activities. A further analysis is conducted to assess gender recognition capability of proposed approach. In addition, to analyze the importance of individual signal features on prediction tasks, feature ranking is done on extracted accelerometer motion signals. The proposed framework can provide robust solutions in AAL for assessing dementia related disease progression of elder people in home environments by tracking their daily activities. Main contributions of this study are given below:

- Proposed framework can reduce dataset variation effects by introducing a combination of local weighting scheme and Random Forest algorithm.

- By utilizing neighboring data points and locally weighting in prediction phase, this approach can be considered for predicting activities with limited number of samples.
- According to ranking of extracted features, signal magnitude area (SMA) feature is the most representative feature for complex activities and correlation between X and Z axis of accelerometer signal feature has the highest representative ability for gender recognition tasks.
- This is the first study that employs local weighted machine learning approach on an accelerometer signal domain.
- The proposed framework outperformed previous study on the same dataset and other machine learning approaches when predicting complex human activities.

The paper is organized as follows; Section II gives an overview of current literature, Section III includes proposed framework, description of PAAL ADL Accelerometry dataset, several preprocessing phases and features and also proposed local weighted approach. Section IV explains evaluation metrics and give experimental results. Lastly, Section V includes conclusions.

II. RELATED WORK

The only related work found on PAAL dataset is published in [5]. So, related work section is mainly constructed with recent studies that have used single three axis accelerometer signals and analyze complex human activities. In literature, some studies focus on hand crafted signal features and traditional machine learning approaches for activity recognition. These hand-crafted features are mainly consisted of statistical and time series characteristics of a signal. On the other hand, deep learning architectures are proposed for datasets that possess large sample sizes. In these deep learning architectures, instead of using hand crafted features, deep learning frameworks extract features automatically and predict human activities.

Climont-Pérez and Florez-Revuelta [5] conducted the prior study that analyzed PAAL accelerometer dataset for activity recognition. They proposed a multi objective evolutionary algorithm called MaOEA to find appropriate weights for extracted features. Aim of this proposed approach is to find a method that hide age and gender of a person while maintaining human motion characteristics. They used PAAL accelerometer dataset which contains 24 activities that include simple movements and complex daily living activities. A single wrist worn accelerometer is used to capture human motions from 52 participants. They extracted time and frequency domain features from these motion signals. Random Forest algorithm is selected as an inductor classifier in their proposed approach. The authors reported accuracy of their approach and indicated that MaOEA algorithm can preserve motion characteristics while concealing gender and age information with a tolerable performance loss. They also reported the case that every feature had equal weights and achieved overall 87.2% accuracy in activity recognition task. Tian *et al.* [7] proposed a robust human

activity recognition approach from single accelerometer signals. Proposed approach is based on kernel discriminant analysis (KDA) method and particle swarm optimized extreme learning machine (QPSO-KELM). KDA is used to extract meaningful features from motion signals. The authors used their own dataset that includes single accelerometer signals. They benchmarked different feature sets and classifiers with their proposed features and classifier. The authors reported that their approach outperformed other feature sets and classifiers in terms of accuracy. Huan *et al.* [9] tackle the problem of complex human activity recognition. They proposed a framework to extract multi-layer features from accelerometer, gyroscope and magnetometer signals. The authors utilized a hybrid deep learning architecture that consists of CNN and RNN architectures. They tested their approach on several open activity recognition datasets. They compared their method with previous works and outperformed them in all evaluation metrics. The authors also stated that location and time domain features are an important indicator for motion signals.

Tian *et al.* [10] proposed ensemble-based filter feature selection (EEFS) approach to optimize the feature set in human activity recognition task. They extracted wavelet decomposition features and filtered them using EEFS approach on a private dataset that includes single accelerometer signals. SVM and kNN are selected as classifiers. They reported that EEFS approach combined with SVM classifier can give high accuracy with less features. Lu and Tong [11] conducted a research on human activity recognition using single three axis accelerometer. In order to reduce the burden of heavy preprocessing phase, the authors proposed a modified recurrence plot by converting motion signals to images. After these conversion phase, images go through a tiny residual neural network for classification. They used their own dataset and ADL open access dataset. Several machine learning approaches are benchmarked, and their approach outperformed others in terms of accuracy and computation time. Guney and Erdas [16] studied how deep learning architectures affect human activity prediction rate from single accelerometer signals. They aimed to do feature free classification using deep Long Short-Term Memory (LSTM) model. They used an open access dataset that has single tri axis accelerometer data. The authors compared their approach with other previous studies and outperformed them in terms of accuracy. Acici *et al.* [17] constructed a complex human activity dataset with single wrist worn Inertial Measurement Unit (IMU). They extracted time and frequency domain features from motion signals. After feature extraction, they compared traditional machine learning approaches on activity prediction and person identification tasks. Random Forest model achieved the highest accuracy in all cases. They also discovered that combination of accelerometer and magnetometer signals can increase prediction performance on person identification and complex activity recognition.

Lu *et al.* [18] provide a different perspective for activity recognition using single accelerometer. The authors

categorize human actions as countable (complex) and uncountable (still) actions and stated that they should have dealt with different feature sets. Therefore, they extracted global and local features from motion signals. Evaluation of their approach is done with several open access datasets. Based on their findings, the authors reported that local features have a bigger impact on countable activities rather than uncountable ones.

Lv *et al.* [19] aim to characterize complex human activities by proposing an end-to-end deep learning model that consists of convolutional neural networks (CNN) and recurrent neural networks (RNN). The authors extracted deep features from multi modal time series data using CNN and fed these features to a RNN model. They tested their approach on two human activity recognition datasets called PAMAP2 and self-collected dataset (SCD). They compared their method with other deep learning architectures and they outperformed others in terms of accuracy in both datasets. Mekruksavanich *et al.* [20] proposed a hybrid RNN based model and investigated its efficiency on complex human activity recognition tasks. The authors compared their approach with other deep learning models and previous works on several open access datasets. The results showed that their approach is better than other classifier models in terms of accuracy, precision, recall and F1 score.

Qin *et al.* [21] used machine learning approaches to track swimming activities. Their objectives are to predict swimming style, count swimming time and predict number of strokes. They analyzed wrist worn accelerometer signals of a swimming team. The authors extracted statistical and time series features from raw accelerometer signals. The authors also proposed a new time counting function based on window slicing. They compared several traditional machine learning approaches on swimming style prediction and found out that SVM outperformed all others in all evaluation terms.

III. MATERIALS & METHODS

A. GENERAL FRAMEWORK

Proposed machine learning approach takes single accelerometer sensor signal with three channels, extract time and frequency domain features from these channels and then feed these extracted representative features to LWRF algorithm. Aim of this machine learning approach is to exploit local patterns in complex human motions by utilizing local weights and Random Forest algorithm. A traditional learning process with training and testing is employed. This process has several phases. First, data acquisition is applied to extract raw sensor data from a single wrist worn accelerometer. Second, a preprocessing phase is applied to reduce noise of accelerometer signal and increase sample size by sliding window approach. After that, time and frequency domain features are extracted from each channel of signal to represent complex human motions. For third stage, training and test data are generated with 10-fold Cross Validation. For fourth stage, classifiers are trained with signal features.

Each observation in the dataset has an activity and a gender label. Trained classifier uses available trained observations to predict the class label of a test observation. At the last stage, classifier performance is evaluated using various metrics. General overview of proposed machine learning approach is given in Fig. 1.

