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Energy-Efficient Human Activity Recognition on Smartphones: A Test-Cost Sensitive Approach

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Abstract— **Human activity recognition is essential for providing services in the Internet of Things. Thanks to their ubiquity, sensing capability, and processing power, modern smartphones have become attractive devices for activity recognition. However, their limited battery capacity places a hurdle to exploit such sensing and processing power. While power is consumed in both the sensing and computation layers of the recognition process, power optimization in the latter layer has not been studied extensively enough. This paper strives towards energy-efficient activity recognition by focusing on the cost of feature extraction. To this end, the energy cost of extracting various features is examined and test-cost sensitive prediction models are employed to recognize activities from features. Experimental results reveal a considerable opportunity to conserve energy by awareness of the cost of feature extraction. With only a small sacrifice in prediction accuracy, the energy cost of computations can be reduced by a factor of three.**

Keywords- Internet of Things (IoT); Human Activity Recognition (HAR); Power-Aware Computing; Pervasive Computing; Test-Cost Sensitive Learning; Ambient Intelligence (AmI)

I. INTRODUCTION

Ambient intelligence (AmI) is an essential prerequisite to improving the quality of human life. AmI refers to environments which can sense context, recognize actions, and intelligently adapt to situations and cater to needs [1]. One fundamental building block of an AmI system is the capability of recognizing human activities. For example, when someone has been walking in a park listening to soft music, the player will switch to upbeat music just after this person starts jogging.

Applications of human activity recognition (HAR) go far beyond this basic example and include, but are not limited to, areas of healthcare, care for the elderly and children, assisted living, sports, and the military.

It is possible to recognize human activities by processing the installed video camera feeds of an environment [2, 3]. However, this is an obtrusive and compute-intensive approach and generally disliked by those inhabiting or frequenting the environment. Another approach involves mounting several sensors on the body of the subjects [4]. This only alters the type of obtrusiveness, from mounting cameras to wearing sensors. Currently for HAR, there is a viable alternative to wearable sensors and video cameras: smartphones. The following properties of today's smartphones make them suitable devices for activity recognition:

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- *Ubiquitous*: Almost everyone owns at least one smartphone.
- *Unobtrusive*: People are accustomed to carrying a smartphone.
- *Sentient*: Smartphones are equipped with various kinds of sensors such as accelerometers, gyroscopes, proximity sensors, etc.
- *Capable*: Smartphones have powerful computational resources and can perform local computations.
- *Connected*: Whenever required, smartphones can offload heavier computational tasks to the cloud.

The generic problem of smartphone-based activity recognition is depicted by Fig. 1. The raw inputs to HAR are the discrete stream of signals collected from phone sensors. Among the various types of sensors found on a typical smartphone, different subsets of sensors have been employed in literature. The current study utilizes tri-axial accelerometer sensor data. Each sample of this sensor is a tuple of three acceleration values in three-dimensional space. The sensor data is usually sampled at a specific fixed period of time. However, to help with power efficiency, sometimes sensor reading rates are lowered when this does not adversely affect recognition accuracy. At the heart of an HAR solution is a model which predicts activities from sensor data. This model is usually data-driven and learnt from labeled training data collected by volunteers over a period of several days or months. The model usually does not consume raw sensor data directly, but rather some informant features extracted from it. For this purpose, the data is segmented into some windows of a specific length, and some features are extracted for each window. These defined features can be of a time-domain (such as mean value and standard deviation), frequency-domain (such as the dominant frequency), or of any other type.

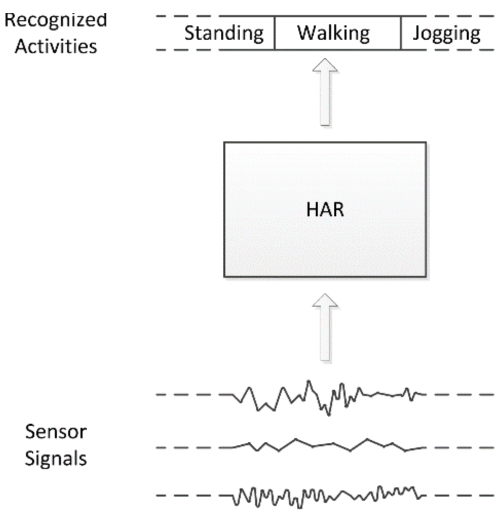


Fig. 1: The problem of human activity recognition.