B. PAAL ADL ACCELEROMETRY DATASET

For this study, a publicly accessible human activity recognition dataset called “PAAL ADL Accelerometry dataset” is used [22], [23]. The dataset consists of accelerometer measurements of 52 healthy participants. Participant gender distributions are 26 men and 26 women. The age of participants ranges between 18 and 77 years. The dataset has 24 daily living activities that include simple movements and complex daily living activities. Activities in the dataset are divided into 6 broad categories (Eating and Drinking, Hygiene, Dressing/Undressing, Miscellaneous and Communication, Basic health indicators, House cleaning). Although these 24 activities sometimes have similar movements, accelerometer signals can capture subtle motion differences in these similar activities on all axes. These daily living activities are given in Table 1. Data capture is done with a single wrist worn accelerometer. The measurements are recorded at 15Hz. In order to capture true nature of activities, participants are asked to wear this wrist worn accelerometer at home or office setting instead of a laboratory environment [22]. Participants did repetitions for every activity at average 5 times. This approach leads to 6072 recording files in total.

TABLE 1. Available activities in the dataset.

Activity Category	Activity Name
Eating and Drinking	drink water, eat meal, open a bottle, open a box
Hygiene	brush teeth, brush hair
Dressing/Undressing	take off a jacket, put on a jacket, put on a shoe, take off a shoe, put on glasses, take off glasses
Miscellaneous and Communication	sit down, stand up, writing, phone call, type on a keyboard, salute (wave hand)
Basic health indicators	sneeze or cough, blow nose, washing hands
House cleaning	dusting, ironing, washing dishes

C. DATA PREPROCESSING & FEATURE EXTRACTION

Feeding proposed classification framework with raw accelerometer signal values is not feasible [24], [25]. It is based on several reasons. Firstly, majority of machine learning classifiers need equal input in order to process data, this is not the case for accelerometer signals since they have different signal lengths [17]. The other reason is that these signals are not in the same time dimension even though they sometimes possess identical signal lengths. This issue makes it hard for machine learning algorithms to exploit local patterns in signal data. Another reason is that the temporal signal measurements sometimes make it harder for machine learning algorithms to predict behavior of motion since these raw measurements sometimes do not reflect motion

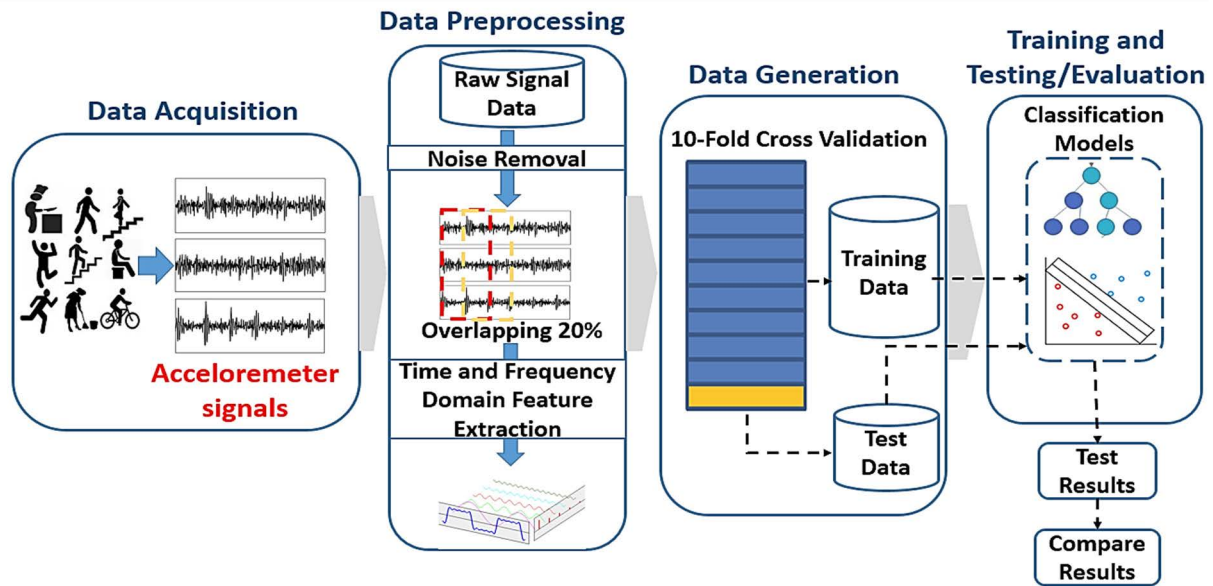


FIGURE 1. General framework for proposed approach.

characteristics. In order to overcome these aforementioned issues, a typical approach is to build a representative feature set from raw accelerometer signals [17], [8]. Preprocessing and feature extraction scheme from previous work on the same dataset [5] is employed to set up the same baseline for prediction tasks.

In order to reduce noise in signal and achieve a robust machine learning model, a two-step preprocessing approach is applied in this study [5]. First, to eliminate high frequency noises while keeping motion characteristics intact, a fourth order Butterworth low pass filter with 15Hz cut off frequency is applied to raw signal. Secondly, in order to eliminate outlier values in time series signal, median filter with third order parameter is applied [5].

To acquire samples from the dataset, data are divided into windowed sections [5]. Feature extraction processes are carried on by 5 second sliding window approach. In this approach, time series signals are divided into multiple windows so that they have 20% overlap between neighboring windows. This sliding window approach outputs 28642 samples. Sample distributions of each activity can be seen in Table 2.

In the previous study, authors extracted several time and frequency domain features from raw accelerometer signals. Time and frequency domain features capture vital characteristics of motions in time series data [5], [8], [17], [26], [27], [28]. In this study, same features that are used in the previous study are extracted. Extracted time and frequency domain features from accelerometer signals are given in Table 3. Features are extracted from each channel (x , y , z) of accelerometer and signal magnitude vector of each observation. At the final stage, these features are concatenated to form a final representative feature vector.

TABLE 2. Number of samples for each activity.

Activity Number	Activity Name	Number Of Samples
1	Blow nose	313
2	Brush hair	273
3	Brush teeth	261
4	Drink water	270
5	Dusting	2344
6	Eat meal	1950
7	Take off glasses	499
8	Put on glasses	1088
9	Ironing	1240
10	Take off jacket	424
11	Put on jacket	259
12	Type on keyboard	260
13	Open bottle	315
14	Open a box	261
15	Phone call	3967
16	Salute	277
17	Take off a shoe	3520
18	Put on a shoe	258
19	Sit down	254
20	Sneeze/cough	278
21	Stand up	2672
22	Washing dishes	1678
23	Washing hands	2729
24	Writing	3252

D. LOCAL WEIGHTED APPROACH

For classification of complex human activities, a hybrid machine learning model called Locally Weighted Random Forest (LWRF) is utilized in this study. This model is first used with multi-channel gait signals to predict the severity of Parkinson's Disease [26]. With the contribution of both Random Forest and local weighting schemes, it outperformed other machine learning approaches in multi-channel gait

TABLE 3. Extracted features from raw accelerometer signals.

Feature Domain	Features
Frequency	σ , mean, percentiles (25 th , 50 th , 75 th), centroid, energy, entropy
Time	σ , mean, median, minimum, maximum, range, correlation between axes, signal magnitude area (SMA), Median absolute deviation (MAD), root mean square (RMS), energy, autocorrelation, Interquartile range (IQR), number of signal peaks, peak to peak amplitude, percentiles (20 th , 50 th , 80 th , 90 th), kurtosis, skewness, coefficient of variation

signal problem domain. Inspired with this succession on multi-channel signals, LWRF model is adapted and used with three channel axis accelerometer signals aiming to provide accurate estimation of human motions.

LWRF algorithm is created to overcome a disadvantage of Random Forest algorithm. This disadvantage is, adjusting the parameters in the learning phase according to all trained samples assuming that all samples are equal [26]. This global approach can sometimes lead to weak parameters that cannot represent all samples in the dataset. When there is high variability in the dataset, it could be hard to find a suitable representation. This situation can happen often in human activity recognition tasks since there are multiple subjects participating in data collection phase. [29], [30]. Dataset variability in human activity recognition can occur due to age, gender and experience of subjects when performing activities [31]. These variabilities in HAR data limit the ability of classifier algorithm to find a global fit model. A possible solution to reduce the variation effect is to create local models that are established on neighbors of the test sample instead of considering every sample as equal on the global model. This can be done via giving weight to each sample in training process and create a local prediction model. Weighting of training samples increases the chance of machine learning algorithm to pay attention to similar available data points. In HAR scenario, weights help to construct a local model for a specific activity by striking out variation effects.

LWRF machine learning model consists of two parts, Random Forest and local weighting [26]. Random Forest is a decision tree algorithm that is based on ensemble learning [32]. It can be used either as a classifier or a regressor according to the problem domain. In this algorithm many decision trees are formed using a bootstrap sample. Random Forest employs ensemble learning strategy by Bootstrap aggression or Bagging process. In this process every tree is constructed separately by using the bootstrap sample. These trees are called random trees. Random Forest uses a random variable selection when creating a branch. Other decision tree approaches aim to find the best branch in all available variables. Reason for this randomness is to minimize correlations between candidate decision trees [33]. This randomness criteria become its advantage when making predictions because if the correlation between these trees becomes high, then it can affect prediction process and thus increase error. In the

final process, outputs of these trees are combined to achieve a final output [34]. Majority voting of all tree outputs is done for classification tasks and averaging of all tree output values for regression tasks.

The second part of the LWRF algorithm is local weighting. Local weighting considered as a non-parametric learning model that utilize local relations on the dataset [35]. The nearest points to the query sample are used to build the local weighted model, rather than building a global model on all available training data. Number of nearest points are usually user defined same as in k nearest neighbor algorithm. A weight value is assigned for every neighboring data sample in the dataset. Target value estimation is affected by these weight values [36]. Data points that are closest to the query have greater weight values compared to those that are further from it. From these closest points, estimated k points are used in training phase to finally define the label of a query point. In LWRF algorithm, local weighting scheme is infused with Random Forest when computing split points and selecting samples for bootstrap [26]. The novelty of LWRF algorithm, is that instead of focusing all of the existing data, LWRF algorithm focuses on similar data points which are defined by distances and by adding weights to these similar data points, it incorporates these weighted data points to Random forest decision making processes. By this incorporation Random Forest selects bootstrap samples among these weighted samples.

Algorithm 1 Locally Weighted Random Forest (LWRF)

Inputs: training data points (S), query point (s), neighborhood size (k)

Output: Predicted activity label of s

Begin:

- 1: Use *Euclidian distance* to calculate distance between s and each training data point (S) in the dataset.
- 2: Estimate (k) nearest neighbors according to distances.
- 3: **for** every neighboring data point
- 4: Calculate weights according to Equation (1).
- 5: Assign weight values to neighboring data points.
- 6: **end for**
- 7: Build Random Forest trees based on these weighted data points.
- 8: Use Random Forest algorithm to predict the label of s .
- 9: Obtain the activity class label of s as a result of majority voting of random trees.

Return Predicted activity label of s

Working mechanism of LWRF algorithm is explained as follows, Weight calculation for each data point is given in (1):

$$W_x = \frac{1}{1 + \text{distance}(s, s_x)} \quad (1)$$

W_x is the weight of x^{th} neighbor, s_x corresponds to x^{th} neighbor, s is the query point and $\text{distance}(s, s_x)$ is the Euclidian distance between query and neighbor point. As can be seen from the equation, data points that are closest to the query will have greater weight and thus greater impact on prediction. Architectural overview of LWRF algorithm is given in Fig. 2.

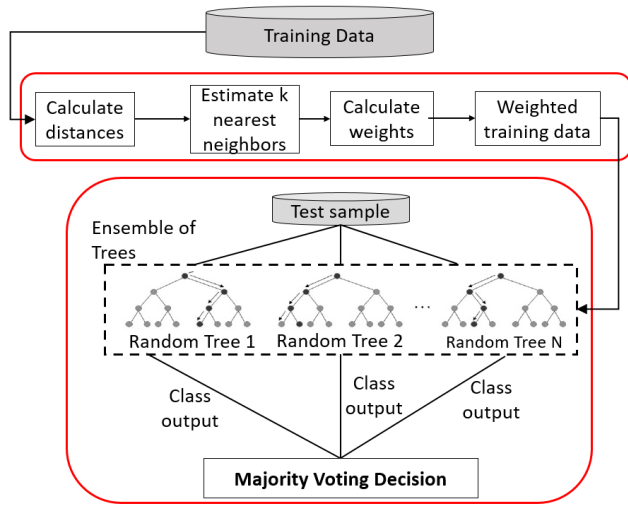


FIGURE 2. Architecture of LWRF algorithm.

IV. RESULTS

A. EVALUATION

All experiments are done using a k-fold cross validation (CV) setup. In this setup, the dataset is randomly split into k folds. Afterwards, each fold is selected for testing phase while remaining k-1 folds are used for training phase. Stopping criteria for CV is if all folds are tested. k value is selected as 10 to establish the same experimental setup as previous work on the PAAL ADL dataset [5].

To evaluate proposed classification framework, several classifier performance metrics are selected. These metrics are Accuracy (A), Precision (Positive predictive Value) (P), Recall (Sensitivity) (R), Specificity (True Negative Rate) (S), Matthews correlation coefficient (MCC) and F1 Score. Formal definitions of Accuracy, Precision, Recall, Specificity, Matthews correlation coefficient and F1 Score are given in (2) (3) (4) (5) (6) (7):

$$\begin{aligned} \text{Accuracy} &= \frac{TP + TN}{TP + FP + TN + FN} \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Precision} &= \frac{TP}{TP + FP} \end{aligned} \quad (3)$$

$$\begin{aligned} \text{Recall} &= \frac{TP}{TP + FN} \end{aligned} \quad (4)$$

$$\begin{aligned} \text{Specificity} &= \frac{TN}{TN + FP} \end{aligned} \quad (5)$$

$$\begin{aligned} \text{MCC} &= \frac{(TP \cdot TN) - (FP \cdot FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \end{aligned} \quad (6)$$

$$\begin{aligned} \text{F1 Score} &= \frac{2 \text{ Precision Recall}}{\text{Precision} + \text{Recall}} \end{aligned} \quad (7)$$

TP, TN, FP and FN abbreviations stand for number of true positives, true negatives, false positives and false negatives respectively.

B. EMPIRICAL RESULTS

To validate proposed framework's performance on prediction tasks, several experiments are conducted with other machine learning algorithms. These machine learning algorithms are J48 Decision Tree (DT) [26], Multilayer Perceptron (MLP) [37], k Nearest Neighbor (kNN) [37], Naïve Bayes (NB) [38], Logistic Model Tree (LMT) [39] and Support Vector Machine (SVM) [40]. Parameter settings for machine learning algorithms are as follows; NB classifier with gaussian distribution is selected for experiments. For DT, confidence factor selected as 0.25, minimum number of objects selected as 2 and number of folds selected as 3. For MLP, learning rate selected as 0.3, momentum selected as 0.2, number of hidden layers selected as 43 for HAR and 32 for gender recognition tasks, number of epochs selected as 500. For SVM, kernel function selected as radial basis function with third degree. For LMT, minimum number of instances selected as 15, fast regression is selected to speed up the training process and no weight trimming is applied. For kNN, k is selected as 1. For Random Forest model in LWRF, number of trees selected as 100 and number of randomly chosen attributes selected as 7.