A major challenge for smartphone-based activity recognition is power efficiency. HAR is a classification machine learning task which has been extensively studied by researchers in terms of prediction accuracy. However, the power consumption optimization of HAR deserves more attention, especially when it comes to smartphones. The limited battery capacity of these devices restricts the energy budget of resource-hungry HAR operations. Power-unawareness can cause excessive heating and rapidly discharge the device's battery, thus leading to poor user experience and low applicability of unoptimized activity recognition approaches.

The majority of previous research in the field of power-efficient HAR has focused on power optimization at the sensing layer. Considering the rapid advancement of low-power sensing technology and the tendency of activity recognition algorithms to become more complex and CPU-intensive, it is also vital to strive for power optimization in the computational layer of HAR tasks. The present study is an effort to optimize the power consumption of the computational part of HAR tasks by employing lazy test-cost-sensitive decision trees, which avoid the calculation of costly features as much as possible.

The rest of the present paper is organized as follows. Section II reviews related work while Section III presents research motivations and the proposed approach. Section IV provides details on the experimental setup and discusses the experimental results. Finally, Section V concludes the paper and presents the future work.

II. Related Work

Along with their power of sensing, computations, and communications, the ubiquity of smartphones has made them the ideal platform for HAR. In [5], the tri-axial accelerometer of a smartphone is used to predict user activities. Machine learning over some features extracted from 10s segments of sensor data was employed to recognize activities such as standing, walking, jogging, and ascending and descending stairs. Ravi et al [6] utilized deep learning over data from both accelerometer and gyroscope sensors for HAR.

While prediction accuracy is the main concern of the works mentioned above and of many others, the limited battery capacity of smartphones has motivated some researchers to take into account the power consumption of prediction operations. HAR tasks consist of different layers of work and power optimization efforts in this area can be best organized and understood by using this layered perspective. Fig. 2 expands previous Fig. 1 by illustrating these different layers. As a place where electrical energy is consumed, within each layer lies an opportunity to conserve energy. The whole task can be decomposed into two layers: sensing and computations. The latter itself consists of two sub-layers: feature extraction and classification. The duty of the sensing layer is to activate and read sensor values and then provide them as a stream of raw data to the layer of feature extraction and preprocessing.

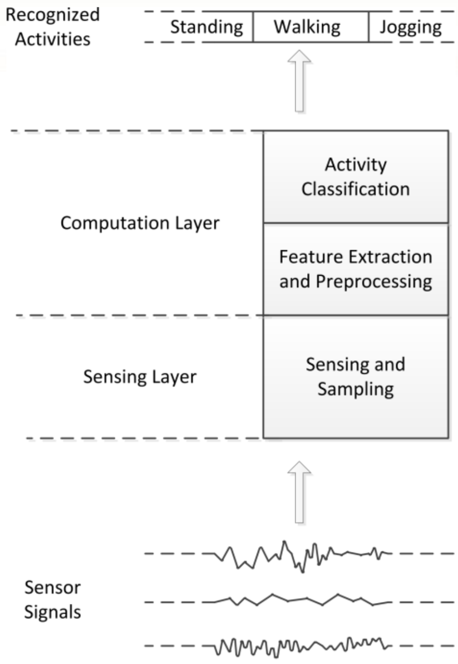


Fig. 2: Layering of a human activity recognition task.