Overall prediction results for activity recognition with a 10-fold CV setting can be seen in Table 4. Proposed locally weighted framework achieved 91%, 90.9%, 91%, 99.5%, 0.91 and 0.91 in terms of Accuracy, Precision, Recall, Specificity, Matthews correlation coefficient and F1 score respectively. As can be seen from Table 4. LWRF algorithm outperformed other classifier algorithms and previous work by Climent-Pérez and Florez-Revuelta [5]. kNN algorithm comes as second and previous work [5] comes as third. Naïve Bayes performed worst when predicting activities from accelerometer signals. A conclusion can be drawn from these classification results that adding local weights to Random Forest algorithm can increase accuracy when detecting complex human activities. Confusion matrix of LWRF algorithm for human activity recognition is given in Fig. 3.

TABLE 4. Overall classification results for activity recognition task (NR: Not Reported).

Model	A (%)	P (%)	R (%)	S (%)	MCC	F1
kNN	88.9	88.7	88.9	99.3	0.88	0.89
NB	47.6	52	47.6	96	0.44	0.5
DT	71.7	71.7	71.7	98.1	0.70	0.72
MLP	74.2	74.1	74.2	98.1	0.72	0.74
SVM	69.2	68.9	69.2	97.4	0.67	0.69
LMT	73.3	73.2	73.3	97.9	0.71	0.73
Previous study [5]	87.2	NR	NR	NR	NR	NR
LWRF	91	90.9	91	99.5	0.91	0.91

LWRF algorithm uses only number of nearest neighbors (k) parameter to carry out predictions. Further experiments are conducted on effects of k parameter value and as

		Predicted																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Actual	1	282	2	0	0	0	3	0	0	0	0	6	7	3	1	0	0	3	0	0	1	0	0	5	0
	2	5	155	6	11	2	0	0	0	3	2	12	10	13	14	2	7	1	0	12	8	0	0	8	2
	3	1	5	146	47	3	5	0	0	3	10	3	2	4	3	0	4	2	1	5	12	1	0	3	1
	4	0	4	45	141	1	2	0	0	3	6	0	7	10	7	0	4	2	2	5	18	0	1	11	1
	5	1	0	1	1	2271	10	1	2	3	3	0	0	0	0	5	1	7	0	0	1	3	8	25	1
	6	0	0	0	1	3	1864	5	13	15	7	1	0	1	0	0	0	0	1	0	1	5	12	15	6
	7	0	1	0	0	2	4	438	27	7	1	0	0	0	0	0	1	0	4	0	0	1	9	1	3
	8	0	0	0	0	1	19	18	983	12	1	0	0	0	0	0	0	0	1	0	1	5	27	2	18
	9	1	1	3	3	9	15	5	2	1082	24	0	0	6	4	0	1	3	0	0	1	14	8	20	38
	10	0	5	14	6	3	7	3	0	53	257	0	1	9	6	2	2	1	1	7	3	6	6	19	13
	11	10	7	3	1	0	2	1	0	3	3	164	37	5	4	0	7	0	3	4	3	0	0	2	0
	12	13	5	8	9	0	0	1	0	1	2	34	146	9	7	0	4	1	8	11	1	0	0	0	0
	13	0	9	19	14	0	0	1	0	3	9	3	3	197	34	1	0	0	4	7	7	1	1	0	2
	14	1	11	8	7	0	0	0	0	2	5	1	5	29	179	0	2	0	3	7	0	1	0	0	0
	15	0	0	0	0	0	0	0	0	0	2	0	0	0	0	3895	0	58	0	0	0	0	0	11	1
	16	1	7	3	11	0	3	5	1	13	6	13	2	6	4	1	169	5	5	7	5	2	0	4	4
	17	0	0	0	0	1	0	0	0	0	0	0	0	0	0	82	0	3417	0	0	2	0	0	18	0
	18	0	0	3	9	0	3	7	0	0	4	2	7	8	6	0	10	0	188	6	1	0	4	0	0
	19	2	16	19	16	0	1	2	0	0	5	16	18	15	18	3	4	2	11	90	12	1	1	2	0
	20	3	6	19	14	2	2	1	1	5	11	8	6	4	5	3	6	10	0	2	159	1	1	7	2
	21	0	3	0	0	1	2	0	4	1	9	0	0	5	0	0	0	0	0	0	0	2550	4	0	93
	22	0	0	1	1	4	16	12	18	16	12	0	0	0	0	0	2	0	0	0	0	13	1535	17	31
	23	0	0	0	1	2	4	0	0	12	0	0	0	0	0	2	0	22	0	1	1	3	20	2646	15
	24	0	0	0	0	0	5	0	3	16	5	0	0	0	0	1	1	0	0	0	0	82	9	19	3111

FIGURE 3. Confusion matrix for human activity recognition task.

a result k value is selected as 55 in experiments. As can be seen in Fig 4., accuracy of LWRF classifier achieved highest when k is selected as 55. After 55 nearest neighbors value, accuracy begins to drop and stabilizes.

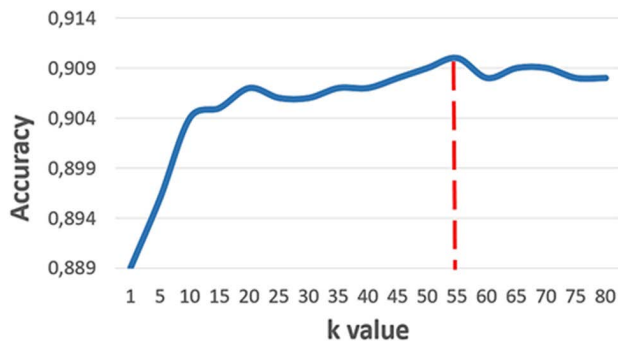


FIGURE 4. Impact of k value on prediction accuracy.

Research on gender recognition using sensors has a great importance and its widely studied [41], [42], [43], [44]. By defining the gender of activity performer, systems can discover more features that are more personalized [41]. Users can get gender-based feedback about their health status and recommendations [42], [43]. Since gender has a correlation with human activity, how the activities are done differ between genders [44]. In order to increase the validity of proposed framework, a further analysis on accelerometer signals

is conducted. In this analysis, gender recognition capabilities of machine learning algorithms are investigated on the same dataset. Main purpose of this investigation is to validate the capability of the proposed framework when exploiting relationships between human motions and gender characteristics. Obtained results can be seen in Table 5. LWRF achieved 91.3%, 91.3%, 91.4%, 91.2%, 0.83 and 0.91 in terms of Accuracy, Precision, Recall, Specificity, Matthews correlation coefficient and F1 score respectively. As can be seen from Table 5. LWRF algorithm outperformed other classifier algorithms and previous work by Climent-Pérez and Florez-Revuelta [5] when predicting gender characteristics of human motions. kNN algorithm comes as second and previous work [5] comes as third. Naïve Bayes performed worst when predicting gender characteristics from accelerometer signals. Confusion matrix of LWRF algorithm for gender recognition is given in Fig. 5.

Experiments are extended to include feature rank analysis. Feature ranking approaches determine which features are important in decision making processes [14], [15]. In this study, feature ranking is done by using a Correlation based feature selection method with ranker approach for both tasks (Human Activity Recognition (HAR) and Gender Recognition (GR)) [45]. By analyzing feature ranks, important time and frequency signal features are identified for both tasks in decision making [46]. Top 10 ranked features according to feature rank analysis algorithm are given in Table 6. According to Table 6., signal magnitude features,

RMS and percentile of time domain signal features hold the most valuable information when determining complex human activities. For GR task, correlation between axes and signal magnitude features play an important role for determining gender. SMA feature is the most valuable one for both tasks. So, we can say that signal magnitude feature of accelerometer features has significant contribution in determining complex activities and gender.

		Predicted	
		woman	man
Actual	woman	12458	1239
	man	1262	13683

FIGURE 5. Confusion matrix for gender recognition task.

TABLE 5. Overall classification results for gender recognition task (NR: Not reported).

Model	A (%)	P (%)	R (%)	S (%)	MCC	F1
kNN	89.9	89.9	89.9	89.9	0.79	0.9
NB	54.8	54.6	54.8	53.3	0.09	0.55
DT	73.9	73.9	73.9	73.8	0.48	0.74
MLP	65.7	65.8	65.7	65.7	0.31	0.66
SVM	59.8	59.7	59.8	59.5	0.19	0.6
LMT	75.7	75.7	75.7	75.6	0.51	0.76
Previous study [5]	88.9	NR	NR	NR	NR	NR
LWRF	91.3	91.3	91.4	91.2	0.83	0.91

TABLE 6. Top 10 ranked features for both tasks.

Task Name	Top ranked features
HAR	Signal Magnitude Area (SMA), mean of signal magnitude, Root Mean Square (RMS), 80th percentile of time domain, standard deviation of time domain Z axis, 50th percentile of time domain, median of signal magnitude, range of Z axis, 90th percentile of time domain and 20th percentile of time domain
GR	Correlation between X and Z axis, SMA, correlation between Y and Z axis, maximum of signal magnitude, maximum value of X axis, Mean Absolute Deviation (MAD) of signal magnitude, 20th percentile of time domain, range of signal magnitude, standard deviation of frequency domain Y axis and RMS

Side by side comparison with previous work on the same dataset can be seen in Fig. 6. As can be seen from Fig. 6, for activity and gender recognition tasks, LWRF algorithm outperformed previous study in terms of accuracy. Previous study utilized Random Forest only as a global model. Whereas LWRF focuses on local models. By using local weighting, dataset variability is minimized and therefore

accuracy is increased. Weighting of samples in Random Forest processes increases the chance of machine learning algorithm to pay attention to similar available data points whereas previous study only consider global samples for Random Forest processes.

The authors that analyzed this dataset mentioned some issues regarding class confusion [5]. They reported that several activities have similar movements and therefore classification model is confused when making activity predictions. Similarities came from same position of hands, symmetry along time axis and lack of movement of wrist when doing activities [5]. Reported most confused activities are “put on a shoe, take off a shoe, open a bottle, open a box, put on glasses, take off glasses, stand up, sit down, phone call, sneeze or cough and blow nose”. As a final analysis, proposed framework is compared with previous study on most confused activities. As can be seen in Table 7, when using LWRF algorithm, accuracies are increased in most of the confused activities. Previous study failed to detect activities that have small sample sizes (open a bottle, open a box, take off glasses, sneeze/cough and blow nose) whereas proposed approach identified these activities with higher recognition rate. A possible inference from these results is that LWRF algorithm’s inclusion of local weights in Random Forest decision making process can overcome the need for more data to achieve global machine learning model. This analysis also shows that proposed framework can detect smallest changes in human motions and identify them correctly in many cases. In addition, ROC curve results of LWRF algorithm for all activities is given as supplementary material (Fig. 7, 8, 9). In these figures, X axis refers to FP rate and y axis refers to TP rate. As can be seen from these results, LWRF maintains a good performance in predicting complex activities.

1) CRITICAL ANALYSIS AND DISCUSSION

According to results presented in “Empirical Results” section, proposed complex human activity recognition framework achieved higher performance when compared with other machine learning models and previous sole study on this dataset. A conclusion can be drawn from HAR task classification results that adding local weights to Random Forest algorithm can increase prediction quality when detecting complex human activities. LWRF algorithm’s parameter effect on recognition tasks are also investigated and 55 neighbor value is selected as suitable candidate for experiments. Gender recognition capabilities of proposed framework are also investigated and similar results achieved. According to achieved results, proposed framework can be a viable tool for exploiting relationships between human motions and gender characteristics.

Feature rank analysis on the extracted features revealed that signal magnitude features, RMS and percentile of time domain signal features hold the most valuable information when determining complex human activities and correlation between axes and signal magnitude features play an important role for determining gender. SMA feature is the most valuable

one for both tasks. Previous study failed to detect activities that have small sample sizes whereas proposed approach identified these activities with higher recognition rate. A possible inference from these results is that LWRF algorithm's inclusion of local weights in Random Forest decision making process can overcome the need for more data to achieve global machine learning model. A final comparison analysis with the previous study reveals that previous study utilized Random Forest only as a global model. Whereas LWRF focuses on local models. By using local weighting, dataset variability is minimized and therefore accuracy is increased. Weighting of samples in Random Forest processes increases the chance of machine learning algorithm to pay attention to similar available data points whereas previous study only consider global samples for Random Forest processes.

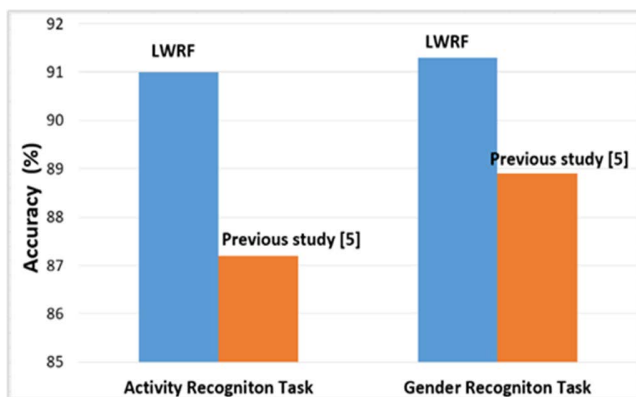


FIGURE 6. Comparison with previous work on both tasks.

TABLE 7. Comparison of previous and current study on most confused activities.

Activity name	Accuracy (%)	
	This study	Previous study [5]
put on a shoe	73	77
take off a shoe	97	55
open a bottle	63	47
open a box	69	41
put on glasses	90	60
take off glasses	88	50
stand up	95	68
sit down	35	58
phone call	98	52
sneeze or cough	57	33
blow nose	90	56

V. CONCLUSION & DISCUSSION

Due to the life expectancy increase, there will be a workforce shortage in elderly care sector in forthcoming years. The best

way to overcome this issue is with the help of AAL systems. A subset of this system, HAR provides an efficient way to tackle this workforce shortage. It can help with evaluating general health and welfare status of elderly by automatically tracking their activities. For example, Lifelogging and home diary applications for dementia disease will reduce the load on physicians and caregivers. Complex activities play a vital role in these applications as they have high level semantic characteristics that truly represent daily life of the user. Therefore, instead of focusing simple activities, recent studies pay attention to the activities that have complex motion behavior. Another important thing is to track these high-level semantic motions with low-cost single sensor systems with efficient machine learning frameworks. To address this challenge, a framework is proposed to predict complex human activities from a single sensor using a local weighted machine learning approach. Proposed framework has several contributions. First, it is the first study that utilize local weighted machine learning approach for accelerometer signal domain. Secondly, proposed model outperformed sole previous study on the same dataset when predicting activities and user gender. Novelty of this approach comes from proposed approach's ability to accurately predict complex activities that have a small movement cycle. These low sample size activities can be harder to predict for global models due to lack of data but LWRF algorithm's inclusion of local weights in Random Forest decision making process can overcome these problems. On the other hand, related studies focused only complex activities that have limited number of activity categories. Proposed approach investigated a dataset that has the largest number of activity categories. The empirical results indicate that this study can provide robust solutions in AAL for assessing dementia related disease progression of elder people in home environments by tracking their daily activities.