A. Sensing Layer

Some researchers have worked on optimizing power consumption at the lowest layer by disabling as many sensors as possible. For smartphone-based activity recognition, [7] proposes an algorithm that attempts to ignore (and turn off) some sensors when data from other sensors provide sufficient informant for prediction. The same concept is used in [4, 8] for activity recognition via multiple wearable sensors. Some researchers have studied the tradeoff induced by the temporal resolution of sampled sensor data. Higher sensor sampling rates can improve prediction accuracy but can also adversely affect power consumption. In addition to adjusting the sampling rate, the duty cycling (sleep scheduling) of sensors can raise power efficiency. Employing both techniques, Yurur et al [9] report 20% to 50% improvement in sensor power consumption at the cost of a 15% accuracy decrease. In [10], a comprehensive study is conducted on the sensor sampling rate's effect on the accuracy of activity recognition and the results show that the tradeoff is, in fact, dependent on the type of activities. In other words, some types of activities, such as ascending stairs, require a high temporal resolution of sensor data to be accurately predicted, while some others, such as sitting and standing, do not. The same holds true for the set of features extracted from raw sensor data, which show that some activities only require time-domain features to be accurately predicted while for some other activities, more compute-intensive frequency-domain features are also needed. The minimum per-activity sampling rate and feature set requirements have been experimentally quantified and the results incorporated into their A3R algorithm. This starts by the maximum requirements, and, as soon as an activity is predicted, it switches to the optimum requirements and remains that way until a threshold of degradation in recognition confidence is observed. The A3R algorithm obviously works at both the sensing and feature extraction layers and achieves a 20% - 25% energy saving.

B. Computation Layer

Computational tasks consume power and the computation layer of Fig. 2 is another place to implement power optimization efforts. The trend of smartphone applications to become smarter, more complex, and thus more power-hungry, along with the ongoing enhancements in low-power sensor hardware is shifting the importance of power optimization from the sensing layer to the computation layer. Some researchers have tackled the problem at this layer by employing types or versions of algorithms which are less compute-intensive. Anguita et al [11] demonstrated that using a fixed point instead of a floating point implementation of SVM algorithm can significantly decrease the power consumption of activity recognition tasks at the price of a subtle increase in the recognition error. Ravi et al [6] proposed a framework for activity recognition based on deep learning, which avoids costly computations and is power-efficient.

C. Feature Extraction Sub-layer

The feature extraction sub-layer extracts informative data from raw sensor readings. These features are the inputs into the classification algorithm. A comprehensive overview of the possible extracted features is given in [12]. This layer can also be the target of energy optimization. Yan et al [10] showed that sometimes ignoring costly frequency-domain features does not significantly decrease the recognition accuracy of some activities such as sitting and standing. In [13], a similar study is conducted for the same purpose. Energy optimization in the feature extraction sub-layer deserves more attention because it involves a significant amount of calculations and is often more compute-intensive than the classification sub-layer.

III. The Proposed Approach

A. Motivation

Feature extraction is a significant part of the computation layer. Power optimization at this sub-layer of HAR is the focus of the present study. Energy consumption is one of the feature extraction costs and it is desirable to avoid calculating as much as possible costly features during classifications. The idea is to conserve feature extraction energy by exploiting the fact that various types of features are not equal in terms of the power they consume and the contribution they make to the prediction outcome. Table 1 presents the features used by [5] for activity recognition on cellphones. The table contains a total of 43 features categorized into 6 different groups. The average amount of energy consumed to compute each feature type is depicted in Table 2. The energy measurement approach will be described later in Section IV.

As shown in the table, the energy demand for feature calculations varies significantly among the groups, from 3.25 μJ (microjoules) for DIST up to 193.6 μJ for RSS.

Table 1: Features for activity recognition from accelerometer data.

Group	Description	Count
AVG	Average acceleration	1 per axis
SD	Standard deviation	1 per axis
AD	Average of absolute difference from mean value	1 per axis
DIST	Distribution over 10 equal-sized bins	10 per axis
RSS	Average of the root of sum of squares of the three axis values	1
TBP	Average time between waveform peaks	1 per axis

Table 2: Energy consumption cost of extracting features in different groups.

Group	Energy (µJ)
AVG	27.4
SD	28.3
AD	28.2
DIST	3.25
RSS	193.6
TBP	36.7

B. *Energy-Efficient Activity Feature Extraction*

Activity recognition is a classification problem, and machine learning classification algorithms may be rendered sensitive to several types of costs, such as misclassification costs and test costs [15]. Test-cost sensitive techniques focus on reducing the cost of testing attributes which act as inputs to the classifier. This term is derived from a medical diagnosis context in which some clinical tests are required, but it is desirable to skip some of the more costly ones (in terms of expense, time, complications, etc.) when the accuracy of the results is not affected by doing so. The present study proposes that the same concept can be applied to fine-grained feature extraction in the field of activity recognition so as to reduce the energy cost of the classification task.