A hybrid machine learning algorithm called Locally Weighted Random Forest (LWRF) is used as a classifier in this problem domain. It is the combination of Random Forest classifier with local weighting. Frequency and time domain features are extracted and fed as an input to LWRF algorithm. LWRF algorithm, outperformed other machine learning algorithms and the previous work on activity recognition and gender recognition tasks. Obtained results suggest that LWRF algorithm can be able to distinguish complex activities even with a limited number of samples. Another conclusion that can be drawn from the experiments is that proposed framework can reduce variation effects in accelerometer signals by introducing local weights in several phases of Random Forest algorithm. In addition, Feature rank analysis on the extracted features revealed that signal magnitude features, RMS and percentile of time domain signal features hold the most valuable information when determining complex human activities and correlation between axes and signal magnitude features play an important role for determining gender. SMA feature is the most valuable one for both tasks. These high rank features can be beneficial for HAR applications that focus on large

number of complex activities and also differentiating gender motions in accelerometer signals.

There are some shortcomings exist in this study. First shortcoming is from selecting the right k value. LWRF machine learning algorithm performance relies on selection of k value. This dependence comes from locally weighted structure of the algorithm. So, in order to achieve good results in prediction tasks, k value needs to be fine-tuned. Another shortcoming of this study is from computational complexity of LWRF algorithm. Computational complexity of proposed approach consists of Random Forest algorithm and local weighting scheme that incorporates in random forest algorithm phases. Random Forest algorithms can have a high computational complexity depending on number of samples and features used. With the inclusion of weight calculations and weight assignments, computational complexity of LWRF algorithm can be high in some cases. So, in order to reduce this possible computational load, several solutions exist in literature. Firstly, feature selection and Principal Component Analysis (PCA) methods can be used to reduce dimensionality and thus reduce computational complexity [47]. Another solution is to employ Graphics Processor Units (GPU) on an advanced centralized computer system to speed up the training process of Random Forest algorithm [48]. Parallel processing techniques can be also considered to overcome this issue [49].

The other shortcoming of this study is with the sample size of the dataset. Unfortunately, the number of samples in the activities was low. Number of data points for each activity in the dataset can be increased. Especially dataset curators can focus on complex activities that have small movement cycles. One possible solution for this issue is to increase number of repetitions for each complex activity. With the inclusion of more samples, more data points can be processed and therefore performance of proposed approach can increase. Another solution to overcome the lack of complex activity samples is by using resampling methods. Methods like ADASYN [50] and SMOTE [50] can be used in training phase to increase sample size. Having small number of samples limits proposed framework's ability to utilize deep learning architectures. Because deep learning architectures need large amount of data to thrive in HAR applications.

To give an overview of recent studies that investigated human activity recognition with single accelerometer or analyze complex human activities, a comparative table is given in Table 8. As can be seen from the Table 8, the dataset that is used in this study has the highest number of activities [5]. In other studies [9], [17], [18], [19], [20], high variety of complex activities can only be handled with inclusion of Accelerometer (A.), Magnetometer (M.) and Gyroscope (G.) sensors. On the other hand, majority of studies that used single accelerometer sensor [7], [10], [11], [16], [21] are mainly focused on limited number of activities due to its challenging nature. In addition, as can be seen from Table 7, studies that investigate high number of complex activities did not achieve as much accuracy as other studies that investigate small number of activities. This result comes from the

TABLE 8. Recent studies that used single accelerometer Sensor or analyze complex human activities.

Study	Features	Sensor	# of activities	Classifier	A. (%)
Current study	Time and Frequency domain	A.	24	LWRF	91.0
[5]	Time and Frequency domain	A.	24	MaOEA	87.2
[7]	Time and Frequency domain	A	6	QPSO-KELM	96.2
[9]	Time, Location, Multi-layer	A., G. M.	13	CNN+LSTM	95.5
[10]	Wavelet decomposition	A.	9	SVM	84.4
[11]	Recurrence Plot	A.	6	CNN	91.3
[16]	Raw signal	A.	7	LSTM	91.3
[17]	Time and Frequency domain	A., G. M.	10	Random Forest	84.4
[18]	Time and Frequency domain	A., G.	13	DT	93.0
[19]	Raw signal	A., G. M.	12	CNN+LSTM	85.0
[20]	Raw signal	A., G. M.	18	CNN+GRU	88.0
[21]	Time and Frequency domain	A.	4	SVM	99.0

challenging task of predicting complex motions. Whereas in this study by using a single accelerometer sensor, a dataset with highest number of activities among other datasets is investigated with numerous machine learning algorithms.

Overview of strengths and limitations of proposed approach are as follows; Main strengths of this study over others can be given as; it is the first study that utilize local weighted machine learning approach for accelerometer signal domain, the proposed framework outperformed previous study on the same dataset and other machine learning approaches when predicting complex human activities, the proposed framework can reduce dataset variation effects by introducing a combination of local weighting scheme and Random Forest algorithm, by utilizing neighboring data points and locally weighting in prediction phase this approach can be considered for predicting activities with limited number of samples. Limitations of the proposed framework compared with other studies can be given as; decision of number of neighbors (k value) needs parameter tuning and LWRF can reach a high computational complexity depending on number of samples and features used. Another problem is the lack of sample size to utilize deep learning architectures.

For future direction of this study, one aim can be benchmarking proposed framework on other human activity recognition open access datasets. Datasets that have different type of sensors can be considered. Fusion of these sensors and their impact on prediction tasks can be investigated. This will increase validity of the proposed approach on different sensor

domains. The location and context of activity could be implemented in the processing if it was available in PAAL dataset. The authors of the PAAL dataset did not include these kind of information, but there are several ways to track context and location of activity in the literature. One possible way is using smart pressure sensors that are installed under the floor at home, so when the sensors are activated user location and user activity can be recorded at the same time [48]. Another solution can be installing motion and door sensors to several locations at home. When a sensor is activated, location of the user can be known and therefore activity and location information can be associated with each other [52], [53]. Lastly, GPS sensors can be utilized but GPS sensors have limited indoor reception capacity so its suitable for detecting general location of user, for example at home or at office [54]. Another future direction can be combining LWRF algorithm with location information. Datasets that have location data can be investigated to explore proposed approach's ability to fuse motion signals with location data. Also, feature selection methods based on optimization algorithms can be considered for future study. Especially, feature selection methods with gradient-based optimizer and grey wolf optimizer are proven to have a positive impact on prediction performance in HAR problems [55]. Also in future studies, LWRF's ability to deal with dataset class imbalance challenges will be investigated in detail. Class imbalance solutions like undersampling and resampling techniques will be analyzed and can be infused with LWRF to overcome class imbalance. Combining traditional machine learning approaches with deep learning architectures can provide good prediction ability in HAR problem domain [56], [57]. Therefore, another future direction could be combining LWRF approach with other deep learning architectures like CNN and LSTM to increase prediction performance. These deep features can also utilize relationships between different accelerometer channels. Last future direction is to investigate how to overcome aforementioned possible high computational complexity.