Despite the fact that test-cost sensitive learning can be very effective in many practical areas, little research has been conducted on this topic. Test-cost awareness in machine learning can be achieved in different ways. Some researchers have employed feature reduction methods for this purpose [16]. This term refers to one of the tasks in the data preprocessing phase of machine learning whose aim is to eliminate some less important features from input dataset, which can then result in lower feature extraction costs. Another approach is to exploit the ability of some learning algorithms to handle missing attribute values [17]. The current work adopts an approach which takes advantage of the fact that some machine learning techniques such as decision trees, inspect input variables in an order and so may come up with a result before having tested all of them. This method slightly modifies the inductive bias of the learning algorithm making it more likely to place the less costly features near the root of the tree.

C. *Test-Cost sensitive Decision Trees for Activity Recognition*

A decision tree is a tree structure that classifies instances based on some testing of attribute values. Starting from the root, each node of the tree performs a test on a specific attribute, with the branch to the next level depending on the test result. The instance descends down the tree until a leaf node is reached, where the classification of the instance is determined. For the case of human activity recognition, the nodes of the tree perform tests on extracted features (the features listed in Table I, for example) and the leaves are labeled with recognized activities, such as walking, sitting, etc. Fig. 3 provides a segment of a sample decision tree.

There are several methods for constructing decision trees from sample instances of data. C4.5 [18] is a well-known greedy algorithm for decision tree induction. It starts from the root node and selects the attribute that best separates the node's training instances of data. Then, the data is split among the child nodes and the same process repeats for attribute selection at the next level. The process continues until data is separated enough where a decision leaf node is placed. The impurity of the classes in the data subset can be quantified using the entropy measure. The definition of this measure is provided by Equation 1, where S is the set of data, p_i is the proportion of S belonging to class i out of c total classes.

$$E(S) = -\sum_{i=1}^{c} p_i \log_2 p_i \qquad (1)$$

The C4.5 algorithm selects test attributes based on their effectiveness in entropy reduction. The measure used for this purpose is called "information gain" and is defined in Equation 2. This equation formulates the information gained after splitting the set S of instances according to the possible values of attribute A. V is a function of A which returns the set of possible values of A while S_v is the subset of A belonging to specific class value v.

$$G(S, A) = E(S) - \sum_{v \in V(A)} \frac{|S_v|}{|S|} E(S_v) \qquad (2)$$

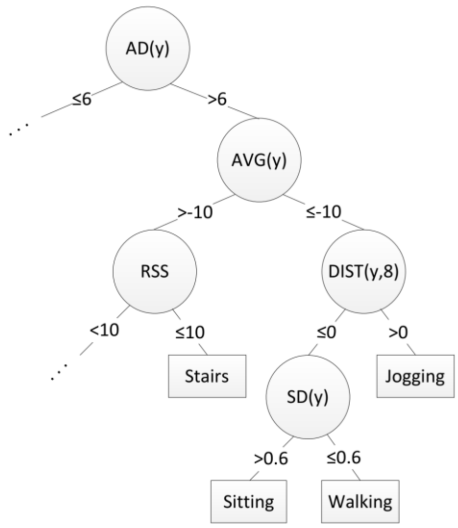


Fig. 3: A sample decision tree segment for activity recognition.

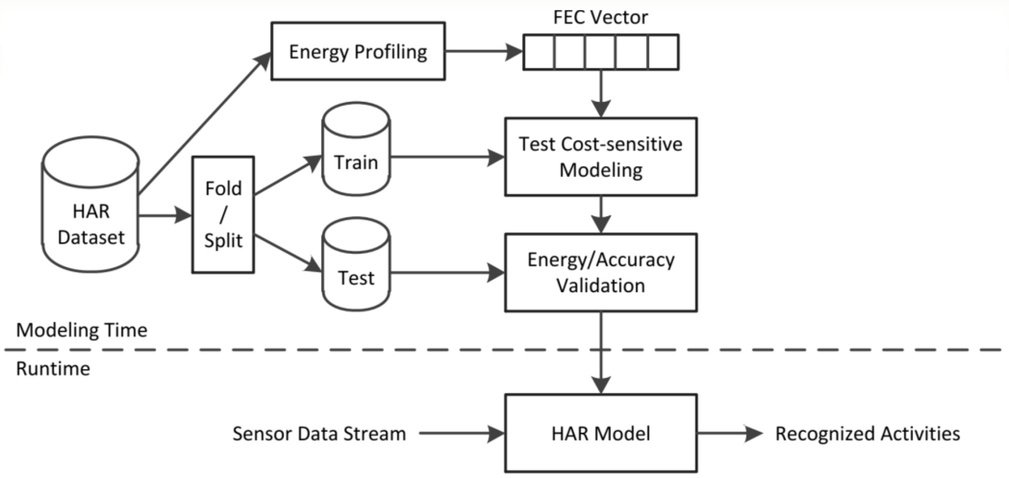


Fig. 4: The proposed HAR energy optimization framework.

For continuous attributes (which is the case for the HAR problem), C4.5 uses maximum entropy-based discretization to split the range of each attribute into two pieces. In this case, function *V* will return these two ranges and S_v is the subset of *A* belonging to range *v*.

The gain measure defined in Equation 2 introduces an inductive bias into the tree learning algorithm, which places more informative attributes nearer to the root of the tree. In order to introduce cost awareness to the learning algorithm, some researchers propose alternative measures, such as the cost sensitive gain (*CSG*) in Equation 3 as suggested by Tan et al [19] in which *C(A)* is the cost of testing attribute *A*.

$$CSG(S,A) = \frac{G(S,A)^2}{C(A)} \quad (3)$$

Nunez et al [20] proposed a weighted CSG measure (Equation 4) which allows adjusting the relative importance of costs by selecting the value of a *w* weight constant.

$$WCSG(S,A) = \frac{2^{G(S,A)}-1}{(C(A)+1)^w} \quad (4)$$

D. *The Proposed Framework*

An overall view of the proposed framework is depicted by Fig. 4. This can be divided into two main parts: Modeling time and runtime. At modeling time, a labeled HAR dataset is employed for energy profiling, training the model, and testing it. The profiling step measures the energy consumption of extracting various features and so produces a Feature Extraction Cost (FEC) vector. This vector is later used by the test-cost sensitive modeling algorithm to train the model using a fraction of the dataset. The trained model is validated in terms of both energy and prediction accuracy. The energy-error product is a viable measure for model validation. A model which passes the validation step can be utilized at runtime for recognizing human activities from sensor data.

IV. Experiments

In order to evaluate the proposed approach's effectiveness in feature extraction cost awareness, a set of experiments are set up. This section presents the details of the experiments and discusses the results.

A. *Experimental Setup*

1) *Dataset*

In order to assure the validity of the evaluations, a real-world dataset is used for the experiments. This dataset, provided by WISDM lab [5], contains cellphone tri-axial accelerometer data collected by 29 volunteer subjects. Each data record contains several fields, namely three acceleration values, a timestamp, a user ID, and an activity class label. Activity class labels feature one of 6 possible values: walking, jogging, ascending stairs, descending stairs, sitting, and standing.

2) *Feature Extraction*

The raw dataset contains more than 1 million sensor reading records sampled at a rate of 20Hz. The 43 features of Table I have to be extracted from the raw sensor signals. For extracting these features, a transformation tool [14] is developed and published by WISDM lab members. This tool segments sensor signals into 10-seconds segments of 200 samples and calculates a feature value tuple per segment. The Java source code of this transformation tool is also released. The present work instruments this Java source with an energy characterization code for discovering the energy cost of feature extraction.

3) *Energy Characterization*

The proposed computational energy optimization approach requires the precise characterization of feature extraction energy costs (The FEC vector in Fig. 4). For the experiments, the present work utilizes an ASUS Zenfone 2 smartphone with an Intel Atom main processor, which runs on an Android 6 operating system. The RAPL (Running Average Power Limit) interface [21] is employed to access the processor energy counters via the Android kernel sysfs interface [22]. In order to minimize any side effects, other processing tasks are disabled while profiling the feature extraction code. Energy usage is measured and averaged over the whole WISDM dataset, with the results having been presented earlier in Table 2.