REFERENCES

- [1] N. Gulati and P. D. Kaur, "FriendCare-AAL: A robust social IoT based alert generation system for ambient assisted living," *J. Ambient Intell. Humanized Comput.*, vol. 13, no. 4, pp. 1735–1762, Apr. 2022.
- [2] C. M. Ranieri, S. MacLeod, M. Dragone, P. A. Vargas, and R. A. F. Romero, "Activity recognition for ambient assisted living with videos, inertial units and ambient sensors," *Sensors*, vol. 21, no. 3, p. 768, Jan. 2021.
- [3] S. Wilhelm, "Activity-monitoring in private households for emergency detection: A survey of common methods and existing disaggregable data sources," in *Proc. 14th Int. Joint Conf. Biomed. Eng. Syst. Technol.*, 2021, pp. 263–272.
- [4] C. Byrne, R. Collier, and G. O'Hare, "A review and classification of assisted living systems," *Information*, vol. 9, no. 7, p. 182, Jul. 2018.
- [5] P. Climent-Pérez and F. Florez-Revuelta, "Privacy-preserving human action recognition with a many-objective evolutionary algorithm," *Sensors*, vol. 22, no. 3, p. 764, Jan. 2022.
- [6] L. M. Dang, K. Min, H. Wang, M. Jalil Piran, C. H. Lee, and H. Moon, "Sensor-based and vision-based human activity recognition: A comprehensive survey," *Pattern Recognit.*, vol. 108, Dec. 2020, Art. no. 107561.
- [7] Y. Tain, J. Zhang, L. Chen, Y. Geng, and X. Wang, "Single wearable accelerometer-based human activity recognition via kernel discriminant analysis and QPSO-KELM classifier," *IEEE Access*, vol. 7, pp. 109216–109227, 2019.
- [8] B. Erdaş, I. Atasoy, K. Açıcı, and H. Oğul, "Integrating features for accelerometer-based activity recognition," *Proc. Comput. Sci.*, vol. 98, 2016, pp. 522–527.
- [9] R. Huan, C. Jiang, L. Ge, J. Shu, Z. Zhan, P. Chen, K. Chi, and R. Liang, "Human complex activity recognition with sensor data using multiple features," *IEEE Sensors J.*, vol. 22, no. 1, pp. 757–775, Jan. 2022.
- [10] Y. Tian, X. Wang, P. Yang, J. Wang, and J. Zhang, "A single accelerometer-based robust human activity recognition via wavelet features and ensemble feature selection," in *Proc. 24th Int. Conf. Autom. Comput. (ICAC)*, Sep. 2018, pp. 1–6.
- [11] J. Lu and K.-Y. Tong, "Robust single accelerometer-based activity recognition using modified recurrence plot," *IEEE Sensors J.*, vol. 19, no. 15, pp. 6317–6324, Aug. 2019.
- [12] A. Patel and J. Shah, "Sensor-based activity recognition in the context of ambient assisted living systems: A review," *J. Ambient Intell. Smart Environ.*, vol. 11, no. 4, pp. 301–322, Jul. 2019.
- [13] D. Thakur and S. Biswas, "An integration of feature extraction and guided regularized random forest feature selection for smartphone based human activity recognition," *J. Netw. Comput. Appl.*, vol. 204, Aug. 2022, Art. no. 103417.
- [14] M. Sharif, M. A. Khan, F. Zahid, J. H. Shah, and T. Akram, "Human action recognition: A framework of statistical weighted segmentation and rank correlation-based selection," *Pattern Anal. Appl.*, vol. 23, pp. 1–14, Feb. 2019.
- [15] N. A. Capela, E. D. Lemaire, and N. Baddour, "Feature selection for wearable smartphone-based human activity recognition with able bodied elderly and stroke patients," *PLoS ONE*, vol. 10, no. 4, pp. 1–18, 2015.
- [16] S. Guney and C. B. Erdaş, "A deep LSTM approach for activity recognition," in *Proc. 42nd Int. Conf. Telecommun. Signal Process. (TSP)*, Jul. 2019, pp. 294–297.
- [17] K. Açıcı, B. Erdaş, T. Aşuroğlu, and H. Oğul, "HANDY: A benchmark dataset for context-awareness via wrist-worn motion sensors," *Data*, vol. 3, no. 3, p. 24, Jun. 2018.
- [18] J. Lu, X. Zheng, M. Sheng, J. Jin, and S. Yu, "Efficient human activity recognition using a single wearable sensor," *IEEE Internet Things J.*, vol. 7, no. 11, pp. 11137–11146, Nov. 2020.
- [19] M. Lv, W. Xu, and T. Chen, "A hybrid deep convolutional and recurrent neural network for complex activity recognition using multimodal sensors," *Neurocomputing*, vol. 362, pp. 33–40, Oct. 2019.
- [20] S. Mekruksavanich and A. Jitpattanakul, "Biometric user identification based on human activity recognition using wearable sensors: An experiment using deep learning models," *Electronics*, vol. 10, no. 3, p. 308, Jan. 2021.
- [21] X. Qin, Y. Song, G. Zhang, F. Guo, and W. Zhu, "Quantifying swimming activities using accelerometer signal processing and machine learning: A pilot study," *Biomed. Signal Process. Control*, vol. 71, Jan. 2022, Art. no. 103136.
- [22] P. Climent-Pérez, Á. M. Muñoz-Antón, A. Poli, S. Spinsante, and F. Florez-Revuelta, "Dataset of acceleration signals recorded while performing activities of daily living," *Data Brief*, vol. 41, Apr. 2022, Art. no. 107896.
- [23] PAAL ADL Accelerometry DataSet V2.0. Accessed: Apr. 12, 2022. [Online]. Available: <https://zenodo.org/record/5785955>
- [24] S. K. Chaurasia and S. R. N. Reddy, "Impact of time domain features & inertial sensors on activity recognition using randomized selection," in *Proc. Int. Conf. Comput., Commun., Intell. Syst. (ICCCIS)*, Feb. 2021, pp. 744–750.
- [25] L. Sanhudo, D. Calvetti, J. P. Martins, N. M. M. Ramos, P. Mêda, M. C. Gonçalves, and H. Sousa, "Activity classification using accelerometers and machine learning for complex construction worker activities," *J. Building Eng.*, vol. 35, Mar. 2021, Art. no. 102001.
- [26] T. Aşuroğlu, K. Açıcı, C. B. Erdaş, M. K. Toprak, H. Erdem, and H. Oğul, "Parkinson's disease monitoring from gait analysis via foot-worn sensors," *Biocybernetics Biomed. Eng.*, vol. 38, no. 3, pp. 722–760, 2018.
- [27] S. Fioretti, M. Olivastrelli, A. Poli, S. Spinsante, and A. Strazza, "ADLs Detection with a wrist-worn accelerometer in uncontrolled conditions," in *Proc. Int. Conf. Wearables Healthcare*, 2021, pp. 197–208.
- [28] A. Poli, A. Muñoz-Antón, S. Spinsante, and F. Florez-Revuelta, "Balancing activity recognition and privacy preservation with multi-objective evolutionary algorithm," in *Proc. 7th EAI Int. Conf. Smart Objects Technol. Social Good*, 2021, pp. 3–17.
- [29] A. Bulling, U. Blanke, and B. Schiele, "A tutorial on human activity recognition using body-worn inertial sensors," *ACM Comput. Surveys*, vol. 46, no. 3, pp. 1–33, Jan. 2014.

- [30] A. Zinnen, C. Wojek, and B. Schiele, "Multi activity recognition based on bodymodel-derived primitives," in *Proc. 4th Int. Symp. Location Context Awareness*, vol. 5561, 2009, pp. 1–18.
- [31] A. Dehghani, O. Sarbishei, T. Glatard, and E. Shihab, "Quantitative comparison of overlapping and non-overlapping sliding Windows for human activity recognition using inertial sensors," *Sensors*, vol. 19, no. 22, p. 5026, Nov. 2019.
- [32] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
- [33] K. Acici, C. Erdas, T. Asuroglu, M. Toprak, H. Erdem, and H. Ogul, "A random forest method to detect Parkinson's disease via gait analysis," in *Engineering Applications of Neural Networks*. Cham, Switzerland: Springer, 2017, pp. 609–619.
- [34] A. Eerdeken, M. Deruyck, J. Fontaine, L. Martens, E. De Poorter, D. Plets, and W. Joseph, "A framework for energy-efficient equine activity recognition with leg accelerometers," *Comput. Electron. Agricult.*, vol. 183, Apr. 2021, Art. no. 106020.
- [35] C. G. Atkeson, A. W. Moore, and S. Schaal, "Locally weighted learning," in *Lazy Learning*. Cham, Switzerland: Springer, vol. 1997, pp. 11–73.
- [36] H. Sanz, F. Reverter, and C. Valim, "Enhancing SVM for survival data using local invariances and weighting," *BMC Bioinf.*, vol. 21, no. 1, Dec. 2020.
- [37] Ç. B. Erdaş, E. Sümer, and S. Kibaroglu, "CNN-based severity prediction of neurodegenerative diseases using gait data," *Digit. Health*, vol. 8, Jan. 2022, Art. no. 205520762210751.
- [38] D. Bužić and J. Dobša, "Lyrics classification using Naive Bayes," in *Proc. 41st Int. Conv. Inf. Commun. Technol. Electron. Microelectron. (MIPRO)*, 2018, pp. 1011–1015.
- [39] E. Nazari, M. Aghemiri, A. Avan, A. Mehrabian, and H. Tabesh, "Machine learning approaches for classification of colorectal cancer with and without feature selection method on microarray data," *Gene Rep.*, vol. 25, no. 3, pp. 1014–1019, 2021.
- [40] J. Ryu, J. Seo, H. Jebelli, and S. Lee, "Automated action recognition using an accelerometer-embedded wristband-type activity tracker," *J. Construction Eng. Manage.*, vol. 145, no. 1, Jan. 2019, Art. no. 04018114.
- [41] J. L. Kröger, P. Raschke, and T. R. Bhuiyan, "Privacy implications of accelerometer data: A review of possible inferences," in *Proc. 3rd Int. Conf. Cryptography, Secur. Privacy (ICCSPP)*, 2019, pp. 81–87.
- [42] A. Jain and V. Kanhangad, "Gender classification in smartphones using gait information," *Exp. Syst. Appl.*, vol. 93, pp. 257–266, Mar. 2018.
- [43] A. Jain and V. Kanhangad, "Investigating gender recognition in smartphones using accelerometer and gyroscope sensor readings," in *Proc. Int. Conf. Comput. Techn. Inf. Commun. Technol. (ICCTICT)*, Mar. 2016, pp. 597–602.
- [44] K. Charlotte, S. Jasper, K. Jacqueline, E. Annette, and T. Jens, "Context-specific outdoor time and physical activity among school-children across gender and age: Using accelerometers and GPS to advance methods," *Frontiers Public Health*, vol. 2, p. 20, Mar. 2014.
- [45] A. Sharma and P. K. Mishra, "Performance analysis of machine learning based optimized feature selection approaches for breast cancer diagnosis," *Int. J. Inf. Technol.*, vol. 14, no. 4, pp. 1–12, 2021.
- [46] B. Dhananjay and J. Sivaraman, "Analysis and classification of heart rate using CatBoost feature ranking model," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102610.
- [47] H. F. Nweke, Y. W. Teh, G. Mujtaba, and M. A. Al-Garadi, "Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions," *Inf. Fusion*, vol. 46, pp. 147–170, Mar. 2019.
- [48] Z. Wen, J. Shi, B. He, Q. Li, and J. Chen, "ThunderGBM: Fast GBDTs and random forests on GPUs," *J. Mach. Learn. Res.*, vol. 21, pp. 1–5, Jan. 2020.
- [49] J. Andreu-Perez, D. R. Leff, H. M. D. Ip, and G.-Z. Yang, "From wearable sensors to smart implants—Toward pervasive and personalized healthcare," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 12, pp. 2750–2762, Dec. 2015.
- [50] K. Açıcı, T. Aşuroğlu, B. Erdaş, and H. Oğul, "T4SS effector protein prediction with deep learning," *Data*, vol. 4, no. 1, p. 45, Mar. 2019.
- [51] C.-H. Lu and L.-C. Fu, "Robust location-aware activity recognition using wireless sensor network in an attentive home," *IEEE Trans. Autom. Sci. Eng.*, vol. 6, no. 4, pp. 598–609, Oct. 2009.
- [52] E. Nakagawa, K. Moriya, H. Suwa, M. Fujimoto, Y. Arakawa, and K. Yasumoto, "Toward real-time in-home activity recognition using indoor positioning sensor and power meters," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops)*, Mar. 2017, pp. 539–544.
- [53] T. Wang and D. J. Cook, "SMRT: Multi-resident tracking in smart Homes with sensor vectorization," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 8, pp. 2809–2821, Feb. 2020.
- [54] M. Straczekiewicz, P. James, and J.-P. Onnela, "A systematic review of smartphone-based human activity recognition methods for health research," *NPJ Digit. Med.*, vol. 4, no. 1, Dec. 2021.
- [55] A. M. Helmi, M. A. A. Al-qaness, A. Dahou, R. Damaševičius, T. Krilavičius, and M. A. Elaziz, "A novel hybrid gradient-based optimizer and grey wolf optimizer feature selection method for human activity recognition using smartphone sensors," *Entropy*, vol. 23, no. 8, p. 1065, Aug. 2021.
- [56] V. Ghate and C. S. Hemalatha, "Hybrid deep learning approaches for smartphone sensor-based human activity recognition," *Multimedia Tools Appl.*, vol. 80, pp. 1–20, Feb. 2021.
- [57] Y. Zou, X. Zhou, and X. Ren, "Action recognition based on a hybrid deep network," *Social Netw. Comput. Sci.*, vol. 2, no. 6, pp. 1–11, Nov. 2021.



TUNÇ AŞUROĞLU received the B.S. degree in computer engineering from the TOBB University of Economics and Technology, Turkey, in 2013, and the M.S. and Ph.D. degrees in computer engineering from Baskent University, Turkey, in 2015, and 2020, respectively. He worked as an Assistant Professor with the Department of Computer Engineering, Baskent University. He also worked as a Guest Researcher at the Faculty of Computer Sciences, Østfold University College, Norway. He is currently a Postdoctoral Research Fellow with the Faculty of Medicine and Health Technology, Tampere University, Tampere, Finland. His research interests include applications of computational intelligence in health informatics and wearable sensor systems.

• • •