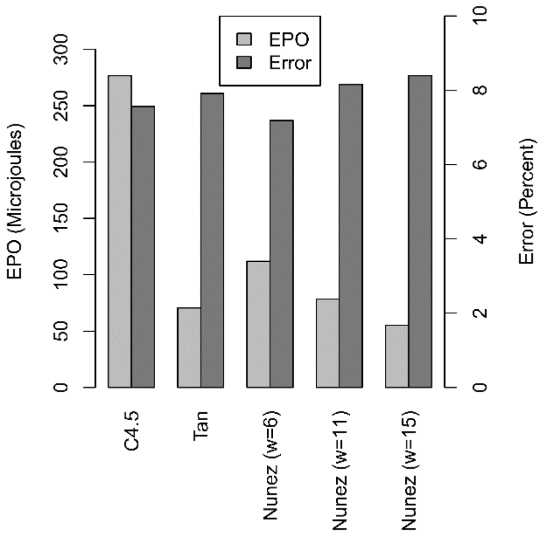


Fig. 5: Recognition error and Energy per Opration for different learning algorithms.

4) *Energy-aware Activity Recognition*

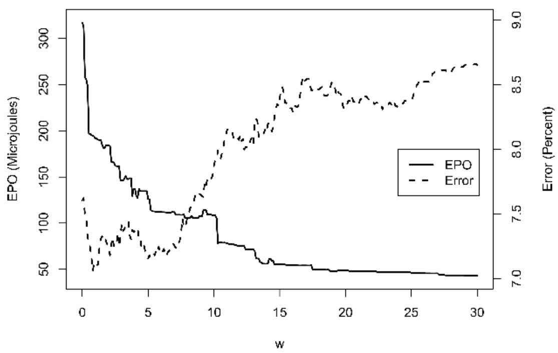
After the energy consumption behavior of the features is characterized, a test-cost sensitive decision tree algorithm employs the cost vector to build the model. For this purpose, the present study extends the open-source Weka [23] data mining software and adds the test-cost sensitive decision tree learning capability. The C4.5 algorithm (known as J48 in Weka) is extended to accept the feature extraction cost vector and to consider costs while constructing the tree. The cross-validation part of the software is also extended to calculate and report the energy cost of the classification operations. Furthermore, to be able to run Weka on the Android platform, it was necessary to remove the graphical parts of the software which are not supported on the Dalvik Java virtual machine. The energy cost of each recognition operation is defined as the sum of the costs of the tests performed until a decision node is visited, with the exception that each node only imposes a cost when it is first visited. The cost of the next visits to the same node is considered as zero since the test cost is already paid. All experiments conducted throughout the current work are performed by 10-fold cross validation.

B. *Results*

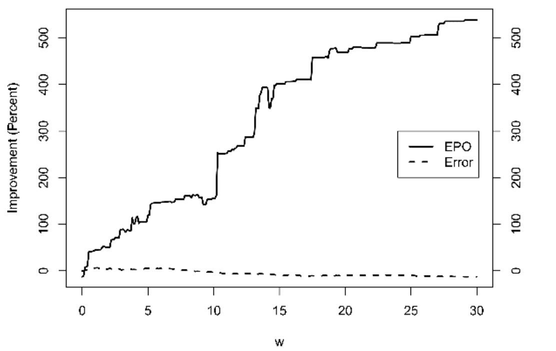
The present study employs two different measures for evaluating the HAR models, namely energy per operation (EPO) as a measure of energy consumption and recognition error as a measure of prediction accuracy. EPO refers to the average amount of energy consumed (in µJ) for each activity recognition operation. Recognition error is the percentage of incorrect predictions. Fig. 5 shows the EPO value for the cost-insensitive C4.5 algorithm and cost-sensitive Tan and Nunez algorithms. The Nunez algorithm experiment is performed for three different *w* constant values. As depicted in Fig. 5, the usage of a proper cost-sensitive model can significantly decrease energy consumption at the low cost of prediction error.

As previously mentioned, the role of constant *w* in the Nunez algorithm is to make a tradeoff possible between energy consumption and recognition accuracy. To study the effect of this constant on error and EPO, the HAR model is built and evaluated for *w* values in the range of [0,30] with an increment step of 0.1. Fig. 6a demonstrates how EPO and error are affected by the gradual increase in the value of *w*. In order to better highlight the outcome of the tradeoff, Fig. 6b reports the same tradeoff variables using similar scales, in terms of the percentage change from each point to the starting point (cost-insensitive model).

As seen in Fig. 6, the outcome of the tradeoff between energy consumption and recognition error is promising. However, a question remains regarding the proper value of weight *w*. One method of choosing this value is to set a maximum threshold value for the modeling error and choose a *w* that leads to minimum energy consumption without exceeding the desired error threshold. Another approach is to utilize a mixed performance measure that is composed of both energy consumption and error measures. Fig. 7 provides the performance of the model for such a measure: energy-error product (EEP). According to this graph, a proper selection for *w* can be around 15 after which no significant decrease in EEP is observed.



(a) Error and EPO vs *w*.



(b) Error and EPO percentage change vs *w*.

Fig. 6: The effect of Nunez *w* constant value on recognition error and Energy per Operation

Table 3: Comparison of the results.

Model	Energy Consumption (µJ)			Accuracy (%)	EEP
	Feature Extraction	Activity Classification	Total		
LR [5]	652.9	21.8	674.7	85.2	9986
MLP [5]	652.9	148.6	801.5	89.7	8256
Ensemble [24]	652.9	187.8	840.7	94.0	5044
C4.5 [5]	276.6	17.4	294.0	92.4	2234
Proposed (Nunez, *w*=6)	112.0	16.1	128.1	92.8	922
Proposed (Nunez, *w*=11)	78.6	15.7	94.3	91.8	773
Proposed (Tan)	70.5	14.4	84.9	92.1	671
Proposed (Nunez, *w*=15)	55.2	15.3	70.5	91.6	592

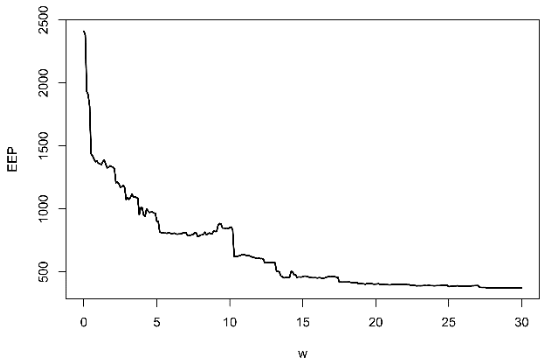


Fig. 7: The effect of Nunez *w* constant value on Energy-Error Product (EEP).

In order to evaluate the merits of the proposed approach, it is compared with some other models: Linear Regression (LR), Multilayer Perceptron (MLP) and Decision Tree (C4.5), which are all used in [5], and an Ensemble of these three models which is used in [24]. The experimental environment is the same as the one used for previous experiments where the dataset provided by the WISDM lab [5] is used as the input dataset and Weka data mining software [23] is utilized for evaluating the compared models. All accuracy values are reported using 10-fold cross validation on the models and the energy consumption values are measured using the RAPL interface [21] of the smartphone under test.

Table 3 provides the results of the comparisons where energy consumption of the two computation layers of Fig. 2 are reported separately. The fact that feature extraction energy cost is significantly higher than the classification cost, approves the main motivation of the paper which is energy optimization at feature extraction layer. The table uses some different configurations of the proposed approach. Although some of the compared models provide a marginally better recognition accuracy, the proposed method consistently outperforms the other models in terms of energy consumption and energy-error product (EEP).

V. Conclusions

While smartphones are convenient and attractive devices for human activity recognition, the challenge posed by their limited battery capacity should not be neglected. The current paper investigates the energy optimization of HAR operations at the computation layer or more specifically, at the feature extraction layer via cost-sensitive decision tree learning. Experiments show that at this layer of HAR tasks lies great opportunity to save energy. Future work involves a comprehensive study of energy bottlenecks in applied learning algorithms on smartphones. Energy bottleneck refers to points of computation where much of energy is consumed for little or no gain in prediction accuracy. Identifying these points can be an important step towards developing a smartphone-friendly machine-learning engine for HAR and other applications in IoT.

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